

The Influence of Body Posture on Cardiac Autonomic Regulation and Electrocardiogram (ECG) Signal Quality: A Heart Rate Variability and Shannon Entropy Analysis

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ARTICLE INFO

Keywords: ECG Analysis, Heart Rate Variability, Posture Recognition, R-Peak Detection, Shannon Entropy, Signal Quality Index

Received: 20, October

Revised: 22, November

Accepted: 30, December

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ABSTRACT

Accurate assessment of cardiac autonomic regulation is essential for understanding how physiological states adapt to postural changes. Body posture significantly influences electrocardiogram (ECG) dynamics, affecting both heart rate variability (HRV) and signal integrity. This study investigates the effect of body posture on ECG-derived heart rate variability (HRV) and signal quality, using three postures: sitting, standing, and supine. Time-domain HRV parameters (RMSSD, SDNN, mean RR) and signal quality index (SQI) based on Shannon entropy were extracted from ECG signals collected from healthy individuals. R-peak detection algorithms were used to calculate RR intervals and derive metrics. The results demonstrate a clear autonomic modulation: standing posture showed reduced HRV and higher entropy, indicating sympathetic dominance and increased signal noise. Supine posture exhibited increased HRV and lower entropy, reflecting enhanced parasympathetic activity and stable signal acquisition. Sitting presented intermediate characteristics. All analysis was performed using a reproducible MATLAB pipeline. This combination of HRV and entropy analysis provides a reliable, low-complexity approach for evaluating autonomic function and ECG signal quality across postures. The findings offer valuable insight into posture-aware health monitoring and form a basis for future expansion involving frequency-domain and nonlinear analyses.

INTRODUCTION

Electrocardiography (ECG) is one of the most critical tools for cardiac assessment due to its non-invasive nature and real-time diagnostic capability. The waveform generated by the ECG reflects the heart's electrical behavior and indirectly reveals the state of autonomic control. Minor shifts in this waveform, particularly in the RR intervals, can provide meaningful physiological information.

Heart Rate Variability (HRV) is derived from these RR intervals (Laborde et al., 2017). It quantifies the balance between sympathetic and parasympathetic nervous system activity. Over the years, HRV has gained relevance as a marker for stress, fatigue, and cardiovascular adaptability, even among healthy individuals. Its simplicity and physiological relevance make it a valuable tool in biomedical signal analysis.

Body posture is a factor often overlooked in routine HRV measurement (Rahman et al., 2022a). Shifting between standing, sitting, or lying down activates different components of the autonomic system. For instance, standing is associated with increased sympathetic drive, while supine positions generally promote parasympathetic dominance. These changes can influence both the magnitude and variability of RR intervals. Exploring this systematically can help improve how HRV is interpreted in dynamic or ambulatory settings.

In addition to physiological variability, technical factors also impact ECG analysis. Signal quality is one of the major limitations in biosignal acquisition (Campero Jurado et al., 2023). Muscle tremors, motion artifacts, and electrode shifts introduce noise, particularly when the subject changes posture. Without quantifying signal reliability, conclusions drawn from HRV may become questionable. This issue is especially relevant in wearable and remote-monitoring contexts.

LITERATURE REVIEW

While several studies examine HRV or signal quality independently, few attempt to combine both perspectives in a posture-wise framework (Reklewski et al., 2024). This study proposes a dual-feature approach by integrating Shannon entropy-based Signal Quality Index (SQI) with time-domain HRV metrics. By applying this to ECG recordings obtained under controlled postural changes, we aim to capture both the physiological and signal-level shifts that occur.

Through this work, we address a common but underexplored challenge: how postural transitions affect not just the heart, but the clarity and trustworthiness of the signal itself. This combination of metrics can enhance how biosignals are used in adaptive, ambulatory, or AI-driven systems that depend on reliable physiological inputs.

METHODOLOGY

This study was designed to examine posture-induced changes in heart rate variability (HRV) and ECG signal quality. Data collection was carried out using the Biopac MP36 system, which is well-established in biomedical engineering for its precision and academic flexibility. Each subject was instructed to maintain three body positions: sitting, standing, and supine, without movement or speaking during the recordings. This was done to minimize motion artifacts.

