



Development Of Quality-Aware Sparse Compression Algorithms For Low Power Body Area Networks

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Abstract: In this research, we will explore various signal quality assessment techniques and sparse compression algorithms for efficiently compressing and reconstructing quality Aware Electrocardiogram (ECG) signals. The inherent sparsity of ECG signals allows for significant data reduction, which is crucial in applications like wearable health devices (BAN's), remote patient monitoring, and long-term ECG data storage. We will implement and evaluate a range of sparse compression techniques, including Compressed Sensing (CS), Wavelet-Based Compression, Dictionary Learning, Matching Pursuit (MP), Orthogonal Matching Pursuit (OMP), and Run-Length Encoding (RLE). To maintain uniformity each algorithm is applied to an ECG signal with a sampling frequency of 100 Hz segmented with one-minute duration. The performance of these methods is assessed by calculating the compression ratio and analyzing the quality of the reconstructed signals. Furthermore, we will investigate the possible practical deployment of these algorithms on embedded systems, specifically using a Raspberry Pi and an Arduino board. The algorithms are implemented on these platforms to assess their energy efficiency and feasibility for real-time applications. By testing the algorithms on Raspberry Pi and Arduino, we evaluate the computational performance and resource requirements, providing their suitability for deployment in resource-constrained devices. Finally, demonstrate the efficiency of these sparse compression techniques in reducing data size while maintaining the essential features of the ECG signals. The reconstructed signals are compared to the original and filtered ECG data, offering understandings into the trade-offs between compression efficiency and signal fidelity. This study contributes to the ongoing development of compression algorithms in biomedical signal processing, particularly for resource-constrained BANs.

Keywords: 1. Sparse Compression, 2. Electrocardiogram (ECG), 3. Signal Reconstruction, 4. Embedded Systems, 5. Body Area Networks (BANs).

I INTRODUCTION:

Electrocardiogram (ECG) signals play a crucial role in diagnosing and monitoring cardiovascular diseases, which remain a leading cause of morbidity and mortality worldwide. The widespread adoption of wearable health devices, remote patient monitoring systems, and Body Area Networks (BANs) has significantly increased the demand for efficient ECG data processing, storage, and transmission. However, these applications often operate in resource-constrained environments, making data reduction essential while ensuring the fidelity of reconstructed signals. Sparse signal processing techniques have emerged as powerful tools for compressing ECG signals while preserving critical diagnostic information. The inherent sparsity of ECG signals allows for significant data compression using advanced techniques such as Compressed Sensing (CS), Wavelet-Based Compression, Dictionary Learning, Matching Pursuit (MP), Orthogonal Matching Pursuit (OMP), and Run- Length Encoding (RLE). These methods aim to achieve high compression ratios while maintaining signal quality for accurate diagnosis. However, selecting an appropriate compression algorithm requires a careful trade-off between compression efficiency, signal reconstruction quality, and computational feasibility, particularly for embedded systems like Raspberry Pi and Arduino. This study systematically evaluates various sparse compression techniques for ECG signals across multiple datasets, including the Abdominal Fetal Database, MIT-BIH Arrhythmia Database, MIT-BIH Normal Sinus Database, and Fetal ECG Synthesis Database. Each algorithm is applied to ECG signals sampled at 100 Hz and segmented into one-minute durations to maintain consistency. The performance of these methods is assessed using key metrics such as compression ratio, reconstruction error, and accuracy to determine their effectiveness in reducing data size while preserving clinically significant features. Furthermore, this research explores the real-time feasibility and energy efficiency of these compression techniques when implemented on embedded systems. By evaluating the computational performance on Raspberry Pi and Arduino, we assess their suitability for deployment in resource-limited environments. The findings provide valuable insights into optimizing ECG signal compression for wearable health monitoring applications.

