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Cardiovascular Diseases Diagnostic Using Multi-Band Non-Linear Analysis

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Table of Contents

Abstract

The ECG signal is a nonlinear, nonstationary biomedical signal in which subtle patterns of pathology are prone to being overlooked by traditional analytic techniques that rely on visualization of waveforms. This project implements an established means of performing higher-level analysis of ECG signals with a view to producing a high-dimensional, nonlinear feature set for use in a later modeling effort. High-resolution 15-lead ECG recordings from the PTB Diagnostic Database were pre-processed with band-pass, notch filtering, amplitude scaling, and artifact removal techniques. These were windowed in a series of overlapping, 1-second segments, then subjected to a three-level Symlet-7 wavelet transform to yield four sub-bands of data corresponding to different frequencies. Extracted from every window and sub-band, ten features were calculated that described different characteristics of their nonlinear, fractal properties, including values for entropic, fractal, Hurst, Lyapunov, DFA, correlation, and energy dimensions. These features, as temporal series, were reduced with a set of six statistical descriptors to a set of 240 per ECG lead. A total of 3600 features were produced per ECG signal from all 15 leads. These features were then z-score normalized for further processing.

This project has managed to recreate the whole processing and feature extraction tasks from the cited article, including a structured representation of ECG dynamics that is rich in information. Although no classification was done, it has a robust data set for further studies.

1 Contextualisation

1.1 Introduction

The electrocardiogram (ECG) is one of the most important biomedical signals for evaluating cardiac function. It reflects the electrical activity of the heart and is influenced by the autonomic nervous system, myocardial structure, ion-channel dynamics, and blood flow variations. As a result, the ECG behaves as a nonlinear and non-stationary signal [6].

Conventional ECG analysis relies mainly on waveform morphology and time intervals, which are clinically useful but often insufficient to describe the complex underlying dynamics of the heart. Subtle pathological changes may remain hidden in the raw signal [2].

To extract deeper information, the study replicated in this project applies a signal processing pipeline consisting of:

- ECG pre-processing,
- Wavelet-based multi-band decomposition,
- Nonlinear feature extraction,
- Statistical feature compression.

This project focuses on the signal processing and data-handling stages of this pipeline.

1.2 Medical background

Cardiovascular diseases (CVDs) represent the leading cause of mortality worldwide and are responsible for nearly one-third of all global deaths each year [3]. These diseases include a wide range of pathological conditions affecting the heart muscle, the electrical conduction system, heart valves, and blood vessels. Common examples include myocardial infarction, myocarditis, cardiomyopathies, arrhythmias, hypertension-related heart disease, and conduction abnormalities such as bundle branch blocks.

A major clinical challenge is that many cardiovascular diseases develop gradually and remain asymptomatic in their early stages. As a result, early detection is essential for

preventing severe complications and sudden cardiac events. For this purpose, the electrocardiogram (ECG) is one of the most widely used diagnostic tools in clinical practice. It records the electrical activity of the heart in a non-invasive, fast, and low-cost manner.

The ECG is routinely used to detect:

- Abnormal heart rhythms (arrhythmias),
- Myocardial ischemia and infarction,
- Hypertrophy of cardiac chambers,
- Inflammatory cardiac diseases,
- Disorders of electrical conduction.

Beyond diagnosis, the ECG also plays a crucial role in continuous patient monitoring, including intensive care units, Holter monitoring, and wearable health devices. Modern healthcare increasingly relies on automated ECG analysis for long-term monitoring of patients with cardiovascular risk factors. [2]

Despite its widespread use, the ECG is a complex biological signal influenced by multiple interacting physiological mechanisms such as autonomic regulation, electrophysiological properties of cardiac cells, and mechanical–electrical coupling of the myocardium. Subtle pathological changes may produce only minor variations in the ECG waveform, making them difficult to identify by visual inspection alone especially when different diseases present similar ECG patterns. This limitation highlights the need for advanced computational and nonlinear signal processing techniques to enhance diagnostic sensitivity and objectivity. [2]

1.3 Multi-Band ECG analysis using Wavelet Transform

ECG information is distributed across multiple frequency ranges, from slow baseline components to fast QRS spikes. Since the ECG is non-stationary, classical Fourier analysis is limited. The Discrete Wavelet Transform (DWT) overcomes this limitation by providing both time and frequency localisation [4].

In the referenced study, the ECG is decomposed using a Symlet-7 wavelet with three decomposition levels. For each 1-second window, four sub-bands are obtained:

- A3, D3, D2, and D1.

