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Detection of Atrial Fibrillation via Analysis of Mean, Entropy, and Heart Rate Parameters Using Electrocardiogram Signals

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ABSTRACT

Atrial Fibrillation (AF), commonly referred to as AFib in clinical practice, is the most prevalent form of sustained cardiac arrhythmia and represents an important challenge in cardiovascular diagnosis and long-term patient monitoring. AF occurs when the normal coordinated electrical activity of the atria is disrupted, resulting in disorganized and irregular propagation of excitation waves and, consequently, an abnormal ventricular response. Accurate characterization of electrocardiographic alterations associated with AF is therefore essential for improving automated detection and supporting reliable clinical assessment. In this study, electrocardiogram (ECG) signals obtained from adult subjects are comparatively analyzed to distinguish healthy cardiac activity from patterns associated with Atrial Fibrillation. The dataset employed in the investigation was compiled from records provided by the American and European Heart Associations and includes subjects from different age groups. Demographic analysis indicates that fewer than 5% of the participants belong to the 40–50-year age group, whereas approximately 5–15% are around 80 years of age, reflecting the increased prevalence of AF among older individuals. A quantitative analysis of heart-rate behavior reveals that patients with Atrial Fibrillation exhibit substantially more irregular temporal dynamics and generally higher heart-rate values than healthy subjects. In AF cases, heart rates are frequently concentrated within the range of 80–100 beats per minute (bpm), with a considerable number of episodes exceeding 100 bpm. In addition to heart-rate analysis, statistical and signal-based features are extracted from processed ECG segments to characterize differences between the two groups. The results demonstrate that AF signals exhibit a lower mathematical mean while presenting considerably higher entropy and energy values than ECG signals obtained from healthy individuals. These findings indicate that statistical characteristics such as mean, entropy, and signal energy can effectively capture the increased irregularity and complexity associated with Atrial Fibrillation. Consequently, the identified features may provide useful discriminatory information for the development of automated ECG-based AF detection and classification systems, particularly in continuous cardiac monitoring and computer-assisted diagnostic applications.

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1. INTRODUCTION

Atrial Fibrillation (AFib or AF) is the most prevalent type of cardiac arrhythmia, characterized by chaotic electrical impulses that do not follow a distinct pathway through the heart. AF occurs when the electrical excitation waves within the atria lack a defined direction, causing the atrial myocardial cells to depolarize and contract asynchronously. Consequently, the coordinated atrial contraction is lost, preventing the atria from effectively pumping blood into the ventricles. Furthermore, ventricular beats dissociate from atrial control, leading to ventricular contractions that occur without a natural sinus rhythm or synchronization with the atria [1].

Atrial fibrillation is frequently asymptomatic, and patients often remain unaware of their condition. The patient population predominantly consists of elderly individuals who frequently present with comorbidities. Although AF is rarely acutely life-threatening on its own, it significantly increases the risk of secondary complications, including chronic fatigue, congestive heart failure, and, most critically, ischemic stroke [2].

On an electrocardiogram (ECG), AF is typically characterized by the absence of the atrial depolarization wave (P-wave) [1]. It stands as the most common form of narrow QRS complex tachycardia [3]. In AF, repetitive, multi-directional, and disorganized atrial depolarizations occur, rendering any effective mechanical contraction impossible; hence, a distinct P-wave is completely absent from the ECG tracing [4]. Instead of organized P-waves, the ECG rhythm in AF displays only baseline oscillations a chaotic, irregular, and completely random fibrillatory wave (f-wave) that can occasionally be so fine that it resembles a flat line [3].

2. METHODOLOGY

This study evaluates and compares the electrocardiogram (ECG) signals of healthy individuals and patients diagnosed with atrial fibrillation. The signals were extracted from the PhysioNet database, specifically the PhysioNet/Computing in Cardiology Challenge 2017 dataset. This benchmark database was curated by the American Heart Association and European societies and made publicly available on PhysioNet. The dataset comprises adult ECG recordings from both healthy controls and AF patients. Demographically, individuals aged 40 to 50 represent less than 5% of the cohort, while those aged 80 account for 5% to 15%. The signals were recorded at various times of the day, sampled at a frequency of 300 Hz, with a voltage scaling of 1000 mV.