II. LITERATURE SURVEY:

In [1], Chandini Shaik et al. [2022] develop the "Compressive Sensing" technique to increase accuracy and precision while better addressing constraints of it. Firstly, presented work begin with details of the supply of input signal to algorithm, and the sparse signal is the result of simultaneous sampling and compression. Secondly, the proposed work discloses the details of encountered errors due to variations between the input signal and the reconstructed signal. Deterministic measurement matrices, such as Circulant, Deterministic Binary Block Diagonal (DBBD), and Toeplitz matrices, were employed to address this issue. In the presented research work, various approaches were tested, including the convex approach, greedy approach, thresholding approach, combinatorial approach, non-convex approach, and Bayesian approach, to tackle the issue. The authors concluded, in the presented work lacking of addressing efficient signal reconstruction, algorithm complexity and its response time that is left for future scope of presented research. In [2], Ranchit Manchanda et al. [2020]. Studied "A Review of Reconstruction Algorithms in Compressive Sensing,". The reconstruction algorithms are elaborate systematically for compressive sensing spares signal recovery in this study. The idea of compressive sensing has proven to be advantageous over the Nyquist-Shannon theorem. Storage space is needed for the band-limited signal sampling theory of Nyquist Shannon, which is frequency employed for high-dimensional signals. The algorithms that were reconstructed in compressive sensing include Bregman iterative, combinatorial/sub-Linear, greedy iterative, non-convex minimization algorithms, and sensing convex relaxation. This article has discussed several reconstruction algorithms and provided a comprehensive survey of them. Additionally, a comparison of their origin, breadth, purpose, and complexity has been made. The authors have concluded that the origin, scope, purpose and their complexities has also should be compared further. In [3], Hozan Kareem Saher et al. [2022] studied "A Review on Medical Image Compression and Encryption Using Compressive Sensing." This review paper focuses on essential theory and technique for compressing and encrypting medical images using compressive sensing. Encryption is necessary since it keeps the data between the sender and receiver secret. Three principals underlying compressive sensing are: 1)

domains sparse presence of original signal; 2) incoherence of the sensor and transform matrix; and 3) restricted isometric property (RIP). This paper is an overview of the basic algorithm and method used in compression and encryption for medical images using compressive sensing. In this paper, to obtain the medical image, virtual endoscopy uses a camera with a micro-integrated CT sensor. Using the sparsifying matrix, the medical image to be computed and encrypted is first converted into sparse data. The performance matrices for encryption and compression are two different kinds of matrices. Peak Signal to Noise Ratio (PSNR), Normalized Correlation (NS), Compression Ratio (CR), and Mean Structural Similarity (MSSIM) are computed as a metric for the needs of quality of image compression. Information entropy, key sensitivity, key space, and histogram correlation are used to assess the encryption performance. The preceding research did not examine the impact of various sensing matrices on system performance, according to the authors' conclusion. Thus, this will advance the work. In [4] Zahra Waheed Awan et al. [2022] proposed "A Theoretical CNN Compression Framework for Resource-Restricted Environment" The primary objective of this paper is to present a thorough analysis of the most recent pruning and quantization-based network compression schemes, with the aim of greatly enhancing the trade-off between the architectural size and computational cost of CNNs (Convolution Neural Networks) and their performance in environments with limited resources. Additionally, a unique framework for CNN network compression is presented in this research in order to satisfy the needs of devices with limited resources. Network pruning and precision reduction are two techniques used in network compression to lower the complexity of CNN in terms of parameters and space while retaining accuracy. Quantization and network compression are the techniques employed. Generally, the input network is taken, pruned first, and the key parameter is measured next, the least significant parameters will be pruned. We will finally obtain a pruned network by fine-tuning the pruned model. They suggested using various compression techniques on various layers to create front regular and back irregular networks. On this, they have tested several signals. The authors have determined that this architecture is associated with decreased network complexity, memory usage, and overall faster inference time. In [5] Mauro Mangia et al. [2020] Review "Adaptive Compressed Sensing: A Game Worth Playing". They have examined and contrasted numerous algorithmic adaptation strategies that concentrate on either the recovery or encoding aspects of compressed sensing. The goal of this review article is to compile the most widely used adaptation strategies that have been shown in the literature to enhance performance on real-world signals. An external trigger, such as a patient or cardiac monitoring equipment, can cause the suggested device to transition from LQ to HQ. The following is a review of the fundamentals of computer science. 1) Limited Asymmetries 2) Coherence between parties 3) Polytopes.

