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IoT driven joint compressed sensing and shallow learning approach for ECG signal-reconstruction

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ABSTRACT

Because biological signal transmission in real time might be very demanding, cloud and internet of things (IoT) infrastructure are required. To do this, the main component of the signal serves as the focal point of a reconstruction strategy that has been developed. The input is transferred to the intended destination once it has been encoded. Security is an important consideration that must not be disregarded. For long-term healthcare monitoring via lightweight wireless networks, electrocardiogram (ECG) compression is a major difficulty. Reducing energy consumption in wireless data transmission and precisely calculating error rates for data reconstruction are two essential components of compressed sensing. The application of effective encoding methods is crucial for these considerations. We present multi-task compressed sensing (MT-CS), a unique method for compressing ECG data. When used to wireless network systems with several embedded sensors, this technique is quite effective. From the ECG data, the model learns the fundamental adaptive properties needed for correlation. We use the multiparameter intelligent monitoring in intensive care (MIMIC-II) dataset to investigate the performance of the suggested MT-CS reconstruction technique in order to assess its strength and application. In comparison to current compressed sensing methods, the simulation results demonstrate that the suggested reconstruction methodology utilizing MT-CS generates high-quality reconstruction signals with fewer observations.

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1. INTRODUCTION

The internet of things (IoT) is becoming more and more common in many businesses, but its adoption in the healthcare industry seems to be happening more slowly [1]. IoT is utilized in the medical profession to build wireless communication networks that make data sharing for patient monitoring and treatment easier. This technology is essential to raising the standard of patient care. IoT integration in healthcare has shown to have major benefits, improving patient outcomes and creating more effective, cost-effective environments that offer top-notch services. One important signal that is recorded using medical equipment is the electrocardiogram, or electrocardiogram (ECG) signal. Heartbeat pulses are detected and amplified by this technique. These signals are capable of identifying a variety of potentially fatal cardiac anomalies. Beat consistency is something that they seldom stray from. Thoroughly capturing and analyzing these signals over an extended duration is crucial. Samples are taken from signals with frequency higher than 100 Hz. A novel method for compressive sensing (CS) has been developed that enables sparse signal compression and sampling to occur simultaneously [1], [2]. A popular method of signal processing with several uses, including as compression, recovery, and biomedical improvement, is compressive sensing [3]. Compressed sensing has been used in earlier research to apply compression methods to ECG signals [4]–[7].

Because of its streamlined architecture and quicker CPU execution time, compression based on CS is thought to be the most energy-efficient option available. CS is a popular choice for compression sensing applications due to its energy-efficient, simple, and quick nature. However, because of the demands of computers, navigating the recovery phase can be difficult and unpredictable. Processors with large amounts of on-board memory, quick speeds, and powerful processing capacities are needed for this. Compressive sensing has emerged as a useful method for reconstructing sparse signals, like the ECG, because of intrinsic sparseness. Deep learning methods can be used to get over some of the limitations in computer science.

- Reconstruction methods and algorithms: Traditional reconstruction methods, such as basis pursuit and orthogonal matching pursuit, come with computational limitations, especially when dealing with ECG data of higher dimensions. Reconstruction methods can now be implemented more efficiently and accurately, thanks to recent research on deep learning techniques such as convolutional neural network (CNN) and recurrent neural network (RNN). These methods enhance the quality of reconstruction while reducing the complexity of processing.
- Robustness towards noise: Noise contaminations and artifacts can have a significant impact on the quality of the CS, particularly in recorded ECG signals. Deep learning techniques have the ability to automatically generate strong features and effectively represent noisy data, resulting in enhanced reliability of ECG reconstruction.
- Adaptable: In compressed sensing, a sensing matrix is used to analyze signals and predict their sparse basis. However, the ECG signal pattern fluctuates over time and differs between individuals. Deep learning models possess the capability to comprehend sparsity structures and data-driven representations, enabling them to discern disparities and enhance reconstruction performances.
- Combining with various data sources: The main objective of compressive sensing is to achieve efficient signal reconstruction and capture. Deep learning enables the seamless integration of ECG readings with various other physiological data, including blood pressure, breathing, and mobility data. By utilizing this advanced technology, a thorough examination and analysis of the patient's health can be conducted, resulting in enhanced performance.