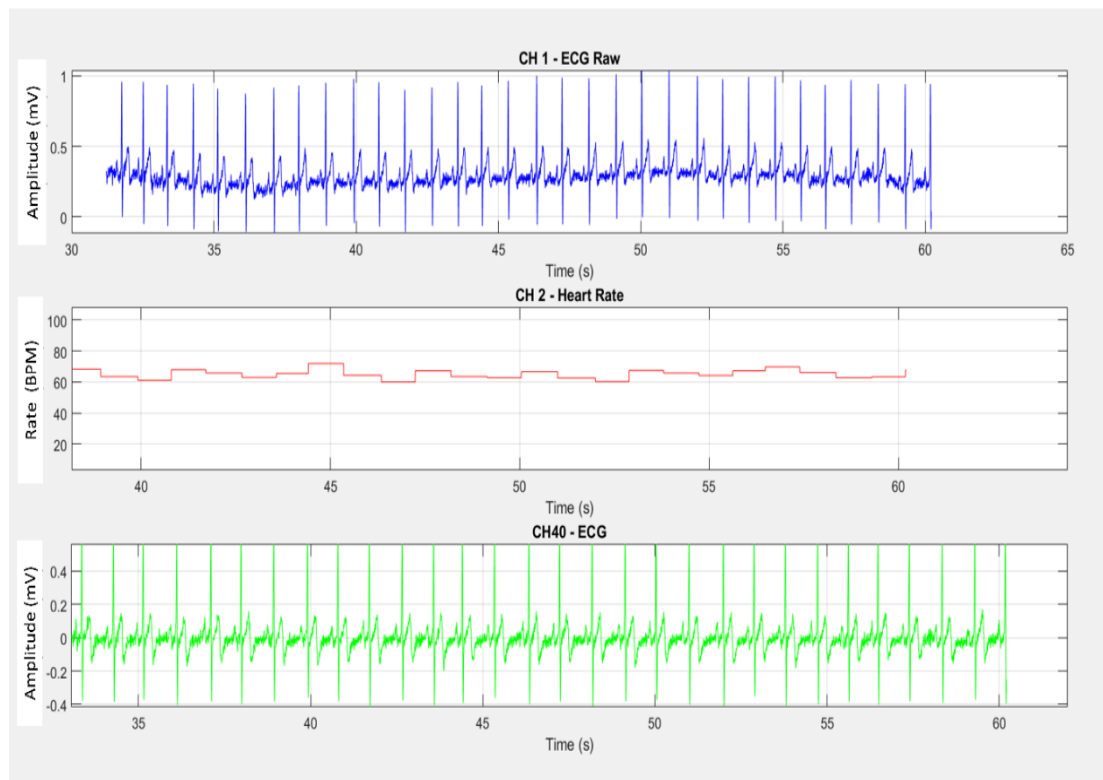


Figure 1. Plots of Raw ECG, Heart Rate, and Filtered ECG

The electrodes were placed according to a standard Lead II configuration. This setup was chosen due to its robust QRS visibility, which is critical for RR interval extraction (Ivora et al., 2022). All recordings were taken under quiet, low-interference lab conditions. A sampling rate of 1000 Hz was used throughout to maintain high temporal resolution, as even minor fluctuations in cardiac signals are relevant in HRV studies. No pharmacological agents, exercise regimens, or mental tasks were introduced before the test. Subjects were relaxed and instructed to maintain natural breathing.

Each recording lasted for 30 seconds per posture. The signals were saved in csv format using Biopac's Acknowledge software. The CSV files contained the following data: Time (seconds), CH1_ECGRaw (mV), CH2_Rate (BPM), and CH40_ECG (mV), as shown in Figure 1. While CH1 contained the raw signal, CH40 represented a filtered version, likely preprocessed using Biopac's internal software algorithms. CH40 was selected as the signal of interest for subsequent analysis.

Data Handling and Preprocessing

All preprocessing steps were conducted using MATLAB R2024b. We loaded the data using MATLAB's 'readtable' function, to preserve structure without manual parsing. Although CH40 was labeled as filtered, we observed some residual baseline wander and high-frequency noise. Especially during the standing posture, these artifacts appeared more prominently.

