**Indonesian Journal of Electrical Engineering and Computer Science**
Vol. 33, No. 1, January 2024, pp. 63~70
ISSN: 2502-4752, DOI: 10.11591/ijeecs.v33.i1.pp63-70 

# Biomedical signal compression using deep learning based multi-task compressed sensing

**Shruthi Khadri[1], Naveen K Bhoganna[2], Madam Aravind Kumar[3]**
[1]Department of Electronics and Communication, BEST Innovation University, Anantpur, India
[2]Department of Electronics and Communications, BGSIT, Adichunchanagiri University, Mandya, India
[3]Department of Electronics and Communications, West Godavari Institute of Science and Engineering, Tadepalligudem, India

**Article Info**

***Article history:***

Received Jul 4, 2023
Revised Sep 26, 2023
Accepted Oct 19, 2023

***Keywords:***

Generalization
MIMIC-II
Multi-task compressed sensing
Reconstruction
Robustness

**ABSTRACT**

Real-time transmission of biomedical signals is immensely challenging and requires cloud and internet of things (IoT) infrastructure. Security is also an important factor; however, to accomplish this, a reconstruction method is developed in which the entire signal is supplied as an input, the primary portion is considered here, and the signal is further encoded and transmitted to the destination. Electrocardiogram (ECG) compression for the lightweight wireless network is quite challenging for long-term healthcare monitoring. Compressed sensing (CS) involves efficient encoding mechanisms for error rate estimation for reconstruction and energy consumption for wireless transmission of data. We propose a multi-task compressed sensing (MT-CS) reconstruction mechanism in this study for ECG compression of data is most chosen for a wireless network system that has various sensors embedded in it. This model further extracts the essential adaptive features for correlation existing in the ECG signals. The performance of the proposed MT-CS reconstruction mechanism is evaluated on the multiparameter intelligent monitoring in intensive care (MIMIC-II) dataset, which ensures its robustness and generalization. The results obtained upon simulation ensure that the proposed MT-CS based reconstruction approach ensures excellent reconstruction signal with fewer measurements in comparison with the existing state-of-art CS techniques.



***Corresponding Author:***

Shruthi Khadri
Department of Electronics and Communication, BEST Innovation University
Anantpur, India
Email: shruthik_12@rediffmail.com

## 1. INTRODUCTION

There is a rapid increase in the internet of things (IoT) being utilized in various fields, however, in the certain domain that includes healthcare, the use of IoT seems to be at a slower pace [1]. IoT in the medical domain has a collection of people as well as equipment that require wireless communication systems for the interchange of data on healthcare, and monitoring of patients resulting in a better-improved quality of patient healthcare. Healthcare IoT improvises the quality of patient life as well as creates an improved cost-efficient environment and higher quality of services. The signal electrocardiogram (ECG) is an essential signal that is recorded by the use of medical equipment, it detects and amplifies signals occurred at heartbeats. Various heart abnormalities can be detected by the use of these signals that could be fatal [2], [3]. The sampling of these signals is done for frequencies more than 100 Hz. Whereas the abnormality in beats seldom varies, hence these signals have to be recorded and studied for an extended period. Recently, an algorithm that is energy-saving and rapid is developed for compressive sensing (CS) that is utilized for compressing and sampling sparse signals simultaneously [1], [2]. CS has a vast range of applications for signal processing that includes biomedical enhancement, compression as well as recovery [3]. CS has also been applied for ECG signals while assuming that these signals can be compressed [4]–[7]. Compression based on CS is given as the best most efficient energy because of its decreased complexity as well as the lesser execution time of central processing unit (CPU). Considering that the phase of compression in CS is fast, not complicated as well as energy efficient, various sensing applications prefer CS for compression. Although, the phase of recovery has high complexity and is non-linear considering demands relating to computation that utilize processors having huge memory on-board, speed as well as capable computations. CS has evolved as an efficient technique for the reconstruction of sparse signals that include ECG by the use of inherent sparse. Besides, there are a few constraints relating to CS that are addressed using deep learning methods being integrated:

