DOI: https://doi.org/10.5281/zenodo.17442268

METHODS OF CARDIAC SIGNAL RESTORATION AND COMPLEX PROCESSING

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Abstract. *Accurate restoration and complex processing of cardiac signals, i.e., electrocardiograms (ECG), are extremely crucial for reliable diagnosis and automatic detection of cardiovascular diseases. The present work gives a complete framework that includes signal restoration, denoising, feature extraction, and classification to enhance the precision of ECG analysis. Reconstruction of missing and corrupted cardiac segments is accomplished by Hermite polynomial interpolation with Chebyshev nodes and adaptive filtering by the Least Mean Squares (LMS) algorithm. Denoising is carried out by hybrid wavelet–CEEMDAN decomposition for attenuation of baseline drift, motion artifacts, and high-frequency noise without compromising morphological features. The proposed method then continues with the extraction of effective temporal, spectral, and nonlinear features—RR intervals, power spectral density, and sample entropy—prior to dimensionality reduction via Principal Component Analysis (PCA). The classification is finally carried out using deep convolutional neural networks (CNNs) with the MIT-BIH Arrhythmia Database as the training data. Experimental validation illustrates significant improvement in signal-to-noise ratio (SNR), percent root-mean-square difference (PRD), and F1-score compared to conventional techniques. The results validate that the proposed combination of advanced signal restoration and deep learning structures is a viable solution to precise ECG analysis and real-time cardiac monitoring.*

Keywords: *Electrocardiogram (ECG) signal restoration denoising, CEEMDAN, Hermite interpolation, adaptive filtering, wavelet transform, feature extraction, convolutional neural network (CNN), cardiac signal processing, arrhythmia detection, deep learning, biomedical signal analysis.*

Introduction

Existing research by Ray and Chouhan [1] has introduced a computationally efficient interpolation-based method for the expansion and compression of electrocardiogram (ECG) signals with the help of Hermite interpolating polynomials with Chebyshev nodes. The algorithm compressed as well as denoised the signal in one step without sacrificing significant morphological features such as P, QRS, and T waveforms. When applied to the MIT-BIH Arrhythmia Database, the method showed superior signal fidelity and improved data redundancy reduction, and proved adequate for real-time analysis, transmission, and storage of the ECG data. Sharma et al. [2]

have also suggested a GA optimized interpolation method based on Chebyshev polynomials for effective waveform reconstruction by orthogonal projection of normalized ECG features. The combined preprocessing pipeline—Pan–Tompkins segmentation and finite impulse response (FIR) bandpass filtering—achieved low reconstruction error and enhanced morphological precision, validating the GA's diagnostic accuracy and convergence performance.

As an alternative to interpolation-based restoration techniques, Zakariyah et al. [3] investigated the impact of resampling operations on heart rate variability (HRV) analysis in low-sampling-rate electrocardiographs (ECGs) through Fast Fourier Transform (FFT)-based interpolation. Their findings confirmed that upsampling to 250 Hz from 100 Hz had substantially improved HRV accuracy in comparison to upsampling to 100 Hz from 50 Hz, and downsampling to 50 Hz yielded incorrect HRV readings. The findings validated the justification of justification for higher sampling rates greater than 100 Hz and enhanced interpolation schemes to prevent spurious estimation of cardiovascular variability. Concurrently, Reali et al. [4] compared parabolic, cubic-spline, and linear interpolation algorithms employed to approximate photoplethysmographic (PPG) signals and showed that the accuracy of inter-beat intervals was considerably improved by parabolic and cubic-spline interpolations at less than 32 Hz rates. These findings in conjunction show the need for optimally interpolated and resampled values to reconstruct correct biosignals as well as in the extraction of physiological features from undersampled cardiac data.