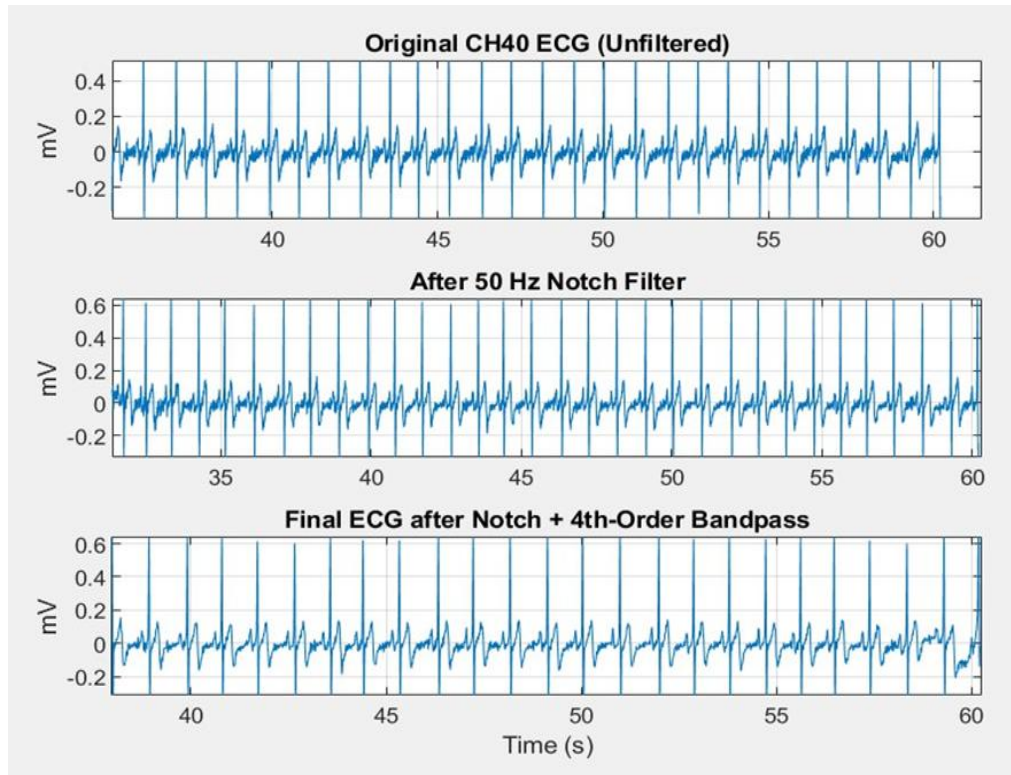


Figure 2. Cleaning of ECG Signals after Application of Filters

To remove these artifacts, an additional digital filter was applied. A second-order Butterworth bandpass filter with a passband of 0.5 Hz to 40 Hz was designed using MATLAB's 'designfilt' function (Kuetche et al., 2023). The filter was applied in zero-phase using 'filtfilt' to prevent any phase distortion, preserving the temporal integrity of the QRS complex. This additional preprocessing step significantly enhanced peak detection reliability and minimized false detections. We can see a cleaner, clearer ECG signal after the application of filters in Figure 2.