The goal of research is to overcome these limitations and improve the accuracy, efficiency, and reliability of ECG data processing methods. Their objective is to create more suitable methods for healthcare systems in the IoT, while also taking into account the advanced learning techniques of computer science. This comprehensive approach can significantly improve the advanced signal quality of the ECG, leading to better patient monitoring and treatment outcomes. Two data learning framework designs, LC-XDJDL and XDJDL, were created to improve the accuracy of ECG and enhance photoplethysmography (PPG) diagnosis [8], [9]. Through the utilization of a combination of K-SVD techniques, the data learning system improves efficiency by optimizing PPG and ECG signals simultaneously. Our approach involves a thorough analysis of their sparsity codes and disease information.

An innovative wearable device for exercise, rehabilitation, and monitoring is discussed in [10], [11]. This technology is designed to provide precise assessments of the efficacy of rehabilitation therapy. This device is capable of measuring a range of physiological parameters, including electromyogram (EMG) signals, body temperature, and exercise intensity. In a study referenced as [12], a method is described that leverages multimodal data to improve the precision of beat detection in ambulatory monitoring. Using the distinct wavelet transform (DWT), wavelets can be generated from the PPG and ECG data in an effective manner. Afterwards, a composite signal feature is derived by computing the average weight using these wavelets. We employ a maximum detection approach to optimize signal combination for maximum effectiveness. In order for this system to function properly, it is necessary to have additional computer sensors and a continuous power supply.

A wristwatch was developed in [13] to monitor ECG signals with low power consumption, utilizing the Internet of Things for power. The device has been meticulously designed to guarantee a lightweight construction and optimal user comfort when worn. This technology not only captures the raw ECG waveforms and heart rate, but also monitors the location and physical activity. Data is collected using the sensory platform for healthcare in residing environments (SPHERE) to assess the health status of patients. In a previous study, researchers developed an affordable ECG device specifically designed for the internet of medical things (IoMT ECG). This device has been meticulously engineered to precisely identify and track cardiac irregularities, serving a multitude of practical uses. Here is a new method to efficiently decrease noise in signals acquired from non-medical devices. This method employs sophisticated deep neural algorithms in the frequency-time domain to efficiently remove noise. The process is completed in two stages to achieve the best possible outcomes. The ECG signal is sent to this domain via the FrST and is then used by the deep RSTN to efficiently remove any interference [14].

The article from Baucas *et al.* [15] describes a method for obtaining the required data by taking into account the sparsity of signal processing tasks. Length adaptable correlating-assisting compression (CCAL) allows for the individual compression of ECG data for each pseudo period, ensuring that pulse details are preserved. When examining the coefficients of neighboring regions, a clear difference in the compression length becomes apparent. Further research and development are needed to improve the accuracy, efficiency, and usefulness of ECG signal processing technologies [16]–[18]. These areas encompass autoencoders, compressive sensors, and deep learning. The gaps encompass a range of subjects, including interpretable deep learning algorithms, scalability for large data dimensions, integration, adaptation to diverse physiological data, and noise robustness. Addressing these concerns improves the efficiency of signal processing and ECG methodologies, resulting in enhanced ECG monitoring and recording.

During the development process, the power consumption of the pulse oximeter sensor has been greatly reduced. This sensor employs compression sensing technology. This sensor is frequently used in body area networks (BAN) to continuously measure heart rate and SpO2, which refers to oxygen saturation, without the need for invasive procedures. In a previous paper [13], a method was presented for compressing ECG data using K-singular value decomposition (K-SVD). The test results show that the method has a good compression ratio and minimal data distortion. I used the BK-SVD method to train a sparse dictionary for signal processing in photoplethysmography PPG.

We utilized the block sparse bayesian learning (BSBL) method to reconstruct the PPG signals from the block sparse data. Biometric technology uses an individual's physiological or behavioral characteristics to analyze and verify an identification, making the process more convenient. With the increasing demand, researchers are putting in more efforts to develop authentication techniques that are reliable and secure. Research is currently being conducted in the identification sector to investigate the potential of bio-identifying technologies that utilize cardiac signals.