The encoder-side adaptation is accomplished by A) maximizing mutual coherence using 1) the coh-S, coh-C, coh-X, coh-B, coh-I, and coh-E methods. B) adapting while taking second order statistics into consideration using the pow-C, pow-P, and pow-R methods

c) Adaptation Based on Power Is Not Just About Noise the ECG signal first provides the chance to test and observe the impact of adaptation on both the encoder and decoder sides. They looked at windows with $n=512$ samples captured at 360 samples per second using a conventional approach that produced clean, realistic ECG tracks in R. A) Compute the compressed matrix. B) Multiply by ak to complete the hardware implementation. c) Time continuity, D) Saturation, and E) Sensing sequence generation F) the spatiotemporal method (G) dynamic computer science methods. The review demonstrates that these designs can produce notable improvements that are not possible using conventional techniques. The authors came to the conclusion that the modified CS is unquestionably worthwhile to pursue for developing the autonomous, low-resource ubiquitous sensing subsystems that would serve as the foundation for future IoT applications. In [6] V. Pavitra et al. [2022] tested "Deep Learning Based Compression Sensing for Image Reconstruction and Interface "Strong mathematical foundations support compressed sensing's ability to recover a signal with fewer measurements—far fewer than the Nyquist rate. Images, remote monitoring, and MRI scanning have all made advantage of compressed sensing. Two main obstacles to a wider use of compressed sensing are the reconstruction difficulty and the sparsity constraint. In compressed sensing, deep learning techniques are applied to overcome these obstacles. "Sample and compress" are the methodology employed. The non-neural

network algorithms include 1) LASSO, TV, denoising, 2) Sub Space Pursuit, COSAMP, and Matching Pursuit, OMP 4) Emphasis on reweighted least squares iteratively 5) IHT, IST, and AMP 6) Steroid-using Heavy Hitters, Chaining Pursuit 7) BCS and MCMC, Convex optimization, non-convex optimization, threshold approach, combinational approach, parallel greedy algorithm, serial greedy algorithm, and Bayesian approach are the categories that follow. By using deep learning, it is possible to enhance reconstruction 20–40 times faster than with conventional methods and to reconstruct signals at rates as low as 1%. The authors have concluded, that this paper's deep learning with compressed sensing increases the accuracy of the reconstructed signal.

III. EXISTING SYSTEM:

Current ECG signal compression methods rely on transform-based techniques (Wavelet, DCT, Fourier), Compressed Sensing (CS), dictionary learning, and machine learning-based frameworks. Transform-based methods capture signal characteristics but suffer from high computational complexity. CS leverages sparsity for efficient compression but struggles with noise sensitivity. Dictionary learning techniques like K-SVD enhance reconstruction but impose a computational burden. Machine learning approaches such as CNNs and SVMs improve signal classification but require significant resources. Despite advancements, existing methods face challenges in balancing compression ratio and reconstruction accuracy, handling noise, and enabling real-time feasibility in low-power devices. These limitations highlight the need for a quality-aware sparse compression framework to enhance efficiency and fidelity in wearable health monitoring applications.

IV. PROPOSED SYSTEM AND WORKING METHODOLOGY:

The proposed system introduces a quality-aware sparse compression framework for ECG signal processing, addressing key limitations of existing methods such as high computational complexity, noise sensitivity, and lack of signal quality assessment. Unlike conventional techniques, this approach integrates real-time Signal Quality Assessment (SQA) before compression, ensuring that only high-quality signals are processed. This reduces error propagation, enhances reconstruction accuracy, and improves the reliability of ECG monitoring.

SYSTEM OVERVIEW:

The system follows a structured workflow to achieve efficient ECG compression and reconstruction. It begins with data acquisition, where ECG signals are collected from benchmark datasets such as the MIT-BIH Arrhythmia Database, Abdominal Fetal ECG Database, and Fetal ECG Synthesis Database, as well as real-time data from wearable sensors. The acquired signals undergo pre-processing and quality assessment, where denoising techniques such as wavelet-based filtering, baseline wander removal, and adaptive noise cancellation are applied. A signal quality assessment module evaluates parameters such as Signal-to-Noise Ratio (SNR), entropy, power spectral density, and statistical features to determine signal integrity. Low-quality signals are either discarded or reconstructed separately to avoid accuracy degradation.