Initially, a dual-stage filtering pipeline was applied to both the normal ECG signals (Figure 1) and the AF ECG signals (Figure 2). First, a low-pass filter was implemented to smooth the signals (Figure 3 and Figure 4), followed by a high-pass filter to remove baseline wander (Figure 5 and Figure 6). The filter outputs successfully isolated the QRS complexes and suppressed prominent noise components. Subsequently, R-peaks were detected and annotated for both normal and AF conditions, as illustrated in Figure 7 and Figure 8, respectively. Finally, the $R-R$ intervals (the time duration between consecutive R-peaks) were computed, from which the heart rate, mean value, entropy, and energy metrics were extracted according to the formulations described below.

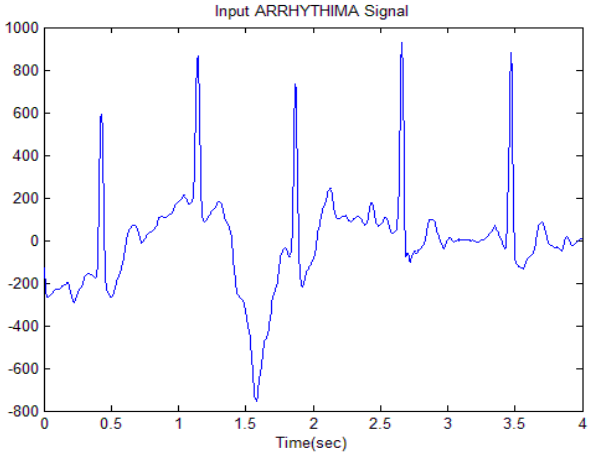

Fig. 1. Raw ECG signal of a healthy subject.

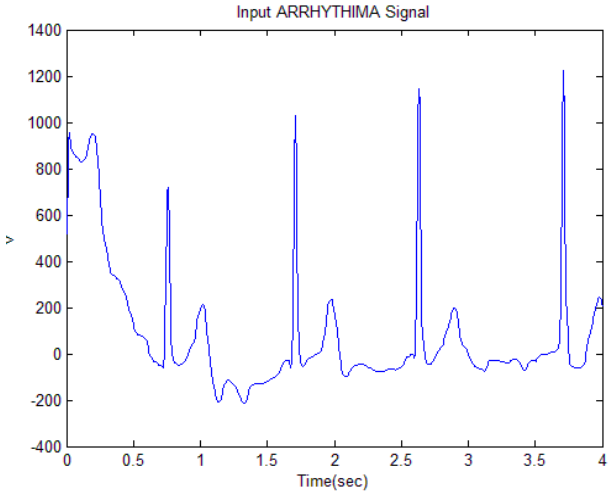

Fig. 2. Raw ECG signal of a patient with atrial fibrillation.

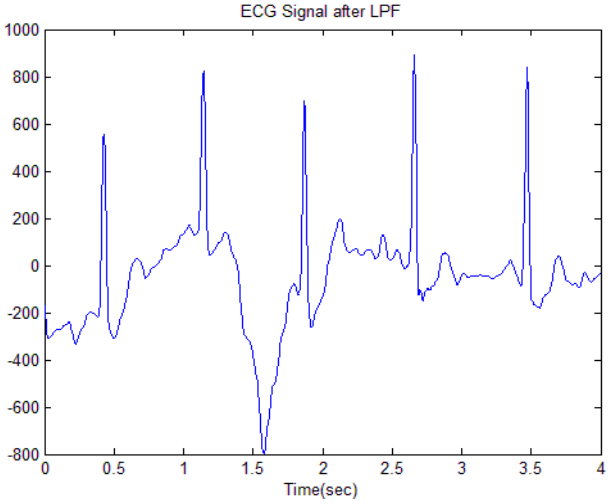

Fig. 3. Healthy subject's ECG signal after low-pass filtering.

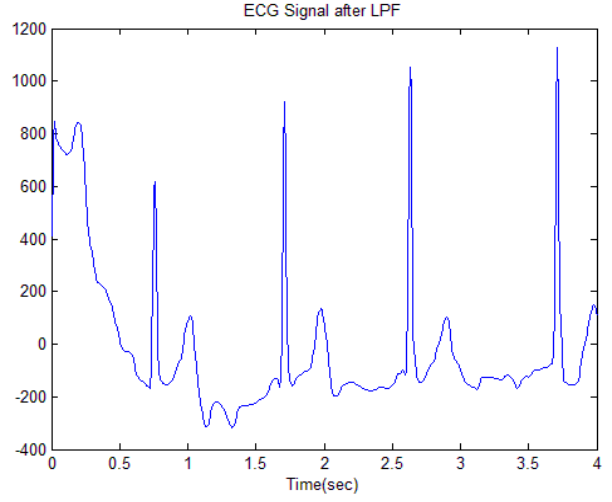

Fig. 4. Atrial fibrillation patient's ECG signal after low-pass filtering.