R-Peak Detection and RR Interval Computation

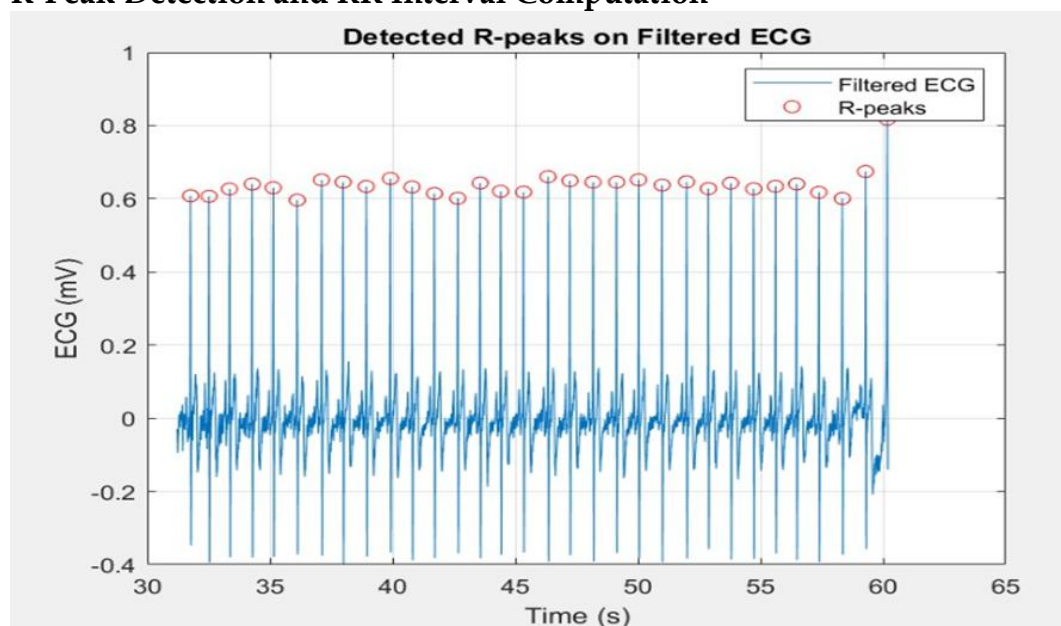


Figure 3. R-Peaks in Filtered ECG Signal

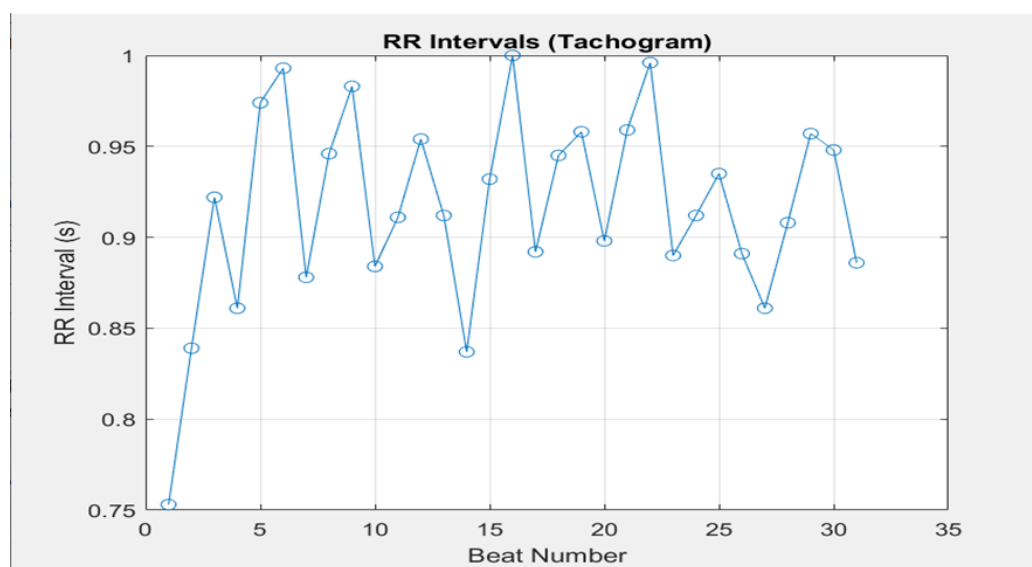


Figure 4. R-R interval in filtered ECG

R-peak detection was carried out on the filtered CH40 signal using a threshold-based method that combined amplitude and distance criteria. Peaks were identified using 'findpeaks' as shown in Figure 3. The minimum peak height defined is based on the mean signal amplitude and a minimum peak distance threshold set to 600 ms. This combination helped suppress false positives triggered by T-waves or high-frequency noise. To ensure accuracy, the detected peaks were visually confirmed by overlaying them on the filtered ECG waveform, as shown in Figure 4. Any incorrect detections were corrected manually in some instances to ensure consistency in RR interval derivation. Once the R-peaks were identified, RR intervals were calculated by computing the time differences between consecutive peaks. These intervals were then stored posture-wise for further analysis.