- Reconstruction methods and algorithms: The CS traditional reconstruction techniques that include orthogonal meeting pursuit (OMP), and base pursuit (BP) consist of constraints on computations, specifically for ECG signals of higher dimension. Recent studies have shown deep learning techniques that include recurrent neural network (RNN), and convolutional neural network (CNN), used as accurate and effective means for reconstruction algorithms, while decreasing the complexity in computations and also improving the quality of reconstruction.
- Robustness towards noise: The recorded ECG signals have various noise contaminations as well as artifacts in them that compromise the quality of the CS. The methods in deep learning can learn features that are robust automatically as well as the noisy data representation that enhances the ECG reconstruction reliability.
- Adaptable: A set sensing matrix is used for CS and a particular sparse base is assumed for the signals. Although, the sparse structure for signals in ECG differs among individuals and over a course of time. Models in deep learning learn representations that are data-driven as well as sparsity structures, hence learning the differences and enhancing performances for reconstruction.
- Combining with various data sources: The main aim of CS is to effective reconstruction and acquisition of signals, combination of ECG signals along with various other physiological data is possible using deep learning, which includes respiration, blood pressure levels, or data motion. This permits a more detailed study and analysis of the patient's medical status, therefore enhancing the performance.

Considering deep learning methodologies are used in CS, researchers work to resolve these constraints and introduce higher accuracy, efficiency as well as the robustness of processing techniques for ECG signals that are more adaptable for healthcare IoT systems. This integrative way can enhance the ECG’s state of art signal as well as affect patient monitoring and care. The researches [8], [9], data learning framework designs are developed, namely consistent label joint crossed domain data learning (LC-XDJDL) and joint crossed domain data learning (XDJDL) for further enhancing the quality of ECG as well as improve the diagnosis based on photoplethysmography (PPG). Further working on methods, the joint data learning proposed framework focuses on the maximum power by optimization of ECG and PPG signals simultaneously along transforms relative to their sparsity codes and information of diseases.

A wearable IoT device for exercise, rehabilitation as well as monitoring is introduced in [10], [11]. This system is developed for efficiency evaluation for training rehabilitation to record parameters physically such as ECG, electromyogram (EMG) signal, exercise as well as the temperature of the body. Van-Sloun *et al.* [12], a data combination multimodal technique is developed to increase the accuracy of beat detection in monitoring ambulatory. The PPG and ECG signals as wavelets are isolated by utilizing wavelet distinct transform (DWT) and emerge as an average weight for the generation of a combined signal feature. The max detection technique is used with the final signal combination. Additional computing sensors as well as power are needed to uphold this technique. Ianni and Airan [13], an ultra-less energy ECG monitor wearable on the wrist was developed based on IoT, wherein the device is wearable and lightweight for the users. Additionally, to measure the ECG raw waveforms as well as heart rate, this equipment also tracks the location and physical activities. Using the sensory platform for healthcare in residing environments (SPHERE), the health condition of patients is evaluated by a collection of data. The researches [14]–[16], an economical internet of medical things (IoMT) ECG is developed for recording and monitoring heart abnormalities that are utilized in real-world applications. To eliminate noise in the signals that are reported using non-medical equipment, a denoising technique based on the cloud is introduced that aims at using deep neural methods with the frequency-time domain in two phases. The ECG signal is sent to this domain using the stockwell fraction transform (FrST) and is applied to the robust deep dual step network (Deep RSTN) to omit noise. The researches [17]–[20], a task sparsity cognizant signal processing method is used to regain the required information. Particularly, length adaptive correlating-assisting compression (CCAL) is introduced for which ECG signal is separately compressed for every pseudo period for withholding information of every individual heartbeat. Due to this, there is a dynamic difference in the length of compression that is seen by evaluating coefficients among adjacent sections. There exist many breaches in the ECG signals methods [21]–[23] of processing that include autoencoders, compressive sensors as well as deep learning that have to be resolved for enhancing its accuracy and efficiency as well as applicability for healthcare IoT networks. These loopholes are inclusive of noise robustness, high data dimension scalability, integration, adapting with various physiological data as well as interpretable methods of deep learning. Resolving these limitations leads to higher efficiency and relating ECG techniques of signal processing, resulting in improved ECG recording and monitoring. The rising need for effective ECG signal processing using IoT systems [24] has encouraged exploring various approaches. The combination of deep learning methods with autoencoders as well as CS produces results of effective and accurate reconstruction of ECG signals. CS minimizes the acquisition of data as well as transfer needs by utilizing ECG sparsity signals, where the autoencoders learn the required presentation of reconstruction accurately. Deep learning methodologies furthermore enhance the efficiency and accuracy of computation in the process of reconstruction. The combined methods resolve limitations of healthcare systems using IoT that provide well-seen enhancements in the monitoring of ECG patients as well as practitioners.