Various studies have shown that it is possible to use cardiac impulses for biometric identification. Previous research has mainly focused on using electrocardiogram (ECG) readings as the primary electrical signals produced by the heart for biometric applications. During the period from 16 to 18 years old In the beginning, they suggested investigating electrocardiograms (ECGs) as a biometric verification method. The ECG signals were classified using support vector machines (SVM) after extracting their dimensional properties through kernel principal component analysis (KPCA). The study currently being published highlights the potential of utilizing photoplethysmography (PPG) signals for biometric applications. PPG signals were obtained from the fingers of 29 healthy volunteers, as mentioned in [19]. The effectiveness of PPG as a biometric modality was validated by performing signal preprocessing, projecting onto the linear discriminant analysis (LDA) space, and classifying using the nearest-neighbor classifier [20].

The researcher has thoroughly examined various techniques such as transform coding, predictive coding, adaptive sampling, and digital combat simulator (DCS). The main study examined data from three separate datasets, which contained information on temperature, CO2 emissions, and seismic activity. From the data, it is clear that the CS had better energy efficiency compared to the AS and TC. The AS and TC demonstrated a decrease in energy consumption by 34% and 62.43%, respectively, while the CS achieved an outstanding energy conservation of 79.4%. The comparison of approaches took into account the labeling and segmentation procedures described in the IEEE 1451 standard [21], [22]. The inquiry focused on the quality of reconstruction and the time it takes for calculations.

The results suggest that compressed sensing (CS) is considerably more complex when compared to conventional labeling and segmentation methods. Traditional methods rely heavily on data reconstruction and noise tolerance, whereas CS outperforms them significantly. On the other hand, earlier research has shown that using event data can reduce transmission distance and ease network congestion [23]. Based on sources [24] and [25], the main emphasis is on demonstrating the immense potential of an application that utilizes the Internet of Things and big data, rather than simply presenting the IoT. According to Li *et al.* [26], the cloud-to-end fusion system's architecture was used to develop the crucial health application. The system consists of several tiers, each with its own specific function, such as cloud-based perception, public health, and public transit. The difficulty in transitioning between different levels stems from the concern of energy usage, especially in the realm of short-range wireless communication. A trajectory is generated for the sink node [27]-[29] to improve movement efficiency. The data within the cluster is consolidated to minimize the transmission of redundant information. This method ensures the security of network routing architecture and effectively ensures the dependability of data transmission.

Motivation and contribution for this research is mentioned here. The necessity to use IoT systems for efficient ECG data processing has grown [19], prompting researchers to investigate a number of approaches. Reconstructing ECG signals with accuracy and efficiency can be accomplished by integrating deep learning methods with autoencoders and computer science. By using ECG sparsity signals, CS efficiently reduces the amount of data that has to be gathered and sent. This makes it possible for the autoencoders to precisely pick up on the presentation needed for reconstruction. Furthermore, deep learning methods improve the reconstruction process's computational correctness and efficiency. Through the integration of many techniques, the approaches address the shortcomings of IoT-based healthcare systems and lead to notable improvements in the monitoring of ECG patients and practitioners.

– A reconstruction technique is developed using multi-task compressed sensing (MT-CS), which effectively incorporates the correlation found in the ECG data.
– A highly effective encoding mechanism is utilized to estimate error rates in reconstruction and energy consumption for wireless data transmission. This is employed in the creation of a compressed sensing model specifically designed for ECG signals.
– The proposed MT-CS approach is a dependable and precise method for retrieving multiple-channel ECG data, ensuring minimal loss of clinical information.

2. PROPOSED METHOD

Let's examine the matrix $W = [w_1, w_2, \ldots, w_K]$ belongs to $Q^{M\times K}$, which shows sample data from an electrocardiogram (MECG) with channels L recorded over a specific time period. A thorough sparse coding strategy is used to produce the sparse representation. According to this method, Υ belongs to $Q^{M\times P}$ where M is lesser than P, where M is lower than P. In (1), this is the equation for this. The matrix Z, $Z = [\beta_1, \beta_2, \ldots, \beta_K]$, is the unknown sparse matrix in (1) and is a member of $Q^{P\times K}$. For each w_h, β_h corresponds to the vector of the sparsity coefficient. In this case, the compressed data for X belongs to $Q^{L\times K}$, is received via a sequential sequence of W. Furthermore, Ψ is a random matrix that is a part of $Q^{L\times M}$, where L is a subset of M. Please find attached (2) for reference.