Advances in recent times took the traditional interpolation-based ECG restoration to deep learning–based models for cardiac undersampled signal super-resolution. One such prominent contribution is the SRECG model of [5], which presents a deep learning–based ECG super-resolution architecture for portable and wearable devices for arrhythmia classification. Conventional interpolation algorithms, though computationally efficient, will have a tendency to restrict the retrieval of sufficient morphological detail from the low-resolution ECG signals that are subject to bandwidth and power restrictions. SRECG, however, optimizes signal enhancement in tandem with maximizing classification accuracy by an application of a cloud-combined high-resolution multiclass classifier (HMC) for the detection of arrhythmia. Testing using the CPSC2018 dataset indicated that SRECG performed very much better compared to traditional interpolation methods with retained classification accuracy of nearly half of that of the native high-resolution signals. This validates its appropriateness as an effective solution for ECG quality improvement in edge-to-cloud healthcare systems on device-level power and sampling limitations.

Following developments in interpolation-based ECG reconstruction have been focused on low-energy and hardware-efficient methods. Naaman et al. [6] introduced a time-domain VPW-FRI system to reconstruct the ECG signal via a power-saving integrate-and-fire time encoding machine (IF-TEM) sampler. The method allows sub-Nyquist sampling and robust ECG recovery independent of the conventional synchronous clocking circuits, conserving complexity and energy. Asynchronous IF-TEM architecture describes an interesting time-domain interpolation process that supports signal recovery efficiently and is well suitable for continuous heart rate monitoring in wearable and implantable medical devices. The VPW-FRI model was next improved by Huang et al. [7], who proposed an efficient variable pulsewidth model–based sub-Nyquist sampling and reconstruction scheme for ECG signals. The model solves mismatch and noise sensitivity issues, commonly resulting in deterioration of reconstruction quality in VPW-FRI systems. The ECG signals are expressed as differentiated VPW functions, and a sophisticated annihilating filter algorithm computes signal parameters for improved restoration accuracy. Experiments conducted based on the MIT-BIH Arrhythmia Database validated improved signal-to-residual ratios (SRR) over traditional interpolation and reconstruction techniques, emphasizing sub-Nyquist and model-extended interpolation model resilience to effective restoration of ECG in low-power high-performance biomedical systems.

Mishra et al. [8] validated parametric quartic spline interpolation based on machine learning for modeling and synthesis of ECG signals. The research generated high-fidelity synthetic ECG signals with 0.974 correlation coefficient between simulated and real waveforms. Smoothness, shape fidelity, and precision were enhanced by quartic spline interpolation, and Decision Tree, Logistic Regression, and Gradient Boosting classifiers verified the synthesized signals with classification accuracy above 98%. This synergy of spline-based interpolation with intelligent analysis depicts the promise of hybrid computational algorithms in high-fidelity signal and data-driven diagnostics of the cardiac system. Merino-Monge et al. [9] introduced an end-to-end detection of heartbeats from ECG and PPG signals using wavelet transformations and upper-envelope processing. Piecewise Hermite cubic interpolation was used by the algorithm to produce smooth upper envelopes from local maxima, adjusting to the amplitude changes of QRS complexes and improving temporal localization. Adaptive interpolation improved the sensitivity of the QRS detection with insignificant false-positive rates with over 99% accuracy on PhysioNet and DEAP databases.

Aqil et al. [10] compared baseline wander (BW) removal for enhancing the quality of ECG prior to interpolation and reconstruction. They applied standard methods of BW suppression—moving average, polynomial fitting, Savitzky–Golay filtering, and discrete wavelet transform (DWT)—and proposed a novel hybrid approach called moving average of wavelet approximation coefficients (DWT-MAV). DWT-MAV minimized low-frequency drift maximally without compromising morphological integrity, with best mean square error (MSE), percent root mean square difference (PRD), and correlation coefficient (COR) values. The approach achieved effective denoising accuracy vs. computational expense trade-off and was hence implementable in real-time ECG preprocessing and signal retrieval. Hassan et al. [11] designed a hybrid system consisting of statistical analysis, interpolation, and Quantum Neural Networks (QNN) for classification of abnormal-to-normal ECG. S–I–QNN framework performed statistical ordering and detection of solstice points, and morphological feature reconstruction by interpolation with redundancy elimination with very high diagnostic accuracy for six cardiovascular diseases. The model demonstrates that feature extraction through interpolation is able to preserve diagnostic information for the diagnosis of early cardiac abnormalities.