- An efficient multi-task compressed sensing (MT-CS)-based reconstruction method is developed that incorporates the correlation existing in the ECG signals.
- A CS model is developed for ECG signals that involve efficient encoding mechanisms for error rate estimation for reconstruction and energy consumption for wireless transmission of data.
- The proposed MT-CS approach is an effective and accurate multiple-channel ECG data retrieval that has the least information loss concerning clinical data.

This research is organized is as follows: first section of the research work starts with background of IoT and ECG, further development of biomedical signal reconstruction with CS is discussed along with various existing model and their shortcomings. This section is concluded through motivation and contribution of research work. Second section presents the mathematical modelling of multi-tasking-based CS along with algorithm. MT-CS is evaluated in fourth section of this research along with comparison with the existing model.

## 2. PROPOSED METHOD

Consider $W = [w_1, w_2, \dots, w_K]$ belongs to $Q^{M\times K}$ depicts sample data of ECG for a fixed period has channels-L. Every sparse is depicted with a sparse coding that is overcomplete $\Upsilon$ belongs to $Q^{M\times P}$ where $M$ is lesser than $P$. This is expressed as follows in (1). In (1) given above, $Z = [\beta_1, \beta_2, \dots, \beta_K]$ belongs to $Q^{P\times K}$ expresses the sparse matrix that is not known, where $\beta_h$ depicts the coefficient vector of sparsity to $w_h$ respectively. Herein, the data that is compressed for $X$ belongs to $Q^{L\times K}$ is received using a linear collection of W as a random matrix $\Psi$ belongs to $Q^{L\times M}$ for which L is lesser than M. This is given in the (2) stated.

$$W = Z\Upsilon \tag{1}$$

$$W = Z\Upsilon \tag{2}$$

Considering the (2), $D$ belongs to$Q^{L\times K}$ expresses the noise matrix that reassures the condition $\|D\|_E$ is lesser than or equal to $\tau$, wherein $\tau$ is the root square mean error. In (2), shows a measurement of various vectors problem (MVV). Adjacent channels have similar features that can be utilized to enhance the learning by the sparse coding as well as result in the reconstruction of sparsity, it is necessary to formulate a sparsity recovery joint problem. The resolution of an MVV problem uses joint sparsity as given in the (3).

$$\text{minimum}_Z 2^{-1}\|X - Z\Upsilon\Psi\|2\ 2\ + \partial\|Z\|_{1,2} \tag{3}$$

In the (3), $\|.\|_{1,2}$ is the L-norm for $1, 2$ that uses sparse correlation for MECG, where $\partial$ is used to denote a parametric regularization that results in a swap between the consistency of data and sparsity? There are collective groups that exist in every row, where every row has coefficients with an L channel that improves accuracy. Orthogonal standardized wavelet based on the reconstruction of CS does not succeed in reconstructing signals that are structured such as ECG for a decreased count of compressed measures. This resulted in widespread study and use of dictionaries, where the data given is trained in a place of fixed transforms that are off the shelf. Considering the given signal data for training from samples I where $W_s = [W_1, W_2, W_3, \dots, W_I]$ for which $W_1$ belongs to $Q^{M\times K}$ is the data channel L from every object and $W_1$ belongs to $Q^{M\times IK}$ data for I samples. The sparse coding aims to obtain an ideal sparse coding $\Psi$ belongs to $Q^{M\times P}$ that sparse the data as a collected of matrix coefficients for various samples, such as $\rho =$

$[\rho_1, \rho_2, \ldots, \rho_I]$ belongs to $Q^{P\times IK}$ for which $\rho_J$ belongs to $Q^{P\times K}$ where $J = 1, 2, \ldots, I$ are sparsity presentations in jth sample. The main purpose of this is to select the best-fit sparsity matrix $\rho_J$ that denotes the stated training data. The $\Psi$ sparse coding is stated as an over complete, for which M is lesser than P. Generally, shallow learning has an iterative approach in update columns in the sparse coding matrix $\Psi$ resulting in sparse presentations of training data $W_s, s = 1, \ldots, I$, and the shallow learning is updated based on the present sparse denoted as $\rho_J$. The (4) solves the given problem of optimization.

$$\text{minimum}_{\Psi,\rho}\{\|W_s - \Psi\,\rho\|_E\} \text{ where } \|\rho_i\|_0 \text{ is lesser than } R(i = 1,2,3 \ldots, K) \tag{4}$$