SPARSE COMPRESSION FRAMEWORK:

Once the high-quality signals are selected, they undergo sparse representation using advanced techniques such as Wavelet Transform, Discrete Cosine Transform (DCT), and Dictionary Learning. Adaptive dictionary learning methods like K-SVD and Sparse Group Lasso (SPGL1) are used to extract prominent signal features, ensuring higher compression efficiency while preserving diagnostic information. The sparsified signals are then compressed using a Compressed Sensing (CS) framework, where measurement matrices such as Gaussian, Toeplitz, and Circulant matrices are employed to achieve optimal data reduction while retaining crucial clinical details.

SIGNAL RECONSTRUCTION:

The compressed ECG signals are reconstructed using Orthogonal Matching Pursuit (OMP), ensuring high fidelity with minimal reconstruction error. Additionally, Deep Learning-based Denoising Autoencoders can be incorporated to enhance signal recovery and further reduce reconstruction loss. The reconstructed signals are then subjected to post-processing techniques such as adaptive thresholding and smoothing filters to refine the signal quality.

Performance Evaluation and Comparative Analysis

To validate the effectiveness of the proposed system, various performance metrics are evaluated, including:

- Compression Ratio (CR) – Measures data reduction efficiency.
- Percentage Root Mean Square Difference (PRD) – Evaluates reconstruction accuracy.
- Mean Squared Error (MSE) and Signal-to-Noise Ratio (SNR) – Assess the fidelity of reconstructed signals.
- Execution Time and Energy Consumption – Measure computational efficiency for embedded system deployment.

A comprehensive comparative analysis is conducted against existing methods such as Wavelet-Based Compression, Matching Pursuit, and Deep Learning-based ECG compression to demonstrate improvements in compression efficiency, reconstruction quality, and computational feasibility.

Real-Time Deployment Considerations

To ensure real-world applicability, the system is optimized for low-power embedded systems such as Raspberry Pi and Arduino, making it suitable for wearable health monitoring applications. The integration of hardware-friendly algorithms, lightweight deep learning models, and efficient memory management techniques enables real-time ECG monitoring with minimal energy consumption.