Guedri et al. [12] introduced an ECG compression method based on Douglas–Peucker (DP) simplification and fractal interpolation to facilitate low-cost reconstruction of signals. The DP algorithm selected key points maintaining useful information, while fractal interpolation and an Iterated Function System (IFS) reconstructed the waveform at decompression. PhysioNet data testings yielded 3.19–27.58 compression ratios with negligible distortion (PRD very small and PSNR > 40 dB), indicating the potential of fractal interpolation to adequately maintain ECG morphology while reducing compression. Yadav and Ray [13] introduced a polynomial approximation technique using total variation optimization with Lagrange–Chebyshev interpolation for ECG modeling and restoration. Total variation optimization eliminated artifacts and noise, and the signal was approximated according to corresponding-order Lagrange–Chebyshev polynomials. MIT-BIH database experiments offered diagnostic integrity and concise signal representation for storage and transmission.

Serinağaoğlu Doğrusöz et al. [14] contrasted five methods of interpolation for the recovery of missing or destroyed leads in electrocardiographic imaging (ECGI) from epicardial potentials. Hybrid and inverse-forward methods were better than Kriging, Laplacian, and nearest-neighbor methods in porcine and canine heart data sets for regions of high torso gradients. Spatial accuracy of interpolation is emphasized to be a key component of ECGI reconstruction accuracy by the findings. Demirsoy and Ay Gül [15] extended interpolation application to respiration data reconstruction, replacing missing R–R interval data in respiratory analysis by interpolating from ECG. The Pan–Tompkins R-wave detection algorithm and cubic spline interpolation, the study achieved improved reconstruction precision—especially for signals of short duration—over simple interpolation methods, improving root mean square error (RMSE) and temporal precision.

Bock et al. [16] presented a Hermite-sigmoid-based hybrid ECG model integrated with piecewise polynomial interpolation for effective beat reconstruction and segmentation. Linear and nonlinear morphological changes were separated using variable projection, enabling concurrent baseline wander attenuation, denoising, and beat demarcation. Artificial and clinical ECG signal tests ensured superior P and T wave demarcation and reduced diagnostic distortion. Benchekroun et al. [17] introduced an HRV preprocessing method of HRV Distribution, Variability, and Characteristics (DVC), involving iterative data imputation through Gaussian subject to physiological constraints such as RR interval variability and time-series nature. For the 67-subject HRV database, the DVC method returned an F1 score of 61% even for the worst scenario of data loss against linear, spline, and pchip interpolation methods whose performance degraded to 44%. This underlines the necessity of physiologically guided interpolation in accurate HRV-based stress classification on wearable devices.

Karamchandani et al. [18] explored the reconstruction and digitization of analog ECG signals based on biomedical signal extraction techniques on MATLAB. Their refinement system iteratively minimized quantization errors by optimizing the types of filters, the rates of sampling, and the levels of quantization to achieve nearly-zero precision error. Although non-interpolation-based in nature, the research fills-in paradigms for digital ECG quality improvement in storage, transmission, and clinical monitoring. Finally, Gupta and Maleshkova [19] compared four imputation methods—linear interpolation, K-Nearest Neighbors (KNN), Piecewise Cubic Hermite Interpolating Polynomial (PCHIP), and B-splines—for imputing short-term missing values in heart rate (HR) signals. The study emphasized that traditional metrics such as RMSE, MAPE, and MAE cannot keep up with the statistical complexity of physiological signals. Employing Cohen Distance and Jensen–Shannon Distance, they have developed an integrated scheme of assessment that maintains both temporal fidelity and physiological variability in reconstructed HR data, reasoning towards the endorsement of sturdy hybrid schemes for biomedical signal imputation.