Considering (4), $\|.\|_E$ is termed the Frobenius norm. $\rho_i$'s are the vectors columns in $\rho$. The problem specified above has a limitation while considering the level of sparsity in signals for training samples that include max non-zeros R that occur for every $\rho_i$. For this study, the k-singular value decompositions data training algorithm is used to learn the sparse coding. The MT-CS reconstruction proposed in this study is performed for ECG compression of data and is most chosen for a wireless network system that has various sensors. A continuing record of multiple channel ECG for a single patient's health monitoring as well as real-time transmission of data. The main motive of this study is the effective and accurate multiple-channel ECG data retrieval that has the least information loss concerning clinical data. Considering various channels having joint sparsity, we utilize their correlation spatially as well as require a sparsity resolution by use of various completing leaning dictionaries developed based on various structures that are obtained in the multiple channel ECG signals. The stated problem is a measurement of various vectors (MVV) problems for the reconstruction of joint CS that can be developed using mixed regularization $k_{2,1}$ stated in (3). We further enhance and improvise this (3) by considering the group sparsity which is given as (5).

$$\text{minimum}_Z 2^{-1}\|X - Z\beth\|2\;2\; + \partial \textstyle\sum_{i=1}^{P} \quad \|z_{fi}^S\|_2 \tag{5}$$

In (5), $z_{fi}^S = [z_{(i,1)}, z_{(i,2)}, \ldots, z_{(i,K)}]$ is the sparsity coefficients of matrix Z in a row that depicts the correlating coefficients of sparsity relating to channel K leading to a collection f and the parameter $\partial$ is a positive regularisation that results in a swap fidelity as well as sparsity of reconstruction in multiple channel ECG. The formulation stated above could be simplified by retaining the count of groups equal to the count of rows Z. This problem of joint sparse minimization is solved in (5), where a method is applied that presents an auxiliary transform and parameter, this method is called alternating primal direction scheme for multipliers (ADMM). This is incorporated into the (7). In (6), $y^T$ depicts the matrix row Y. Here, the lagrangian form augmented for the above-stated problem is resolved as (7).

$$\textstyle\sum_{i=1}^{P} \quad \|y_i^S\|_2 = \text{minimization}_y\|Y\|_{2,1} \text{ such that } Y = Z \text{ and } X = Z\beth \tag{6}$$

$$\text{minimum }_{Z,Y}K\left(Y, Z, \lambda_1^{(j)}, \lambda_2^{(j)}\right) = \text{minimum }_{Z,Y}\|Y\| - \lambda_1^S(Y - Z) + \rho_1(2)^{-1}\|Y - Z\|_2^2 - \lambda_2^S(\beth Z - X) + \rho_1(2)^{-1}\|\beth Z - X\|_2^2 \tag{7}$$

Considering the (7), $\lambda_1$ belongs to $Q^{P\times K}$ and $\lambda_1$ belongs to $Q^{M\times K}$ are both multiplier matrices, $\rho_1, \rho_2$ greater than 0 are termed parametric penalties. The solved ADMM problem in this phase is primal, hence the updating of expressions $\lambda_1$ as well as $\lambda_2$ are phases of gradient descent. The resolution of the above problem with the ADMM primal framework is as given in (8).

$$Z \leftarrow \frac{\rho_1 Y - \lambda_1 + \rho_2 X\beth^S + \beth^S\lambda_2}{\rho_1 H + \rho_1\beth^S\beth} \tag{8}$$

$$Y \leftarrow (Z + {\rho_1}^{-1}\,\partial_1, {\rho_1}^{-1}) \text{ Shrink by row} \tag{9}$$

$${\lambda_1}^{(1+J)} \leftarrow {\lambda_1}^J - \alpha_1\rho_1\,(Y - Z) \tag{10}$$

$${\lambda_2}^{(1+J)} \leftarrow {\lambda_2}^J - \alpha_2\rho_2\,(Z\Psi - X) \tag{11}$$

$$y^S = \text{maximum }\{\|q^S\|_2 - {\rho_1}^{-1}, 0\}\,\frac{q^S}{\|q^S\|_2} \text{ for which } q^S{=}z^S + {\rho_1}^{-1}\,{\partial_1}^S \tag{12}$$

In which $\alpha_1$ and $\alpha_2$ are parameters of relaxation. The range allowed for ADMM is an interval of $(0, \frac{\sqrt{5}+1}{2})$ corresponding to the same (7), while convergence is rapid, Y is updated for shrinkage of row given as mentioned in (12). The MT-CS ECG reconstruction algorithm is mentioned below in algorithm 1 and stated above aids the computation of a given problem. The proposed methodology proves that the basic phases of the multi-adaptive multiple-channel ECG based sparse coding reconstruction process are given in the algorithm below. Where initially assumed $W_{int}$ for multiple-channel ECG data. However, orthogonal meet pursuit (OMP) can produce a much swifter sparse approximately in comparison to the basic pursuit.