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

$$X = D + W\Psi \tag{2}$$

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 τ, wherein τ 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 sparse coding as well as resulting 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 makes use of sparse correlation for MECG, with ∂ standing for parametric regularization, which switches between the data's consistency and sparsity. Every row has groups that are arranged collectively, and each row has coefficients that improve accuracy via a L channel. With a reduced count of compressed data, orthogonal standardized wavelet reconstruction based on CS reconstruction is unable to successfully recover structured signals such as the ECG. Rather of relying on pre-set off-the-shelf transformations, dictionaries have been produced using trained data due to their broad usage and careful analysis.

Taking into account the signal data from samples I that were supplied for training, where $W_s = [W_1, W_2, W_3, \ldots, W_I]$ and W_1correspond to the data channel L from each object and the $Q^{M\times IK}$data for I samples. In an effort to provide the best possible sparse coding, data is sparsely represented by Ψ as a collection of matrix coefficients from various samples. For example, sparsity in the jth sample is represented as $\rho = [\rho_1, \rho_2, \ldots, \rho_I]$ belongs to $Q^{P\times IK}$, where ρ_I is a member of $Q^{P\times K}$ and $J = 1, 2, .., I$. Finding the sparsity matrix ρ_J that most closely fits the given training set is our main goal. With M being smaller than P, it is argued that the Ψ sparse coding is overcomplete. The training data $W_s, s = 1, \ldots, I,$ are presented sparsely during the shallow learning process through an iterative procedure in the update columns of the sparse coding matrix ΰ. The current sparse value, represented by ρ_J , is used to update the sparse coding. The following formulation is used to handle the optimization problem.

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

In (4), the Frobenius norm is defined as $\|.\|_E$. ρ_i's are the names given to the vector columns in ρ. The following problem is constrained by taking into account the degree of sparsity in signals for training samples with a maximum number of non-zero elements R for each ρ_i. This study's sparse coding was obtained using the k-Singular Value Decompositions data training method. MT-CS, a reconstruction method that is ideally suited for wireless network systems with a variety of sensors, is presented in this study. Its purpose is to compress ECG data especially. For a multichannel ECG to send data in real time and track the health of a single patient, a continuous log is kept.

Finding a highly accurate and efficient way to retrieve multiple-channel ECG data with the least amount of clinical information lost is the primary goal of this research. We take into account the fact that different channels show combined sparsity. Therefore, we make use of their spatial connection and need to use various over-completing leaning dictionaries to resolve the sparsity. The many structures derived from the multiple channel ECG signals are the foundation upon which these dictionaries are built. We must solve the measurement of multiple vectors (MVV) problem in order to rebuild joint CS. In (3) explains how to use the mixed regularization $k_{2,1}$to remedy this. By taking into account the group sparsity, which is provided as follows, in (3) is improved to (5).

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

In (5), $z_{fi}^S = [z_{(i,1)}, z_{(i,2)}, \ldots\ldots, z_{(i,K)}]$ The sparsity coefficients for channel K are shown in the row of sparsity coefficients in matrix Z, creating a collection f. The regularization parameter ∂ provides fidelity and encourages sparsity in the reconstruction of the multiple channel ECG. Simplifying the foregoing statement would mean maintaining the same number of groups as rows Z. In (5) offers a solution to the joint sparse minimization issue. This is accomplished by using the auxiliary transform and parameter that are part of the alternating direction method of multipliers, or ADMM, technique. This data is included in (6).

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

The matrix row Y is represented as y^T in (6). In this instance, In (7) has allowed us to solve the issue in its Lagrangian form. The variablesρ_1, ρ_2, which are larger than 0, in (7) are referred to as parametric penalties. Furthermore, the matrices $\lambda_1$from $Q^{M\times K}$ and $\lambda_1$belongs to $Q^{P\times K}$ function as multiplier matrices. The updating of expressions λ_1 as well as λ_2 indicates the primordial gradient descent phases, since the ADMM problem has been resolved in this phase. In (8) uses the ADMM primal framework to provide a solution to the previously stated issue. Parameters for relaxation are α_1 and α_2. Even if convergence happens fast, in (12) updates Y for row shrinkage, and the range of the ADMM that may be used is $(0, \frac{\sqrt{5}+1}{2})$, which is in line with (7).