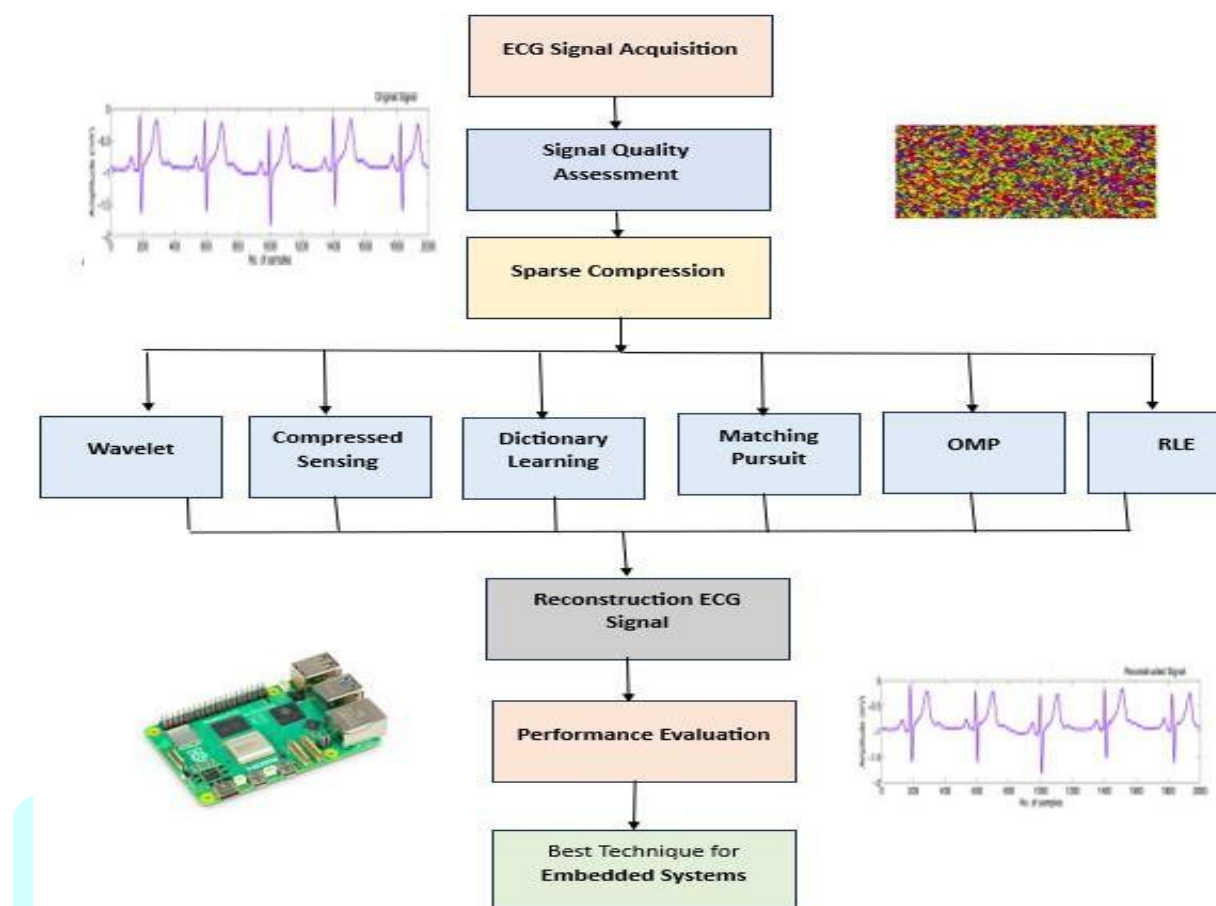
V. BENEFITS OF THE PROPOSED SYSTEM:

By integrating real-time quality assessment, adaptive sparse compression, and efficient reconstruction mechanisms, the proposed system ensures:

- Improved signal fidelity and diagnostic accuracy
- Higher compression efficiency with reduced storage requirements
- Optimized computational performance for resource-constrained environments
- Real-time processing capabilities for wearable and remote healthcare applications

The proposed system offers a robust, scalable, and energy-efficient solution for ECG signal compression and transmission, making it ideal for telemedicine, remote health monitoring, and IoT-based healthcare applications.