Algorithm 1. MT-CS ECG reconstruction

Input: $X,\ \Psi, \Upsilon,\ \Upsilon_{M,P}$ and $\Upsilon_{P1}, \Upsilon_{P2}, \Upsilon_{P3}, \dots, \Upsilon_{Pp}$ and Thresh
CS reconstruction by OMP
Step 1: $\text{minimum}_{\text{Zbelongs to}Q^{P\times K}} \|Z\|_0$ such that $X = Z_{OMP}\Psi\Upsilon$
Step 2: $W_{int} = \Upsilon Z_{OMP}$
Step 3: $c_{maximum} = \text{maximum} \mid (W_{int}) - \underline{W_{int}} \mid$
Step 4: if $c_{maximum}$ is lesser than Thresh then
Step 5: $\text{minimum}_{\text{Zbelongs to}Q^{P\times K}} \|Z_{MP}\|_{1,2}$ such that $X = Z_{MP}\Psi\Upsilon_{MP}$
Step 6: $W = Z_{MP}\Upsilon_{MP}$
Step 7: else
Step 8: for $J = 1$ to $M_E$ do
Step 9: if $\mid |(W_{int})| - \underline{W_{int}} \mid$ greater than $c_{maximum}$ then
Step 10: $\vartheta = \text{round}\left(\frac{j*p}{M_E} + \frac{1}{2}\right)$
Step 11: $\text{minimum}_{\text{Zbelongs to}Q^{P\times K}} \|Z_{P\vartheta}\|_{1,2}$ such that $X = Z_{P\vartheta}\Psi\Upsilon_{P\vartheta}$
Step 12: $W = Z_{P\vartheta}\Upsilon_{P\vartheta}$
Step 13: end if
Step 14: end for
Step 15: end if
Step 16: return W

## 3. PERFORMANCE EVALUATION

The experimental analysis here is carried out in Matlab, and the resultant outcome of the simulations depicts the effectiveness of the proposed model. To carry out the simulations it requires a 200 m*200 m square of surveillance and has 280 densely placed sensor nodes. The energy required is 10 J for each sensor node. The sink node is placed in external premises outside observation. The settings for data collection are $w\ 1 = 0.5, 0.1$ and $0.4$; $w\ 2 = 0.9, 0.5,$ and $0.9$; the range of intervals is $R = 10$ m; and time is $T = 950$ s. The proposed algorithm is evaluated on the MIMIC-II dataset [25], which ensures its robustness and generalization.

### 3.1. EEG signal reconstruction

The resultant graph is plotted as shown in Figure 1, by comparing the proposed method with the existing MIC-CSDG [26] technique based on reconstruction error (RE) with various other parameters considered. The below graph depicts the original signal and reconstructed signal of the transmission line with a training iteration count of 50. For evaluation purposes, the 250 sample points are evaluated in the testing phase. The reconstructed signal in the graph mirrors the original signal's path and the value is increased by providing accurate precision for the reconstructed signal in comparison with the proposed method. The reconstructed signal almost follows the same path as the original signal.

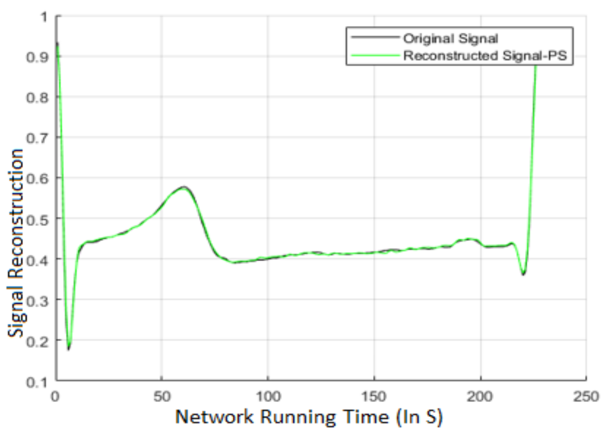


Figure 1. ECG signal reconstruction

### 3.2. Reconstruction error comparison

Figure 2 demonstrates the reconstruction error comparison of the proposed method with the existing method the network running time is less in comparison with the existing method, which states that the proposed model has minimum error reconstruction. Whereas, in the existing system, the error reconstruction is increased with the network running time it reaches a maximum value when the network running time is 900. Whereas the proposed method has the least reconstruction error even though the network running time is increased when the network running time reaches 900 values also the proposed method depicts reconstruction error, upon conclusion the proposed method performs effectively in comparison with the existing system.