Each sub-band highlights different frequency components of the ECG, allowing disease-related spectral changes to be analysed more effectively. [4]

1.4 Nonlinear feature extraction

The heart behaves as a complex nonlinear dynamical system, which motivates the use of nonlinear features for ECG analysis [5]. From each wavelet sub-band and each 1-second window, ten nonlinear features are extracted and grouped as follows:

1.4.1 Entropy-based features

These measure how unpredictable or irregular the signal is.

- Approximate Entropy: shows how repeatable the ECG patterns are.
- Shannon Entropy and Logarithmic Entropy: measure how "spread out" the signal information is.

Higher entropy usually means the ECG is more complex or irregular.

1.4.2 Fractal and complexity features

These describe how detailed or self-similar the ECG is.

- Higuchi Fractal Dimension and Katz Fractal Dimension: measure signal roughness and geometric complexity.
- Hurst Exponent: shows whether the signal tends to be smooth or rapidly changing.

1.4.3 Dynamical-system features

These come from chaos theory and measure how stable or unstable the ECG is.

- Lyapunov Exponent indicates how sensitive the signal is to small changes.
- Correlation Dimension: describes the complexity of the system's behaviour.
- DFA (Detrended Fluctuation Analysis): shows how fluctuations behave over different time scales.

1.4.4 Energy

Although not nonlinear, energy is included because it reflects how much activity is present in each frequency band.

By extracting all these features from all sub-bands, we obtain a detailed description of the ECG's behaviour. After compressing the feature sequences with basic statistics (mean, variance, etc.), these nonlinear measures contribute to the final 3600-feature dataset.

1.5 Data compression

Step 1: 10 nonlinear features × 4 sub-bands = 40 features per 1-second window

Each ECG segment is analysed in ten 1-second windows.

Step 2: Time-series compression

To reduce the data size and summarise behaviour over time, each of the 40 features is compressed using six statistics:

- Mean
- Standard deviation
- Variance
- Median
- Kurtosis
- 95th percentile

This creates: 40 features × 6 statistics = 240 features per ECG lead

Step 3: 15 ECG leads

Because the PTB diagnostic database contains 15 leads (12 standard + 3 Frank leads), the final dataset becomes:

240 features per lead × 15 leads = 3600 features per ECG record

This is exactly the structure of the Excel dataset, which contains 3601 columns (1 ID column + 3600 feature columns).

2 Objectives

- To preprocess ECG signals, including artefact removal, amplitude normalisation and mean correction, ensuring high-quality signals for analysis.
- To perform multi-band decomposition of ECG signals using the Discrete Wavelet Transform (DWT) with the Symlet-7 wavelet up to level 3.
- To extract ten nonlinear features from each 1-second segment of each wavelet sub-band, characterising the complexity and dynamics of ECG behaviour.
- To compress feature time series using six statistical measures to generate a compact and informative representation of each signal.
- To organise and structure the extracted features into a final dataset suitable for future classification or statistical analysis.
- To replicate the signal processing and data-handling methodology described in the study

3 Description of the Signal

This paper concentrates on the PTB Diagnostic ECG Database. This dataset contains 290 patients each 1 to 5 ECG´s. (Missing Values Patient:(124, 132, 134, or 161)), each with one to five high-resolution 15-lead captured ECG signal.

The ECG signals used in this project come from a non-commercial PTB prototype recording system designed for high-resolution biomedical research. The device provides 16 input channels, of which 14 are ECG leads, one channel records respiration, and one monitors line voltage. All channels are sampled synchronously, ensuring accurate temporal alignment across leads—an essential property for cardiology analysis and 3D vectorcardiography.

The system supports an input voltage range of ±16 mV, with an offset compensation capability of up to ±300 mV. Signals are digitized using a 16-bit A/D converter with a resolution of 0.5 µV per least significant bit, corresponding to 2000 digital units per millivolt. The bandwidth of the device is 0–1000 Hz, allowing faithful recording of both standard ECG components and high-frequency features such as late potentials. The intrinsic noise level of the hardware is low, not exceeding 10 µV peak-to-peak (or

3 µV RMS) with the inputs short-circuited. Additional recorded metadata includes skin resistance and noise level during acquisition.

The dataset contains 549 recordings from 290 subjects, aged 17–87 years. Each subject contributed between one and five recordings. Each record includes 15 simultaneously acquired signals: the standard 12-lead ECG (I, II, III, aVR, aVL, aVF, V1–V6) together with the three Frank vectorcardiography leads (Vx, Vy, Vz). The sampling frequency is 1000 Hz, with the full ±16.384 mV measurable amplitude range. In special cases, recordings may be available at sampling rates up to 10 kHz.