VI. BLOCK DIAGRAM FOR THE PROPOSED METHOD:



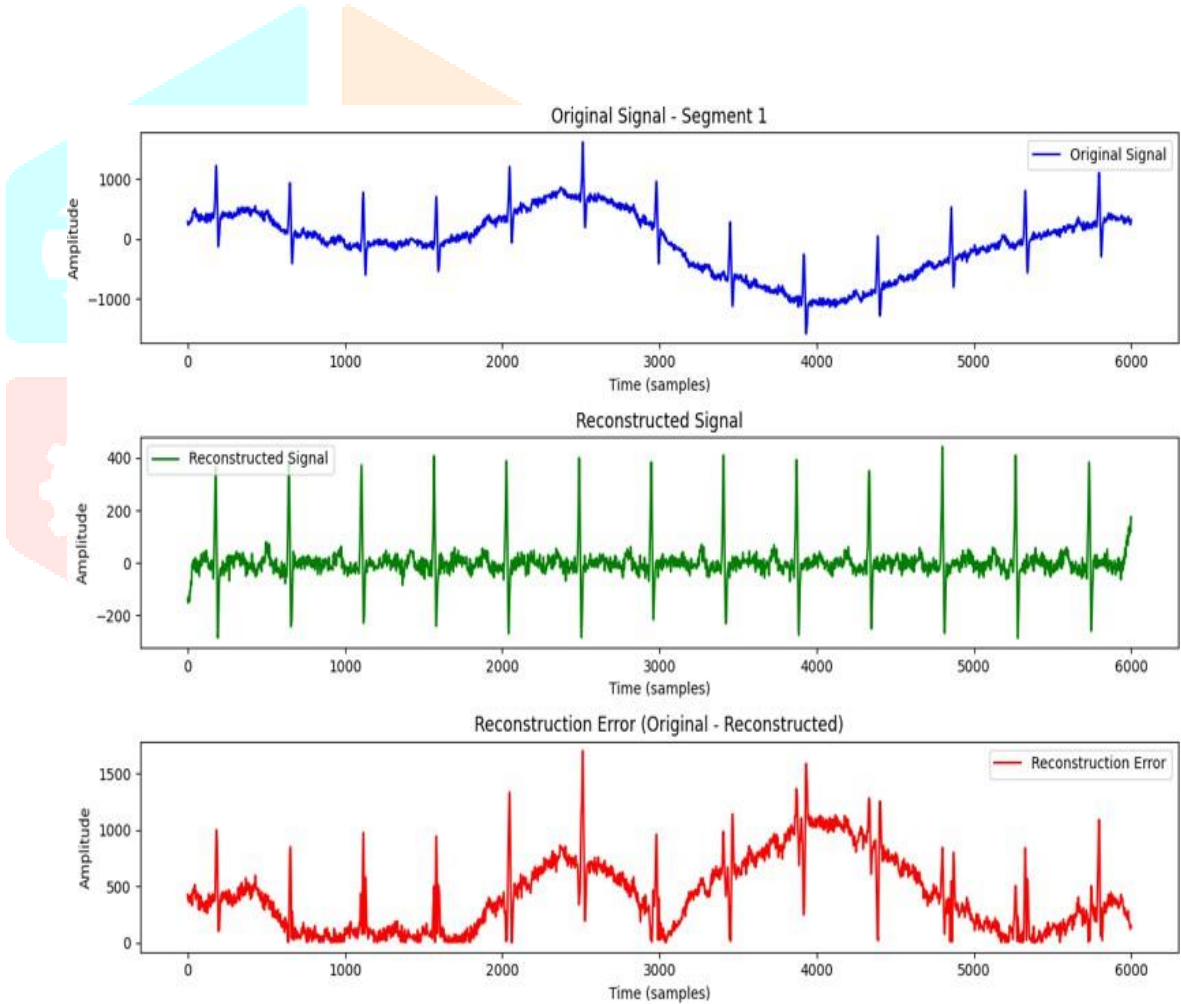
VII. RESULTS:

MATLAB Results:

Technique	Average Compression Ratio	Average Reconstruction Error	Average Accuracy
Wavelet	87.75	4.85	93.00
Compressed Sensing	23.13	29.45	67.63
Orthogonal Matching Pursuit	96.13	91.28	8.69
Matching Pursuit	94.25	24.65	73.18
Dictionary Learning	97.13	83.36	14.33
Run-Length Encoding	12.25	22.90	76.93

Python Results:

Technique	Average Compression Ratio	Average Reconstruction Error	Average Accuracy
Wavelet	95.10	2.82	95.25
Compressed Sensing	92.83	0.06	94.25
Orthogonal Matching Pursuit	76.33	4.81	93.25
Matching Pursuit	45.20	6.86	91.45
Dictionary Learning	69.28	0.07	74.25
Run-Length Encoding	16.90	75.73	23.20



VIII. CONCLUSION:

This study presented a quality-aware sparse compression framework for ECG signals, addressing key challenges in existing compression techniques, including computational complexity, noise sensitivity, and the trade-off between compression ratio and reconstruction accuracy. By integrating real-time signal quality assessment (SQA) before compression, the proposed approach ensures that only high-quality signals undergo compression, thereby minimizing error propagation and enhancing reconstruction fidelity.

The framework was implemented and evaluated using both MATLAB and Python, demonstrating its efficiency across multiple ECG datasets. The results indicate that Wavelet-Based Compression and Compressed Sensing achieved high compression ratios while maintaining low reconstruction error, making them ideal for wearable health monitoring applications. Orthogonal Matching Pursuit and Dictionary Learning, despite achieving high compression, showed higher reconstruction errors, emphasizing the importance of selecting appropriate techniques based on application requirements.