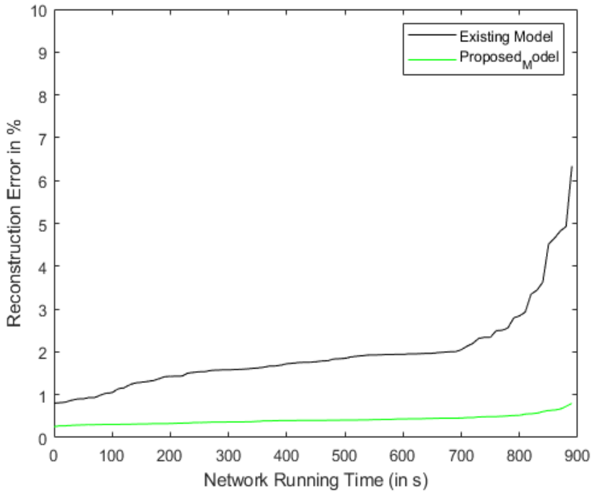


Figure 2. Reconstruction error comparison

### 3.3. Energy comparison for reconstruction

Figure 3 demonstrates the energy comparison for the reconstruction of the proposed method with the existing method, the amount of energy consumed by the sensor nodes for reconstruction is evaluated, and the sample nodes considered by the existing system enhance the network's efficiency. These results in higher energy comparison for the sensor nodes, the maximum drift in energy consumption is seen for 250 sensor nodes, as in case of the proposed system the energy consumption for reconstruction is less in comparison with the existing method for 250 sensor nodes the energy comparison is less than the existing system. Henceforth the proposed model utilizes less energy in comparison with the existing system.

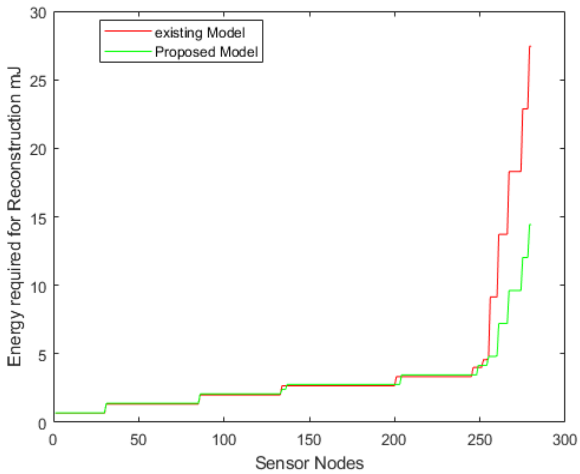


Figure 3. Energy required for reconstruction comparison

## 4. CONCLUSION

In this paper, an efficient MT-CS-based reconstruction approach is proposed, which extracts the features of the ECG signal to enhance the reconstruction quality for the CS mechanism. An MT-CS approach is developed which generates a reconstruction method, which is further evaluated on the MIMIC-II dataset. The experimental evaluation is carried out for various testing ECG signals with a repeated number of iterations and the results are plotted in the form of a graph estimating the energy comparison for the reconstruction method, reconstruction error comparison, and ECG signal reconstruction, which generates better results in comparison with the existing system. In a given real-time scenario, it is necessary to enhance the energy utilization for the ECG signals acquired using a reconstruction mechanism. To conclude the proposed MT-CS approach performs efficiently in generating accurate results.

## REFERENCES


[1] A. John, S. J. Redmond, B. Cardiff, and D. John, "A multimodal data fusion technique for heartbeat detection in wearable IoT sensors," *IEEE Internet of Things Journal*, vol. 9, no. 3, pp. 2071–2082, Feb. 2022, doi: 10.1109/JIOT.2021.3093112.

[2] C. Beach *et al.*, "An ultra low power personalizable wrist worn ECG monitor integrated with IoT infrastructure," *IEEE Access*, vol. 6, pp. 44010–44021, 2018, doi: 10.1109/ACCESS.2018.2864675.