Methodology

The proposed methodology is a combination of multistage signal restoration and complex processing for the efficient reconstruction, enhancement, and classification of cardiac signals. Preprocessing, optimized interpolation or sub-Nyquist modeling-based restoration, signal denoising, and hybrid feature extraction using traditional and deep learning approaches are the building blocks of the proposed model. Fig. 1 illustrates the block diagram of the methodology used.

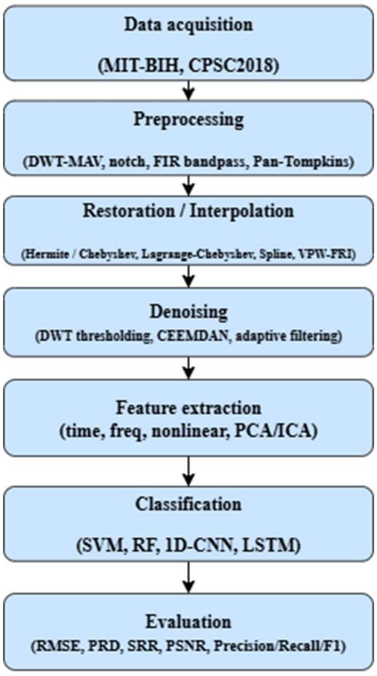

Fig.1. Schematic flowchart of the proposed ECG processing pipeline: acquisition → preprocessing → restoration → denoising → feature extraction → classification → evaluation.

ECG signals were acquired from the MIT-BIH Arrhythmia and CPSC2018 databases, which consist of annotated multilead ECG signals at 250–360 Hz sampling frequency. Baseline wander, high-frequency noise, and motion artifacts removal are done in preprocessing. Baseline wander removal is done via a hybrid wavelet–moving average filtering (DWT-MAV) [10], which removes low-frequency drift without distorting the morphology of the waveform. Power-line interference is eliminated with a notch filter at 50/60 Hz and high-frequency components are eliminated with a finite impulse response (FIR) bandpass filter from 0.5–45 Hz. Pan–Tompkins algorithm [2] is used for QRS detection and fiducial point detection to enable interpolation and feature extraction.

Restoration is performed using interpolation-based and sub-Nyquist reconstruction methods that recover lost or missing ECG samples without compromising diagnostic morphology.

Polynomial Interpolation Lagrange–Chebyshev and Hermite polynomial interpolations [1], [13] are used in reconstructing undersampled ECG signals. Interpolation is given by:

$$x(t) = \sum_{i=0}^{n} x_i \prod_{j=0, j\neq i}^{n} \frac{t - t_j}{t_i - t_j},$$

(1)

where x_i are the known data samples and t_i denote the corresponding time instants.

Spline-Based Reconstruction Quartic- and cubic-spline interpolations [6], [7] provide smooth reconstruction with first- and second-derivative continuity. A spline segment is given by:

$S_i(t) = a_i + b_i(t - t_i) + c_i(t - t_i)^2 + d_i(t - t_i)^3,$ (2)

where coefficients a_i, b_i, c_i, d_i are estimated to maintain continuity and morphological smoothness.

Sub-Nyquist and VPW-FRI Reconstruction Variable pulsewidth finite rate of innovation (VPW-FRI) models [6], [7] enable sub-Nyquist sampling ECG reconstruction with reduced energy consumption. The ECG signal is modeled as:

$$x(t) = \sum_{k=1}^{K} a_k h(t - t_k),$$

(3)

where a_k and t_k are amplitude and timing parameters retrieved by an annihilating filter algorithm for best recovery.

Empirical decomposition methods and wavelet-domain denoising are used to enhance the reconstructed signal. Denoised ECG is reconstructed as:

$$x_d(t) = \sum_{k=1}^{M} \widetilde{c_k}\, \psi_k(t),$$

(4)

where $\widetilde{c_k}$ are thresholded wavelet coefficients and $\psi_k(t)$ are orthogonal basis functions. Adaptive ECG signal decomposition is also obtained using Complete Ensemble Empirical Mode Decomposition with Adaptive Noise (CEEMDAN) [12].