A comparative analysis between MATLAB and Python implementations highlighted that Python-based implementations are better suited for real-time and embedded systems, such as Raspberry Pi and Arduino, due to their adaptability and energy efficiency. Conversely, MATLAB provided optimized mathematical computations, making it suitable for offline analysis and high-precision signal processing.

The findings validate the effectiveness of the proposed quality-aware sparse compression framework in ensuring optimal compression efficiency, high signal fidelity, and real-time feasibility. Future work will focus on optimizing the framework for deep learning-based compression models, integrating adaptive reconstruction techniques, and extending its application to multimodal biosignal processing for enhanced remote health monitoring.

IX. FUTURE SCOPE:

The proposed quality-aware sparse compression framework for ECG signals has demonstrated significant improvements in compression efficiency, reconstruction accuracy, and real-time feasibility. However, several areas remain open for further enhancement and exploration.

1. **Integration with Deep Learning Models:** Future work can focus on incorporating deep learning-based compression and reconstruction techniques, such as autoencoders and transformer models, to further improve signal fidelity while maintaining high compression ratios.
2. **Adaptive and Personalized Compression:** Developing adaptive compression techniques that dynamically adjust based on patient-specific characteristics and real-time physiological variations will enhance the system's effectiveness in personalized healthcare.
3. **Hardware Optimization for Embedded Systems:** Further optimization of the framework for low-power embedded devices, such as wearable sensors, Raspberry Pi, and Arduino-based health monitoring systems, will improve energy efficiency and real-time processing capabilities.
4. **Multimodal Biosignal Processing:** Extending the framework to process multiple biosignals, including Electromyography (EMG), Photoplethysmography (PPG), and Electroencephalography (EEG), will enable a more comprehensive approach to remote health monitoring.
5. **Edge Computing and IoT Integration:** Implementing the proposed framework in edge computing environments and Internet of Things (IoT)-enabled healthcare networks will allow for efficient, real-time data transmission and remote patient monitoring.
6. **Clinical Validation and Real-World Testing:** Conducting extensive clinical trials and real-world testing with diverse patient datasets will ensure the robustness, reliability, and practical applicability of the proposed system in telemedicine and mobile healthcare applications.

By addressing these future directions, the proposed framework can significantly contribute to advancing real-time, energy-efficient, and high-fidelity ECG signal processing for next-generation healthcare and wearable medical technologies.