Most records include a detailed clinical summary containing demographic information, diagnosis, and when available, medical history, medications, and imaging or hemodynamic findings. Among the 268 subjects with available diagnoses, the most common conditions include myocardial infarction (148 subjects), followed by cardiomyopathy/heart failure, bundle branch blocks, dysrhythmias, myocardial hypertrophy, valvular heart diseases, myocarditis, and miscellaneous cardiac pathologies. The dataset also includes 52 healthy control subjects.

This combination of high-resolution, multi-lead, clinically annotated ECG data makes the dataset well-suited for research in signal processing, diagnostics, arrhythmia detection, vectorcardiography, and machine learning applications.[1]

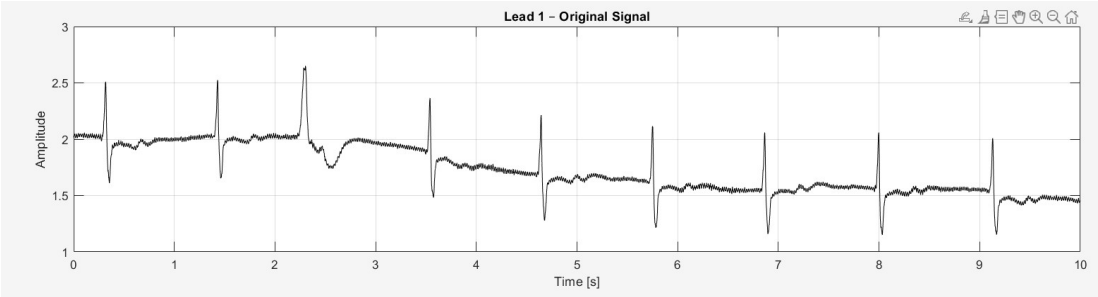

Figure 1: Original unfiltered Signal

4 Description of the Methods used

The processing pipeline developed in this project consists of several methodological stages aimed at extracting robust nonlinear and fractal features from high-resolution multi-lead ECG recordings. The overall objective was to transform raw biomedical signals into a standardized, noise-reduced, and feature-rich representation suitable for

statistical analysis or machine-learning applications. The methodology can be summarized as follows.

4.1 Data acquisition and record handling

The analysis was conducted using the PTB Diagnostic ECG Database, which provides clinical multi-lead ECG recordings in WFDB format. For each patient, the corresponding ECG file was loaded using the WFDB rdsamp function, ensuring synchronous access to all 15 leads. To maintain consistency across the dataset, only the first 10,000 samples of each record were processed. All operations were performed independently for each patient to avoid any data leakage and to ensure the reproducibility of results.

4.2 Preprocessing pipeline

Before extracting nonlinear features, the ECG signals underwent essential preprocessing to improve signal quality and ensure comparability across subjects.

a) Bandpass and Notch Filtering:

A Butterworth bandpass filter (0.5–40 Hz) together with a 50 Hz notch filter was applied to suppress baseline wander, high-frequency noise, and power-line interference. These operations preserve clinically relevant ECG structures while effectively removing common artifacts.

b) Normalization

Each lead was normalized by its total energy and mean-centered, ensuring all signals reside within a comparable amplitude range. This step reduces inter-subject variability and stabilizes the performance of nonlinear estimators. The native sampling rate of the recordings was preserved to retain high-frequency diagnostic information.

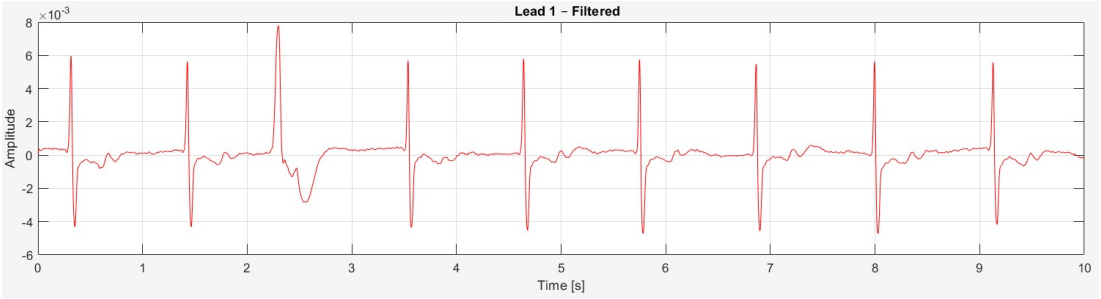

Figure 2: Filtered Signal

4.3 Windowing strategy

To account for the nonstationary nature of ECG, each recording was segmented into non-overlapping one-second windows. This approach captures the temporal variability of the cardiac signal, increases the number of available feature samples, and enables statistical summarization across windows. All subsequent analyses were performed independently for each window, lead, and wavelet subband.