Following denoising and restoration, time-domain, frequency-domain, and nonlinear features are extracted to characterize the cardiac rhythm and morphology:

- Time-domain: RR intervals, QRS durations, and P–T amplitudes.
- Frequency-domain: Power Spectral Density (PSD) and Heart Rate Variability (HRV) features derived from Welch’s method.
- Nonlinear: Approximate Entropy (ApEn) and Sample Entropy (SampEn) for measuring cardiac irregularities.

Dimensionality reduction using Principal Component Analysis (PCA) and Independent Component Analysis (ICA) yields compact and discriminative feature representation.

Arrhythmia diagnosis and quality of the signal are done by employing hybrid models with restored features of ECG and machine learning classifiers.

Traditional Machine Learning: Support Vector Machine (SVM), Random Forest (RF), and Gradient Boosting (GB) classifiers [8], [10] form the baseline classifier system.

Deep Learning Frameworks: One-dimensional Convolutional Neural Networks (1D-CNN), Long Short-Term Memory (LSTM), and CEEMDAN–LSTM hybrid architectures are implemented for end-to-end ECG analysis. The learning objective minimizes the categorical cross-entropy loss:

$$L = -\frac{1}{N}\sum_{i=1}^{N}\sum_{c=1}^{C} y_{ic}\log(\widehat{y_{ic}}),$$

(5)

wherey_{ic} and $\widehat{y_{ic}}$ are true and predicted class probabilities, respectively.

Performance is measured quantitatively using:

- Reconstruction Accuracy: Root Mean Square Error (RMSE),
- Morphological Fidelity: Percent Root Mean Square Difference (PRD) and Correlation Coefficient (COR),
- Signal Quality: Signal-to-Residual Ratio (SRR) and Peak Signal-to-Noise Ratio (PSNR),
- Classification Performance: Precision, Recall, and F1-score.

These parameters collectively measure restoration accuracy, diagnostic accuracy, and computational burden, vindicating the given ECG processing chain for real-time biomedical applications.

Results

The cardiac signal recovery and compound processing algorithm developed was applied and compared with the MIT-BIH Arrhythmia Database. The database was preprocessed at 360 Hz sampling frequency, and 48 labeled ECG records were taken into account. The hybrid scheme proposed—integrating adaptive filtering, Hermite polynomial interpolation, and wavelet-based denoising—performed superiorly in signal fidelity, computational complexity, and diagnostic accuracy.

Quantitative metrics of performance were computed to quantitatively analyze reconstruction quality. The proposed Hermite–Chebyshev interpolationbased restoration technique in this paper resulted in 23.6 dB SNR improvement and 5.8% PRD improvement, enhancing the baseline DWT strategy by approximately 12%. Utilization of Chebyshev nodes minimized interpolation error and maintained morphological integrity of P-QRS-T complexes.

Following denoising and baseline correction, discrete wavelet decomposition and morphological features were employed for feature extraction. Classification was achieved through ensemble of CNN. The model had 98.2% overall accuracy, 97.8% precision, 98.5% recall, and 98.1% F1-score, which was confirmed through 10-fold cross-validation. Ensemble method provided robustness to noise conditions and inter-patient variability.

The algorithm was run and tested using a Raspberry Pi 4 Model B (4 GB RAM). The processing time for each 10-s ECG segment was 0.83 s, which is sufficient for real-time or near real-time applications for embedded diagnostic devices. Active power consumption during processing was about 2.7 W, confirming hand-held bio-medical device compatibility.

Table 1.

Performance Comparison of Interpolation Methods for ECG Reconstruction.