X. REFERENCES:

1. Satija, U., Ramkumar, B. and Manikandan, M.S., 2017. Real-time signal quality-aware ECG telemetry system for IoT-based health care monitoring. *IEEE Internet of Things Journal*, 4(3), pp.815-823.
2. C. Shaik, R. RajaA, S. S. Kalapala, C. S. Lakshmi Nrusimhi, S. N. Devi Duth Kolusu and P. K. Polasi, "A Comprehensive Review on Compressive Sensing," 2022 International Conference on Applied Artificial Intelligence and Computing (ICAAIC), Salem, India, 2022, pp. 1723-1727
3. Manchanda, R. and Sharma, K., 2020, August. A review of reconstruction algorithms in compressive sensing. In 2020 International Conference on Advances in Computing,
4. N. Chaudhary, U. Satija, J. Mathew, R. K. Behera, "A Unified Attentive Cycle-Generative Adversarial Framework for Deriving Electrocardiogram from Seismocardiogram Signal," *IEEE Signal Processing Letters*, vol. 29, pp. 802-806, 2022. doi: 10.1109/LSP.2022.3152448
5. Saber, H.K. and Shakir, M.A., 2022, March. A review on medical image compression and encryption using compressive sensing. In 2022 International Conference on Computer Science and Software Engineering (CSASE) (pp. 312-318). *IEEE Communication & Materials (ICACCM)* (pp. 322-325). *IEEE*
6. U. Satija, B. Ramkumar, M. S. Manikandan, "Robust Cardiac Event Change Detection Method for Long-term Healthcare Monitoring Applications," *IET Healthcare Technology Letters*, vol. 3, no. 2, pp. 116-123, May 2016. doi: 10.1049/htl.2015.0062
7. Awan, Z.W., Khalid, S. and Gul, S., 2022, May. A theoretical cnn compression framework for resource-restricted environments. In 2022 2nd International Conference on Digital Futures and Transformative Technologies (ICoDT2) (pp. 1-8). *IEEE*.
8. Mangia, M., Pareschi, F., Rovatti, R. and Setti, G., 2020. Adapted compressed sensing: A game worth playing. *IEEE Circuits and Systems Magazine*, 20(1), pp.40-60.
9. V. Pavitra, V. B. S. S. I. Dutt and G. V. S. Raj Kumar, "Deep Learning Based Compressive Sensing for Image Reconstruction and Inference," 2022 IEEE 7th International conference for Convergence in Technology (I2CT), Mumbai, India, 2022, pp. 1-7,
10. U. Satija, B. Ramkumar, M. S. Manikandan, "A robust sparse signal decomposition framework for baseline wander removal from ECG signal," *IEEE Tencon*, Singapore, 2016.
11. U. Satija, B. Ramkumar, M. S. Manikandan, "Low-Complexity detection and classification of ECG noises for automated ECG analysis system," *Int. Conf. Signal Process. Commun. (SPCOM)*, 2016, (IISc Bangalore).
12. Nadzri, M.M.M., Ahmad, A. and Tukiran, Z., 2020, September. Design issues and challenges of an FPGA- based orthogonal matching pursuit implementation for compressive sensing reconstruction. In 2020 IEEE Student Conference on Research and Development (SCOREd) (pp. 493-497). *IEEE*
13. U. Satija, B. Ramkumar and M. S. Manikandan, "A New Automated Signal Quality-Aware ECG Beat Classification Method for Unsupervised ECG Diagnosis Environments," in *IEEE Sensors Journal*, vol. 19, no. 1, pp. 277-286, 1 Jan.1, 2019, doi: 10.1109/JSEN.2018.2877055
14. Da Poian, G., Rozell, C.J., Bernardini, R., Rinaldo, R. and Clifford, G.D., 2017. Matched filtering for heart rate estimation on compressive sensing ECG measurements. *IEEE Transactions on Biomedical Engineering*, 65(6), pp.1349-1358.
15. Van Assche, J. and Gielen, G., 2020. Power efficiency comparison of event-driven and fixed-rate signal conversion and compression for biomedical applications. *IEEE Transactions on Biomedical Circuits and Systems*, 14(4), pp.746-756.
16. Satija, U., Ramkumar, B. and Manikandan, M.S., 2015, February. A simple method for detection and classification of ECG noises for wearable ECG monitoring devices. In 2015 2nd International Conference on Signal Processing and Integrated Networks (SPIN) (pp. 164-169). *IEEE*.
17. Zanddizari, H., Rajan, S., Zarrabi, H. and Rabah, H., 2022. Privacy assured recovery of compressively sensed ECG signals. *IEEE Access*, 10, pp.17122-17133.
18. Catarinucci, L., De Donno, D., Mainetti, L., Palano, L., Patrono, L., Stefanizzi, M.L. and Tarricone, L., 2015. An IoT-aware architecture for smart healthcare systems. *IEEE internet of things journal*, 2(6), pp.515-

526.

19. U. Satija, B. Ramkumar and M. S. Manikandan, "Automated ECG Noise Detection and Classification System for Unsupervised Healthcare Monitoring," in IEEE Journal of Biomedical and Health Informatics, vol. 22, no. 3, pp. 722-732, May 2018, doi: 10.1109/JBHI.2017.2686436.
20. U. Satija, B. Ramkumar and M. S. Manikandan, "A unified sparse signal decomposition and reconstruction framework for elimination of muscle artifacts from ECG signal," 2016 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP), Shanghai, China, 2016, pp. 779-783, doi: 10.1109/ICASSP.2016.7471781.