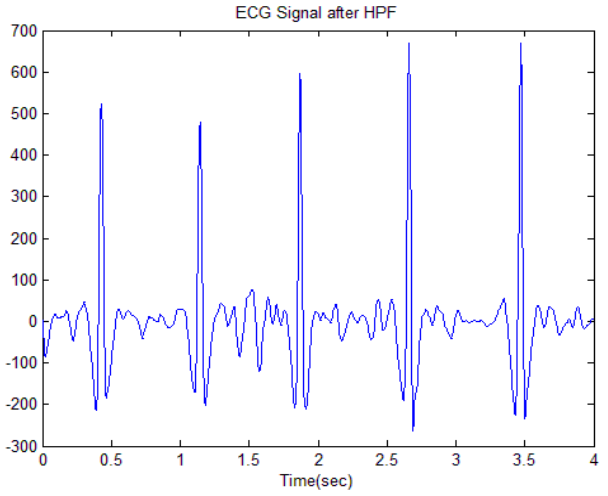

Fig. 5. Healthy subject's ECG signal after high-pass filtering.

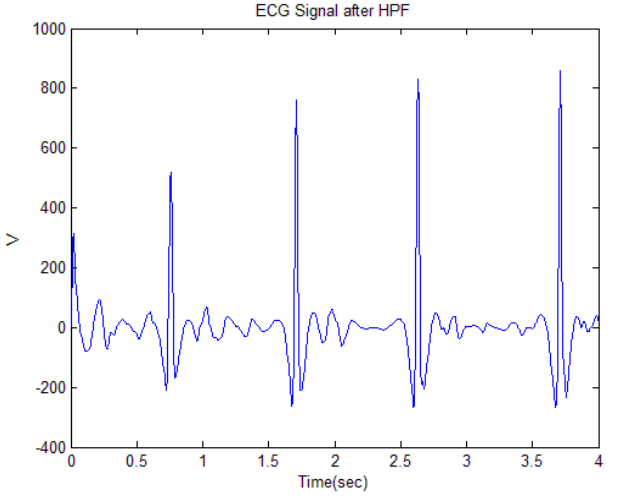

Fig. 6. Atrial fibrillation patient's ECG signal after high-pass filtering.

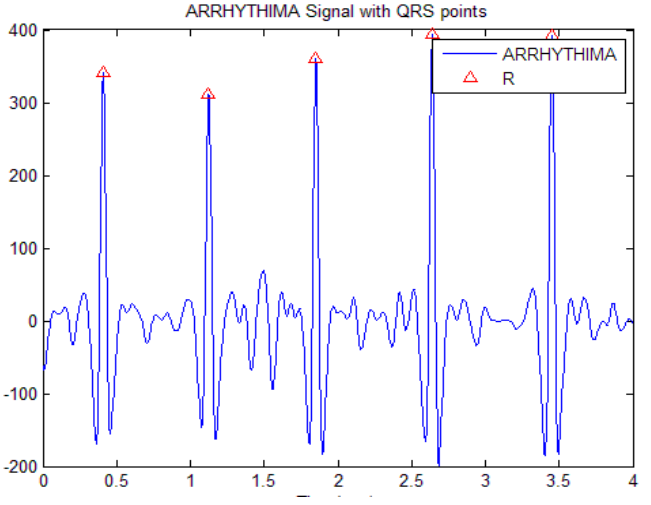

Fig. 7. Detected and annotated R-peaks in the healthy subject's ECG signal.