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

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

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

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

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

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

The MT-CS ECG reconstruction this algorithm enables the resolution of a specific problem. The following algorithm outlines the key steps of the reconstruction process for multi-adaptive multiple channel ECG-based sparse coding. This technique demonstrates the initial anticipation of W_{int} for multiple-channel ECG data. However, when compared to the basic chase, orthogonal meet pursuit (OMP) has the potential to generate a significantly faster sparse estimate. Algorithm 1 is mentioned below.

Algorithm 1. Multi-task compressed sensing (MT-CS) ECG Reconstruction

```
Algorithm
Multi-task compressed sensing (MT-CS) ECG Reconstruction
Input: X,Ψ,Y,Y_{M,P} Y_{P1},Y_{P2},Y_{P3},...,Y_{Pp} and Thresh
CS Reconstruction by OMP
Step 1: minimum_{Zbelongs toQ^{P×K}} ||Z||_0   such that X = Z_{OMP}ΨY
Step 2: W_{int} = YZ_{OMP}
Joint CS Reconstruction by ADMM
Step 3: c_{maximum} = maximum
Step 4: if c_{maximum} is lesser than Thresh
Step 5:minimum_{Zbelongs toQ^{P×K}} ||Z_{MP}||_{1,2}   such that X = Z_{MP}ΨY_{MP}
Step 6: W = Z_{MP}Y_{MP}
Step 7: else
Step 8:        for J = 1 to M_E do
Step 9:               if ||(W_{int})| − W_int |  greater than c_{maximum} then
Step 10: ϑ = round((j*p)/M_E + 1/2)
Step 11: minimum_{Zbelongs toQ^{P×K}} ||Z_{Pϑ}||_{1,2}   such that X = Z_{Pϑ}ΨY_{Pϑ}
Step 12: W = Z_{Pϑ}Y_{Pϑ}
Step 13:              end if
Step 14:          end for
Step 15: end if
Step 16: return W
```

2.1. Simultaneous ECG data compression

Throughout the sampling phase, the compressed sensing mechanism collects various samples from multiple channels to capture recurring data. The input undergoes compression using a sensing matrix, regardless of the resulting isometric property. Various sensing matrices are available for different applications, but unfortunately, none of them are efficient in terms of computation or energy usage. Applications that need fast calculations and efficient implementation of computer science mechanisms use the binary matrix. This provides a basic method for signal approximation using the CS-based approach when collecting data. There are a number of entries at various positions, each with similar values of 1/√f, along with empty values in each column. Efficient memory is the simplest in terms of computational complexity, as it utilizes a specific sensing mechanism to minimize energy consumption.

2.2. Shallow learning-based R-peak Detection

To train the signal for adaptive shallow learning for distinctive representations, the main aim here is to use it as an adaptive mechanism for specific features in the ECG mechanism for the compressive sensing-based ECG reconstruction mechanism. The related features associated with the ECG are denoted through various comparisons fixed through various transformations. The proposed framework is organized in two stages.

2.2.1. Feature engineering through diverse channels

Feature engineering through diverse channels: the specific detection algorithm is dynamically associated with a peak-search-based window mechanism for windows of different lengthsTo generate peak values for windows along the length of the ECG signal, it is essential to have a thorough understanding and effective implementation of the following searching techniques. Appropriate samples must be used for this purpose. The ECG frame displays the most significant deviation from the average value. This method utilizes a QRS (Q, R, and S) complex to depict a threshold, effectively emphasizing the intricate mechanism at the edge of the frame.

2.2.2. Compressed sensing-based shallow learning approach

Compressed sensing-based shallow learning approach: in this particular case, the ECG data is divided into frames of different sizes. The precise position of the intricate frame is assigned to a frame of comparable length using the non-overlapping temporal window technique. Ensuring a consistent width is maintained across the presented time scale value. These channels utilize a comparable approach to merging various locations. In addition, a subgroup is formed by combining multiple channels into a single sub-group to categorize the training signals for the relevant location that corresponds to the QRS position. This procedure involves creating positions using different techniques, then generating sub-models with signal elements for different segments using a primary approach and a relevant sub-module grouping mechanism.

The QRS scheme utilizes reconstruction mechanisms and sparse coding to analyze complex regions of the ECG signal, enabling the differentiation and training of the baseline. The ECG segments are recorded across distinct channels, thanks to a sophisticated baseline mechanism that is divided into many channels. The QRS scheme is commonly employed to differentiate the baseline technique.