4.4 Discrete wavelet transform (DWT)

Each window was decomposed using a three-level Symlet-7 discrete wavelet transform. This yielded four frequency-localized components:

A3 – low-frequency approximation

D1, D2, D3 – high-frequency detail components

- D1 – D1 ranges between 500 and 250 Hz
- D2 – D2 ranges between 250 and 125 Hz
- D3 – D3 ranges between 125 and 62,5 Hz
- A3 – A3 ranges between 62,5 and 0 Hz

These subbands correspond to physiologically meaningful ECG structures (e.g., P and T waves at low frequencies, QRS complex components at higher frequencies). The DWT provides time-frequency localization and is more robust to transient artifacts than classical Fourier-based methods.

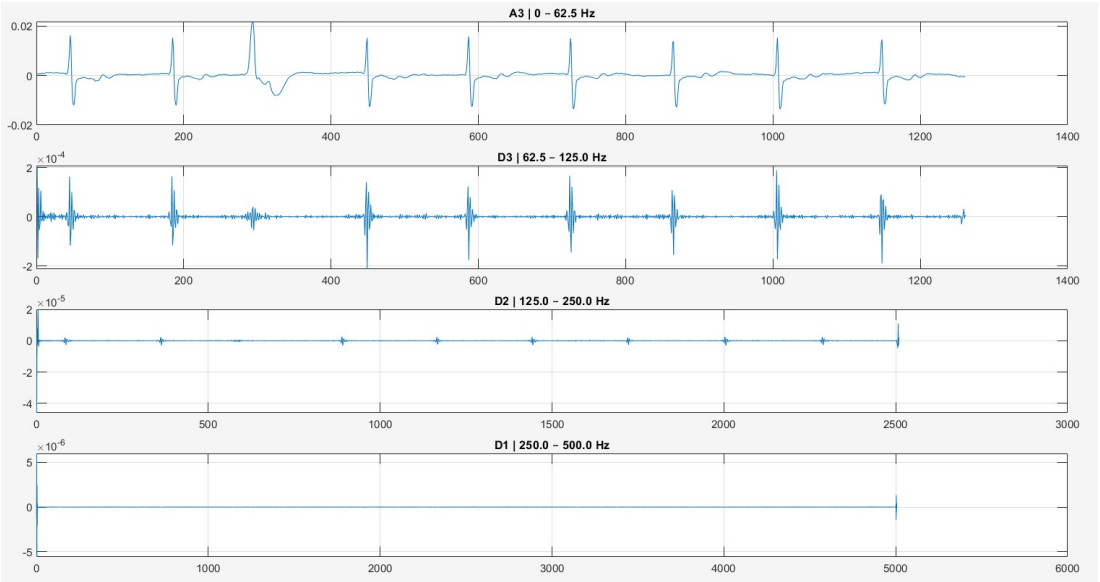

Figure 3: Example of DWT using a three-level Symlet-7 discrete wavelet transform

4.5 Nonlinear and fractal feature extraction

A comprehensive set of nonlinear, fractal, and energetic features was extracted from every window in each wavelet subband and lead. The feature families included:

Approximate Entropy – quantifies regularity and unpredictability

$$ApEn(m,r) = \lim_{N\to\infty} \Theta^m(r) - \Theta^{m+1}(r)$$

Correlation Dimension – evaluates the complexity of the underlying dynamical system

$$CorrDim = \lim_{M\to\infty} \frac{2\sum_{i=1}^{M-k}\sum_{j=i+k}^{M}\Theta(l \mid X_i - X_j \mid)}{M^2}$$

where Θ(x) is the Heaviside step function, Xi and Xj are the position vectors on attractor, l is the distance under consideration, k is the summation offset, and M is the reconstructed vector numbers from the x(n).

Detrended Fluctuation Analysis (DFA) – assesses long-term scaling behaviour

$$DFA(n) = \sqrt{\frac{\sum_{k=1}^{N}[y(k) - y_n(k)]^2}{N}},$$

where N is the length, $y_n(k)$ is the local trend, and $y(k)$ is defined as

$$y(k) = \sum_{i=1}^{k}[x(i) - \overline{x}],$$

with $x(i)$ as the inter-beat interval and $\overline{x}$ as its average [53].