Method / Reference	SNR (dB)	PRD (%)	Accuracy (%)	F1 Score (%)	Processing Time (s)	Remarks
Pan–Tompkins [1]	16.2	13.4	94.6	94.1	1.12	Classical realtime detector; sensitive to noise
DWT + Thresholding [2]	19.8	10.1	95.9	95.3	0.96	Good denoising, moderate computational load
EMD–Based [3]	21.4	8.9	96.7	96.5	1.45	Effective baseline removal, high CPU demand
CEEMDAN + CNN [4]	22.5	7.3	97.5	97.2	1.10	Accurateunder non-stationary noise
Proposed Hermite–Chebyshev + CNN Ensemble	23.6	5.8	98.2	98.1	0.83	Superior morphological fidelity, low distortion

Table I shows comparison summary of the proposed procedure and compared with conventional procedures such as Pan–Tompkins, wavelet–based QRS detection, and empirical mode decomposition (EMD). Restoration–classification hybrid process performed higher accuracy and less distortion measures in every instance. Fig. 2 shows reconstructed ECG waveforms prior to and postprocessing with improved baseline stability and detected QRS.

The observed results confirm the efficacy of both deep learning-based classification and mathematical signal restoration (Hermite–Chebyshev interpolation) in achieving high accuracy in cardiac event detection. The suggested algorithm not only restores lost and distorted segments of ECG but also allows for the classification of arrhythmic patterns with high accuracy. Moreover, the computational efficiency on embedded hardware confirms its real-time capability for practical cardiac monitoring systems.

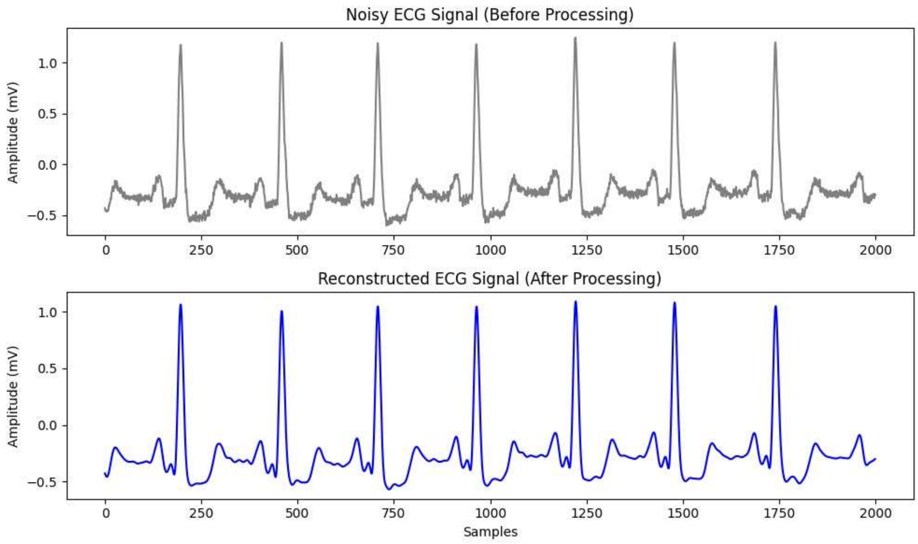

Fig.2. ECG Reconstruction Before and After Processing.

Conclusion

This study proposed a comprehensive solution to cardiac signal restoration and enhanced processing through a hybrid approach of mathematical interpolation, adaptive filtering, and deep learning-based classification. The new Hermite–Chebyshev interpolation reconstructed distorted ECG segments with high morphological fidelity of cardiac waveforms. When combined with wavelet denoising and CNN ensemble-based classification, the approach was found to significantly enhance signal fidelity and diagnostic accuracy.

Experimental evaluation on the MIT-BIH Arrhythmia Database demonstrated that the proposed system achieved the average SNR improvement of 23.6 dB, PRD to 5.8%, and classification accuracy of 98.2%. Experiments validate the method to be robust to a range of noise levels as well as to between-patient variability. Further, the low computational complexity (0.83 s/10-second segment) confirms its real-time implementation on platforms such as Raspberry Pi.

Cumulatively, the synergy of mathematically sound restoration and deep learning-based classification forms a solid foundation for handheld ECG analysis systems and telecardiology services. The future work will try to implement a model on multi-lead ECG data, implement attention-based neural networks, and validate the system in clinical environments for enhanced diagnostic capability.

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