[3] P. Aghaomidi *et al.*, "DeepRTSNet: deep robust two-stage networks for ECG denoising in practical use case," *IEEE Access*, vol. 10, pp. 128232–128249, 2022, doi: 10.1109/ACCESS.2022.3225899.

[4] X. Bian, W. Xu, Y. Wang, L. Lu, and S. Wang, "Direct feature extraction and diagnosis of ECG signal in the compressed domain," *IEEE Sensors Journal*, vol. 21, no. 15, pp. 17096–17106, Aug. 2021, doi: 10.1109/JSEN.2021.3081577.

[5] M. Al Disi *et al.*, "ECG signal reconstruction on the IoT-gateway and efficacy of compressive sensing under real-time constraints," *IEEE Access*, vol. 6, pp. 69130–69140, 2018, doi: 10.1109/ACCESS.2018.2877679.

[6] M. Abdelazez, S. Rajan, and A. D. C. Chan, "Signal quality assessment of compressively sensed electrocardiogram," *IEEE Transactions on Biomedical Engineering*, vol. 69, no. 11, pp. 3397–3406, Nov. 2022, doi: 10.1109/TBME.2022.3170047.

[7] Y. Chen, Q. Zhao, X. Hu, and B. Hu, "Multi-resolution parallel magnetic resonance image reconstruction in mobile computing-based IoT," *IEEE Access*, vol. 7, pp. 15623–15633, 2019, doi: 10.1109/ACCESS.2019.2894694.

[8] Y. Liu, A. Liu, X. Liu, and X. Huang, "A statistical approach to participant selection in location-based social networks for offline event marketing," *Information Sciences*, vol. 480, pp. 90–108, Apr. 2019, doi: 10.1016/j.ins.2018.12.028.

[9] V. Jelicic, M. Magno, D. Brunelli, V. Bilas, and L. Benini, "Benefits of wake-up radio in energy-efficient multimodal surveillance wireless sensor network," *IEEE Sensors Journal*, vol. 14, no. 9, pp. 3210–3220, Sep. 2014, doi: 10.1109/JSEN.2014.2326799.

[10] T. Mekonnen, P. Porambage, E. Harjula, and M. Ylianttila, "Energy consumption analysis of high quality multi-tier wireless multimedia sensor network," *IEEE Access*, vol. 5, pp. 15848–15858, 2017, doi: 10.1109/ACCESS.2017.2737078.

[11] G. Yang *et al.*, "DAGAN: deep de-aliasing generative adversarial networks for fast compressed sensing MRI reconstruction," *IEEE Transactions on Medical Imaging*, vol. 37, no. 6, pp. 1310–1321, Jun. 2018, doi: 10.1109/TMI.2017.2785879.

[12] R. J. G. Van-Sloun, R. Cohen, and Y. C. Eldar, "Deep learning in ultrasound imaging," *Proceedings of the IEEE*, vol. 108, no. 1, pp. 11–29, Jan. 2020, doi: 10.1109/JPROC.2019.2932116.

[13] T. D. Ianni and R. D. Airan, "Deep-fUS: a deep learning platform for functional ultrasound imaging of the brain using sparse data," *IEEE Transactions on Medical Imaging*, vol. 41, no. 7, pp. 1813–1825, Jul. 2022, doi: 10.1109/TMI.2022.3148728.

[14] K. Dinashi, A. Ameri, M. A. Akhaee, K. Englehart, and E. Scheme, "Compression of EMG signals using deep convolutional autoencoders," *IEEE Journal of Biomedical and Health Informatics*, vol. 26, no. 7, pp. 2888–2897, Jul. 2022, doi: 10.1109/JBHI.2022.3142034.

[15] S. H. Sreedhara, V. Kumar, and S. Salma, "Efficient big data clustering using adhoc fuzzy C means and auto-encoder CNN," in *Lecture Notes in Networks and Systems*, vol. 563, 2023, pp. 353–368.

[16] H. Jiang, S. Zhao, Z. Shen, W. Deng, P. A. Wilford, and R. Haimi-Cohen, "Surveillance video analysis using compressive sensing with low latency," *Bell Labs Technical Journal*, vol. 18, no. 4, pp. 63–74, Mar. 2014, doi: 10.1002/bltj.21646.

[17] R. Mohammadian, A. Amini, and B. H. Khalaj, "Compressive sensing-based pilot design for sparse channel estimation in OFDM systems," *IEEE Communications Letters*, vol. 21, no. 1, pp. 4–7, Jan. 2017, doi: 10.1109/LCOMM.2016.2613086.