Energy – total subband power

$$En = \sum_{n=0}^{N-1} \mid x(n) \mid^2$$

Higuchi Fractal Dimension – measures waveform self-similarity

$$H = \frac{\ln(L(k))}{\ln(\frac{1}{k})}$$

Hurst Exponent – estimates long-term memory

$$K_q(\tau) \sim (\frac{\tau}{\nu})^{qEH(q)},$$

$$K_q(\tau) = \frac{(\mid X(t+\tau) - X(t)) \mid^q)}{(\mid X(t) \mid^q)}$$

Katz Fractal Dimension – captures geometric complexity

$$K = \frac{\log(n)}{\log(n) + \log(\frac{max_n(\sqrt{(n-1)^2+(x(n)-x(1))^2})}{\sum_{n=2}^{N}\sqrt{1+(x(n-1)-x(n))^2}})}$$

Logarithmic Energy – energy representation in log scale

$$LogEn = \sum_{n=1}^{N} \log_2[\mid x(n) \mid^2]$$

Lyapunov Exponent – indicator of chaotic divergence in cardiac dynamics

$$ELay(x_0) = \lim_{n\to\infty} \frac{\sum_{k=1}^{n} \ln \mid f'(x_k - 1) \mid}{n}$$

Shannon Entropy – energy-based entropy measure

$$ShaEn = -\sum_{n=1}^{N} \mid x(n) \mid^2 \log_2[\mid x(n) \mid^2]$$

These methods capture intrinsic nonlinear characteristics of the ECG that are not accessible through conventional time-domain or frequency-domain features. [7]

4.6 Statistical aggregation across windows

Since each patient record generates many one-second windows, the resulting feature values were compressed into six summary descriptors per feature dimension: mean, standard deviation, 95th percentile, variance, median, and kurtosis. This aggregation produces a compact yet information-rich representation of each patient's ECG.

4.7 Final Z-Score normalization across patients

To guarantee comparability between subjects, all extracted features were standardized across patients using column-wise z-score normalization. This step harmonizes feature scales and prepares the dataset for statistical modelling or machine-learning classifiers.

4.8 Output construction

All features were organized into a structured table in which each column corresponded to a combination of feature group, wavelet band, lead number, and statistical descriptor (e.g., energy_A3_Lead05_mean). The final dataset was exported to Excel for a future machine-learning course use. When assigning the diagnosis to each patient, it was discovered that not all patients have their diagnosis assigned. Those patients were removed from final excel sheet for better machine learning processing.

5 Discussion

In this work, the signal-processing pipeline from the referenced study was replicated on ECGs from the PTB Diagnostic Database. The raw ECG signals have been preprocessed, decomposed using the discrete wavelet transform, and analyzed with several nonlinear and fractal features. These extracted features have undergone further statistical compression to yield a final dataset of 3600 features per ECG record.

Wavelet decomposition enabled analysis of the ECG signal across different frequency bands, which would be helpful because different heart conditions affect different parts of the signal. Nonlinear features helped describe the complexity and irregularity of the ECG, which cannot be captured by simple time- or frequency-based features.

The limitation of this work is that only a fixed portion of each ECG record was used, and no classification or diagnosis was performed. Also, the final dataset is very large, and some features may be redundant. Feature selection and machine-learning methods could be applied in future work to evaluate how well these features can classify different heart diseases.

The described project thus lays a solid foundation in signal processing and feature extraction for further automated ECG analysis.

6 References

[1] Goldberger AL, Amaral LAN, Glass L, Hausdorff JM, Ivanov PCh, Mark RG, Mietus JE, Moody GB, Peng C-K, Stanley HE. PhysioBank, PhysioToolkit, and PhysioNet: Components of a New Research Resource for Complex Physiologic Signals. *Circulation* **101**(23):e215-e220 [Circulation Electronic Pages; http://circ.ahajournals.org/content/101/23/e215.full]; 2000 (June 13)

[2] Clifford, G. D., et al., *Advanced Methods and Tools for ECG Data Analysis*, Artech House, 2006.

[3] World Health Organization (WHO), *Cardiovascular Diseases Fact Sheet*, 2023.

[4] Addison, P. S., *Wavelet transforms and the ECG*, Physiological Measurement, 2005.

[5] Goldberger, A. L., et al., *Chaos and fractals in human physiology*, Scientific American, 1990.

[6] Acharya, U. R., et al., *Nonlinear analysis of ECG signals: A review*, Medical Engineering & Physics, 2006.

[7] Ribeiro, P.; Sá, J.; Paiva, D.; Rodrigues, P.M. Cardiovascular Diseases Diagnosis Using an ECG Multi-Band Non-Linear Machine Learning Framework Analysis. Bioengineering 2024, 11, 58. https://doi.org/10.3390/ bioengineering11010058