The framework utilizes the proposed model for updating purposes. With the current sparse coding approach, the estimation of the sparse coefficient matrix is modified based on the ECG data. An efficient method has been developed to reconstruct signals in the CS-based model using features obtained from the single-channel ECG. The sparse coding model is initialized with a random Gaussian process, where each distribution is independent and identical. The discrete cosine transform, also known as DCT, is utilized to initiate the sparse coding process. This section provides a description of the adaptive learning strategy for the sparse coding learning goal function.

$$\mu, D \qquad \sum_{k=1}^{K} \{||Z_{v_k} - \mu, D||_G^2\} \text{ subject to } \forall_{mn,} \|d_{mn}^V||_0 \leq U_0 \tag{13}$$

Here Z_{v_k} the set of training signals, μ is shallow learning, A is the collective set of sparse coefficients matrix and U_0 shows the sparsity co-efficient. In the first stage consider the sparse coding stage, by assuming that the μ is initialized via the DCT sparse coding, by considering the above optimization mechanism problem as a result of sparse representation of the column matrix D. Upon expanding the matrix multiplication mechanism the penalty function is segmented into a variety of multiplication for the vectors considered, the optimization problem is rewritten as (14).

$$\mu, D \qquad \{||Z_{v_k} - \mu_u d_{mk}^V, \text{ subject to } \forall_{mn,} \|d_{mk}^V||_0 \leq U_0 \tag{14}$$

Here d_{mn}^V denotes the sparse matrix D, which denotes the $k-\text{th}$ group and satisfies the sparsity constraint: $\|d_{mk}^V||_0 \leq U_0$. The optimization problem is addressed by the OMP (orthogonal matching pursuit) algorithm, If U_0 is small this solution is a better approximation. To update the sparse coding mechanism and repeat the process for the items updated through the shallow-learning model. By considering the features in the ECG signal the various dictionaries are trained in the above manner, the $v-\text{th}$ sub-dictionaries $\mu_P = [\mu_{P1}, \mu_{P2}, \mu_{P3} \ldots\ldots\ldots\mu_{P_p}]$ are learned through the simultaneous reconstruction of the regions consisting of P features in p locations consisting of samples across different channels of the ECG signal.

3. PERFORMANCE EVALUATION

In this instance, MATLAB is used for the experimental inquiry, and the results of the simulations show how successful the recommended model is. In order to conduct the simulations, 280 sensor nodes must be arranged densely inside a 200×200 m surveillance square. Ten J of energy are needed for each sensor node. The sink node is situated on exterior property, outside the viewing area. The values of w 1 (0.5, 0.1, and 0.4); w 2 (0.9, 0.5, and 0.9); an interval range of 10 m (represented by R); and a period of 950 s (represented by T) make up the data collecting parameters. The MIMIC- II dataset is used to assess the robustness and generalizability of the proposed method [20].

3.1. EEG signal reconstruction

The graph in Figure 1 analyzes the reconstruction error (RE) and a number of other parameters to compare the proposed method with the existing MIC-CSDG methodology. The transmission line's original signal and its reconstruction following fifty training iterations are shown in the graph below. The 250 sample points are carefully examined for evaluation during the testing procedure. The graph's reproduced signal shows increased precision in following the route of the original signal. The path of the reconstructed signal is quite similar to that of the original signal. The reconstruction of the ECG signal is shown in Figure 2 at $W_1 = 0.1$ and $W_2 = 0.5$.

3.2. Reconstruction error comparison

The reconstruction errors for the current method and the proposed approach can be observed in Figure 3. The recommended method has a shorter network running time compared to the existing method. According to the data, the proposed model shows the lowest error reconstruction when compared to the current setup. The error reconstruction of the current system reaches its peak at 900 and continues to rise as the network operates. Our proposed method outperforms the current one in practical applications. At 9:00, the network running time increases, but there is a silver lining as the reconstruction error reaches its lowest level. The suggested approach also highlights the potential for inaccuracies in reconstruction.