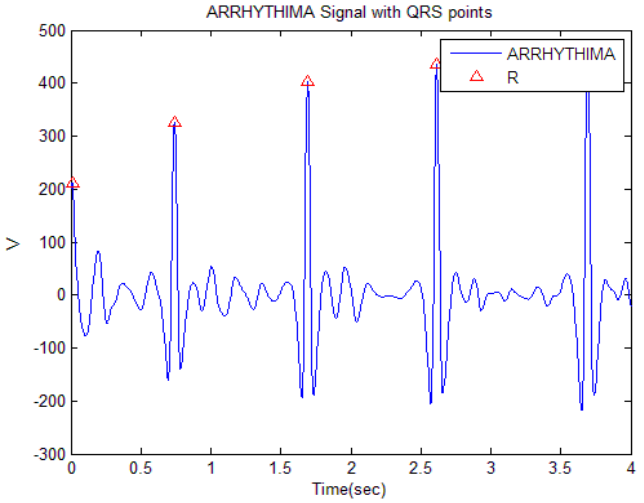

Fig. 8. Detected and annotated R-peaks in the atrial fibrillation patient's ECG signal.

3. SIGNAL PROCESSING METHODOLOGY

This section describes the signal processing methodology, which encompasses preprocessing, filtering, time-domain and frequency-domain feature extraction, the derivation of heart rate variability (HRV) from the electrocardiogram (ECG) signal, R-peak detection, and the computation of the mean, entropy, and energy metrics.

Signals generated by physiological organs are inherently susceptible to cross-talk or corruption by environmental and biological noise [5]. Biological signal processing aims to isolate the target signal from contaminated and noisy recordings, subsequently extracting clinically relevant parameters for medical diagnosis. The processing of biological signals is systematically executed in four sequential stages [6, 7]:

a. Signal acquisition or recording
b. Signal transformation (Preprocessing)
c. Computation of signal parameters (Feature Extraction)
d. Interpretation or classification of signals

In the first stage, transducers are utilized to record and acquire physiological signals from the body [8]. Here, mechanical or chemical events are converted into electrical signals, which are subsequently amplified [9]. A critical consideration during signal acquisition is minimizing entropy or randomness meaning the signal should be captured with minimal disturbance, thereby maximizing the Signal-to-Noise Ratio (SNR) [8]. The analog recorded signal is then sampled (digitized) for computerized processing.

In the second stage, specific transformations are applied to the signal to facilitate the extraction of meaningful parameters in the subsequent phase [10]. This stage, termed preprocessing, aims to attenuate noise and achieve data reduction, thereby simplifying the feature extraction process in the third stage.

During the third stage, suitable and mathematically meaningful parameters, known as features, are extracted from the conditioned signal [11]. The outputs of this stage serve as the foundation for the decision-making process in the fourth stage.

In the fourth stage, either a clinician or an automated computer algorithm delivers the final clinical interpretation based on the extracted features. This process of interpreting or classifying signal features is formally recognized as pattern recognition [12].

3.1. Signal Filtering and QRS Complex Detection

Signal filtering refers to the elimination of undesired spectral components from the frequency spectrum of a signal. In the filtering process, the Fourier Transform of the signal is computed to delineate its spectrum. After suppressing the undesirable frequency components, the inverse Fourier Transform is applied to reconstruct the filtered, noise-free signal in the time domain [13]. Standard linear filters include:

a. Low-pass filters
b. High-pass filters
c. Band-pass filters
d. Band-reject (Notch) filters

For the detection of the QRS complex in the ECG signal, a band-pass filter was implemented to mitigate baseline wander, high-frequency noise, and powerline interference [14]. The primary objective is the accurate localization of the QRS complex within the electrocardiogram. To achieve this, a detection thresholding technique is employed, whereby the ECG signal segments that exceed a predefined dynamic threshold are designated as QRS complexes [15].

The performance of the detection algorithm is benchmarked against the minimization of False Positives (FP) and False Negatives (FN). The Receiver Operating Characteristic (ROC) curve plots the True Positive (TP) rate against the False Positive (FP) rate. For every distinct detection threshold, a specific coordinate on the ROC space is obtained. By continuously sweeping the threshold from low to high values, a continuous ROC curve is generated, graphically demonstrating the classifier's detection performance across various thresholds [16].

3.2. Time-Frequency Feature Extraction from Heart Rate Variability (HRV) Signals

Wavelet analysis evaluates a signal by comparing it against a selected wavelet function to yield coefficients that quantify the correlation between the signal and the wavelet [17]. The reference wavelet function is called the *mother wavelet*, which is appropriately scaled (dilated) and shifted (translated) in the time domain prior to its comparison with the signal.