[18] S. K. Sharma, E. Lagunas, S. Chatzinotas, and B. Ottersten, "Application of compressive sensing in cognitive radio communications: A survey," *IEEE Communications Surveys and Tutorials*, vol. 18, no. 3, pp. 1838–1860, 2016, doi: 10.1109/COMST.2016.2524443.

[19] M. Abdelazez, S. Rajan, and A. D. C. Chan, "Transfer learning for detection of atrial fibrillation in deterministic compressive sensed ECG," in *Proceedings of the Annual International Conference of the IEEE Engineering in Medicine and Biology Society, EMBS*, Jul. 2020, vol. 2020-July, pp. 5398–5401, doi: 10.1109/EMBC44109.2020.9175813.

[20] M. J. Baucas, P. Spachos, and S. Gregori, "Internet-of-things devices and assistive technologies for health care: applications, challenges, and opportunities," *IEEE Signal Processing Magazine*, vol. 38, no. 4, pp. 65–77, Jul. 2021, doi: 10.1109/MSP.2021.3075929.

[21] B. Lal, R. Gravina, F. Spagnolo, and P. Corsonello, "Compressed sensing approach for physiological signals: a review," *IEEE Sensors Journal*, vol. 23, no. 6, pp. 5513–5534, Mar. 2023, doi: 10.1109/JSEN.2023.3243390.

[22] X. Zhang, J. Li, Z. Cai, L. Zhao, and C. Liu, "Deep learning-based signal quality assessment for wearable ECGs," *IEEE Instrumentation and Measurement Magazine*, vol. 25, no. 5, pp. 41–52, Aug. 2022, doi: 10.1109/MIM.2022.9832823.

[23] W. Bin Qaim *et al.*, "Towards energy efficiency in the internet of wearable things: a systematic review," *IEEE Access*, vol. 8, pp. 175412–175435, 2020, doi: 10.1109/ACCESS.2020.3025270.

[24] A. M. Rahmani, W. Szu-Han, K. Yu-Hsuan, and M. Haghparast, "The internet of things for applications in wearable technology," *IEEE Access*, vol. 10, pp. 123579–123594, 2022, doi: 10.1109/ACCESS.2022.3224487.

[25] D. J. Scott *et al.*, "Accessing the public MIMIC-II intensive care relational database for clinical research," *BMC Medical Informatics and Decision Making*, vol. 13, no. 1, p. 9, Dec. 2013, doi: 10.1186/1472-6947-13-9.

[26] Z. Sun, L. Lan, C. Zeng, and G. Liao, "A novel efficient data gathering algorithm for disconnected sensor networks based on mobile edge computing," *Wireless Communications and Mobile Computing*, vol. 2022, pp. 1–11, Apr. 2022, doi: 10.1155/2022/4763153.

## BIOGRAPHIES OF AUTHOR


**Shruthi Khadri** obtained B.E. degree in Telecommunication Engineering from Atria Institute of Technology affiliated to VTU Belagavi. She has obtained M.Tech. degree in Digital Electronics and Communication from M S Ramaiah Institute of Technology college affiliated to VTU Belagavi and currently pursuing PhD at Bharthiya Engineering Science and Technology Innovation University. She has published 5 papers in renowned journals and conferences. Her area of interest is signal processing, Bio medical signals and artificial Intelligence. She can be contacted through this email: shruthikhadri@gmail.com.

**Dr. Naveen K Bhoganna** obtained B.E. degree in Electronics and Communication Engineering, M.Tech. degree in VLSI Design and Embedded System and Ph.D. from Visvesvaraya Technological University, Belagavi. Currently he is working as a Professor and R&D co-ordinator at BGS Institute of Technology, Adichunchanagiri University. He has 13 years of teaching experience and 9 years of research experience. His areas of research interest are VLSI, Embedded systems, bio medical signal processing, Image processing, communication and networking. He can be contacted through this email: naveenkb@bgsit.ac.in.

**Dr. Madam Aravind Kumar** obtained B.Tech. degree in Electronics and Communication Engineering, M.Tech. degree in VLSI system design from JNTUH and Ph.D. from GITAM university, Vishakapatnam. He is working at West Godavari Institute of Science and Engineering as Principal. He has 15years of teaching experience. His area of research interest are speech and signal processing, Bio medical signal processing and image processing. He can be contacted through this e-mail: drmaravindkumar@gmail.com.