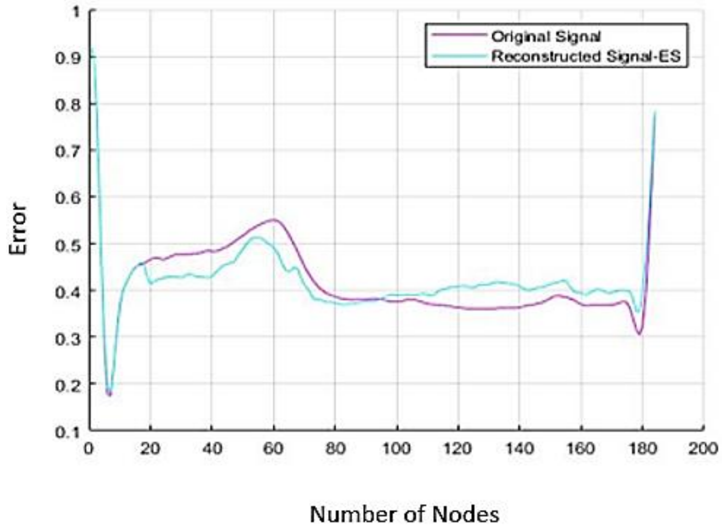

Figure 1. ECG signal reconstruction at parameter $W_1 = 0.5$ and $W_2 = 0.9$

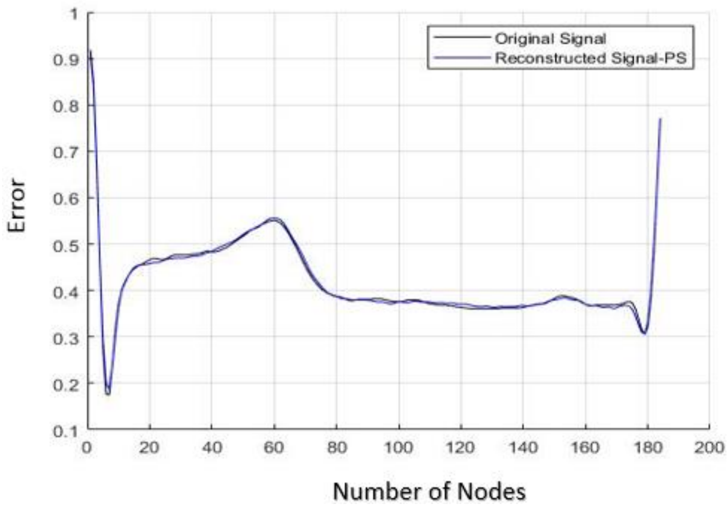

Figure 2. ECG signal reconstruction $W_1 = 0.1$ and $W_2 = 0.5$

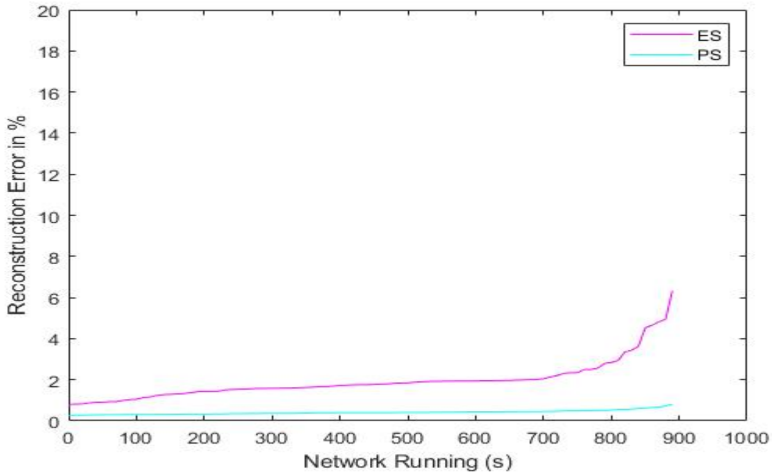

Figure 3. Reconstruction error comparison in %

3.3. Energy comparison for reconstruction

Figure 4 shows a comparison between the proposed and existing methodologies for the energy usage of the sensor nodes during the reconstruction process. In this case, the sample nodes that the present system takes into account improve network efficiency, which raises the energy efficiency of the sensor nodes. Compared to the existing approach, the reconstruction energy consumption of the suggested system is lower. In particular, the energy comparison favors the suggested model, which uses less energy than the present system, when 250 sensor nodes are taken into account. The energy usage of the 250 sensor nodes varies noticeably.