Wavelet coefficients are typically mapped onto a two-dimensional plane, where the y-axis represents the wavelet scale parameter (inversely proportional to frequency) and the x-axis represents the translation parameter along the time axis. For a given target signal and a specific mother wavelet, the continuous wavelet coefficients are mathematically derived using Equation (1) [21]:

$$\omega(a,b) \equiv \int_{-\infty}^{\infty} f(t) \frac{1}{\sqrt{|a|}} \dot{\psi}\left(\frac{t-b}{a}\right) dt \tag{1}$$

$$\dot{\psi}\left(\frac{\mathrm{t-b}}{\mathrm{a}}\right) = \omega_{\mathrm{a,b}}^{\cdot}(\mathrm{t}) \tag{2}$$

In Equation (1), a represents the scale factor, and b represents the translation factor. Utilizing the base (mother) wavelet, the heart rate variability (HRV) signal can be decomposed into four distinct sub-signals. The power spectrum of each sub-signal corresponds to one of the standard frequency bands of the HRV power spectrum: Very Low Frequency (VLF), Low Frequency (LF), Medium Frequency (MF), and High Frequency (HF) [18].

Entropy quantifies the complexity and irregularity of a signal, yielding lower values for regular, deterministic time series and significantly higher values for irregular, chaotic time series [19]. This feature is robustly applicable to deterministic, stochastic, or hybrid signals. In this study, entropy is computed using two distinct methods: Approximate Entropy (ApEn) and Wavelet Entropy (Wen). Both entropy measures were implemented using the Wavelet Toolbox in MATLAB software.

Furthermore, to compute the mean parameter from the ECG signal, the duration between a specific R-peak and the subsequent R-peak (the R-R interval) is required. In this research, these intervals and their statistical dynamics are evaluated using the Poincaré plot [20].

4. CONCLUSION

Atrial Fibrillation (AF) is the most clinically prevalent cardiac arrhythmia, and its early, automated detection can substantially improve patient survival and quality of life. While AF is rarely acutely life-threatening on its own, it acts as a primary catalyst for severe secondary medical complications, including chronic fatigue, congestive heart failure, and most notably, ischemic stroke. Electrocardiogram (ECG) tracings during AF episodes are typically characterized by the complete absence of organized atrial depolarization waves (P-waves).

This study utilized ECG signals from both healthy controls and patients diagnosed with AF, obtained from the benchmark PhysioNet/Computing in Cardiology Challenge 2017 database, originally compiled by the American Heart Association and European societies. The signals were processed via MATLAB to extract the heart rate, mean values, and entropy metrics from the $R-R$ intervals.

The computed quantitative features are summarized in Table 1. The experimental results demonstrate that the heart rate in AF patients is highly irregular and elevated, typically presenting within a range of 80 to 100 beats per minute (bpm) or exceeding 100 bpm. Furthermore, the statistical analysis confirms that individuals with Atrial Fibrillation exhibit a significantly lower mean $R-R$ interval value, alongside higher entropy and energy levels compared to healthy subjects. These findings validate that non-linear parameters like entropy combined with statistical features provide a robust framework for autonomous AF detection.

Table 1. Extracted Statistical and Non-linear Features from ECG Signals

ECG Record	ECG Condition	Mean (R−R Interval)	Entropy	Heart Rate (bpm)
A00001	Normal	228.4737	412.7175	78
A00002	Normal	305.2069	337.9213	60
A00003	Normal	207.8140	915.9597	87
A00006	Normal	307.6207	332.0531	60
A00007	Normal	284.258	350.063	64
A00010	Normal	276.593	719.637	65
A00011	Normal	207	456.9944	88
A00012	Normal	276.5625	357.4931	66
A00014	Normal	312.2941	194.8860	58
A00018	Normal	332.4615	301.8451	54
A00004	Atrial Fibrillation	282	348.7049	64
A00009	Atrial Fibrillation	189.2826	481.0707	94
A00015	Atrial Fibrillation	213.6667	287.8448	82
A00027	Atrial Fibrillation	196.9318	463.396	90
A00054	Atrial Fibrillation	263.2424	365.3170	68
A00067	Atrial Fibrillation	218.7500	430.4148	82
A00071	Atrial Fibrillation	189.0426	492.2145	96
A00087	Atrial Fibrillation	178.5000	517.2886	102

Declaration

We acknowledge that we used ChatGPT to enhance the academic writing of our manuscript while ensuring the originality and integrity of our work.

Transparency Statement

The data supporting this study are available upon reasonable request to the corresponding author, subject to ethical and confidentiality considerations.

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Declaration of Interest

The authors declare that they have no competing interests.

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