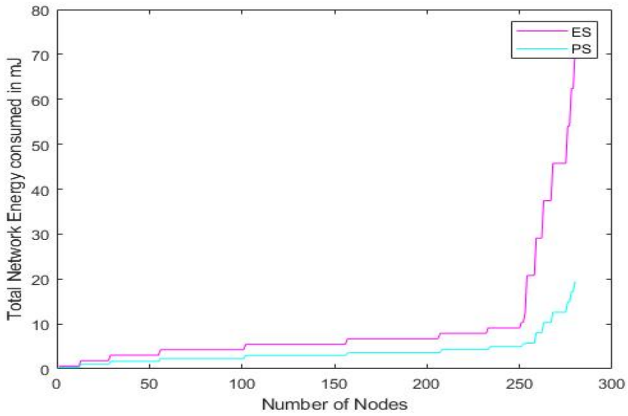

Figure 4. Total network energy consumed in mJ

3.4. Energy consumed in aggregation and reconstruction

In this investigation, we provide a comparison between the energy used in the aggregation and reconstruction process and the number of nodes exhibited and measured in mJ. The graph that contrasts the proposed MT-CS with the existing system is shown in Figure 5. The reconstruction mechanism and the energy needed for aggregation and reconstruction are examined.

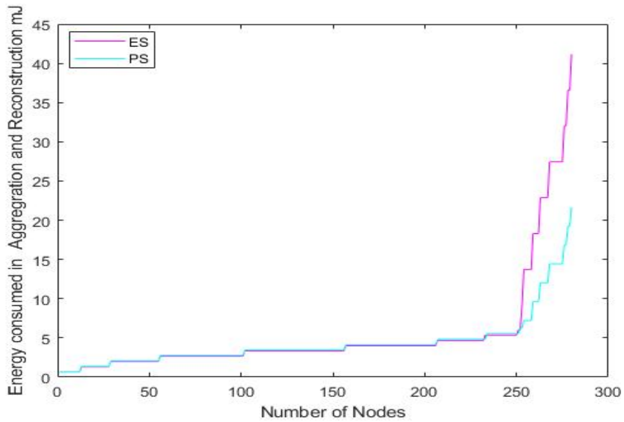

Figure 5. Energy consumed in aggregation and reconstruction mJ

3.4. Packet arrival rate in %

Here, we utilize the MT-CS reconstruction mechanism technique to tackle the issue of packet loss. Figure 6 compares the packet arrival rate (PAR) of the current system with the proposed MT-CS reconstruction mechanism approach. A comparison is made between the proposed MT-CS-based reconstruction mechanism and the current method. The simulations are conducted with an initial setup of 280 sensor nodes and 50 messages per sensor node simultaneously. According to the results of the simulation, the proposed strategy fulfills the necessary requirements. The PAR for p*=1 may closely approach the theoretical upper bound (UB) in a manner reminiscent of technical writing.

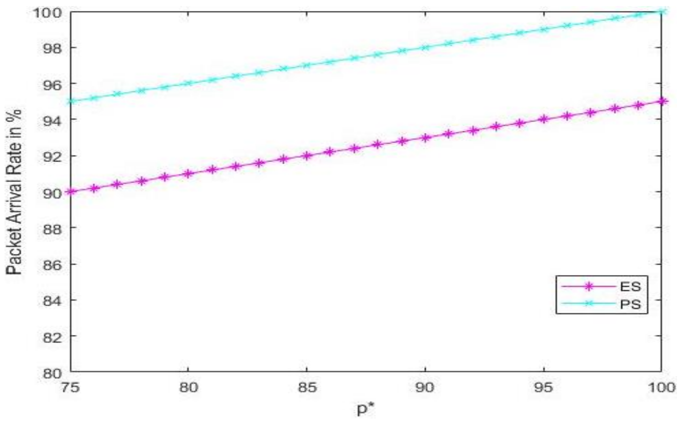

Figure 6. Packet arrival rate in %

4. CONCLUSION

This study introduces a new method for improving the quality of compressed sensing in ECG signals. It utilizes the MT-CS approach and extracts signal characteristics to achieve this enhancement. A reconstruction technique is created using an MT-CS approach and is subsequently assessed on the MIMIC-II dataset. When the results are plotted as a graph, it is evident that the reconstruction method, reconstruction error comparison, and ECG signal reconstruction surpass the current system. The experimental evaluation requires the testing of ECG signals through multiple iterations. To achieve optimal energy efficiency for the reconstructed ECG signals, it is crucial to take into account a particular real-time scenario. In summary, the recommended MT-CS method produces accurate results with remarkable efficiency.

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