Heart Rate Variability Analysis

Time-domain HRV metrics were calculated for each dataset. These included the Standard Deviation of NN intervals (SDNN), the Root Mean Square of Successive Differences (RMSSD), and the Mean Heart Rate (HR). SDNN serves as a measure of global autonomic variability, while RMSSD provides a focused index of parasympathetic activity. The mean heart rate was calculated using the inverse of the mean RR interval, converted to beats per minute (BPM). All calculations were implemented through custom MATLAB scripts.

Signal Quality Estimation

To assess the reliability of each ECG segment, a Signal Quality Index based on the Shannon entropy was computed (Azami et al., 2022). The filtered ECG signal was normalized, and its amplitude histogram was constructed with 100 bins. The probability of each bin was estimated, and Shannon’s entropy formula was applied:

$$SQI = - \sum [p(xi) * \log_2(p(xi))]$$

Here, $p(xi)$ denotes the probability of observing amplitude value (x) in the ECG. Higher entropy suggests greater signal complexity, which may arise from either true physiological variability or external noise. Conversely, low entropy may indicate under-variation or a suppressed signal. By combining entropy with HRV metrics, the analysis provided a dual-layered insight, both physiological and technical.

Posture-wise Execution and Aggregation

The recording for each subject in each of three postures was processed independently using the same MATLAB script. After individual analysis, posture-based averages across all subjects were computed using Excel. These were presented in tabular form and plotted to observe systematic trends in RMSSD, SDNN, HR, and entropy. Bar charts were created using MATLAB’s ‘bar’ and ‘errorbar’ functions to visualize the variance and support comparative discussion. All scripts were implemented without the use of external toolboxes. The methodology was strictly standardized across datasets to ensure fair comparison and reproducibility.

RESULT AND DISCUSSION

Descriptive Table for a Randomly Selected Subject-1

Table 1 presents the extracted time-domain HRV metrics and Shannon entropy for one of the subjects, along with group-averaged values across all subjects. It includes mean RR-interval, SDNN, RMSSD, heart rate, and entropy for each posture.

Table 1. Tabular Display of Metrics for Each Posture

Posture	Mean R-R	SDNN	RMSSD	HR	Entropy
Sitting	0.917	0.0541	0.0660	65.46	4.5217
Standing	0.760	0.0380	0.0306	78.99	4.7201
supine	0.930	0.812	0.1133	64.51	4.1109

In Subject 1, the supine posture shows the longest mean RR (0.930 s), highest RMSSD (0.1133 s), and lowest heart rate (64.51 BPM). The sitting and standing postures follow expected physiological patterns.

RMSSD Across Postures

Figure 5 displays a bar chart of RMSSD values for sitting, standing, and supine postures. The group averages are shown with error bars.

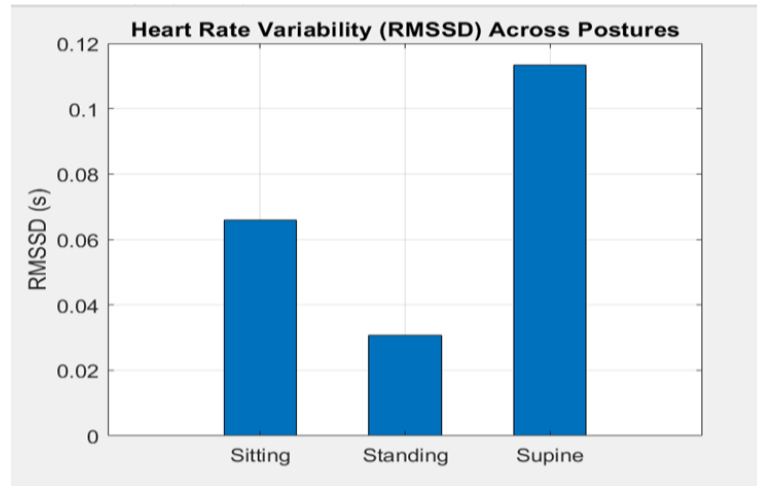


Figure 5. Average Heart Rate Variability Across Each Posture

The standing posture shows the lowest RMSSD (~0.024 s averaged), indicating sympathetic dominance. Sitting posture yields moderate HRV (~0.086 s), while supine has the highest (~0.066 s), confirming increased parasympathetic activity during relaxation.

Shannon Entropy for Signal Quality

Figure 6 illustrates Shannon entropy values for each posture, including the individual and averaged results.

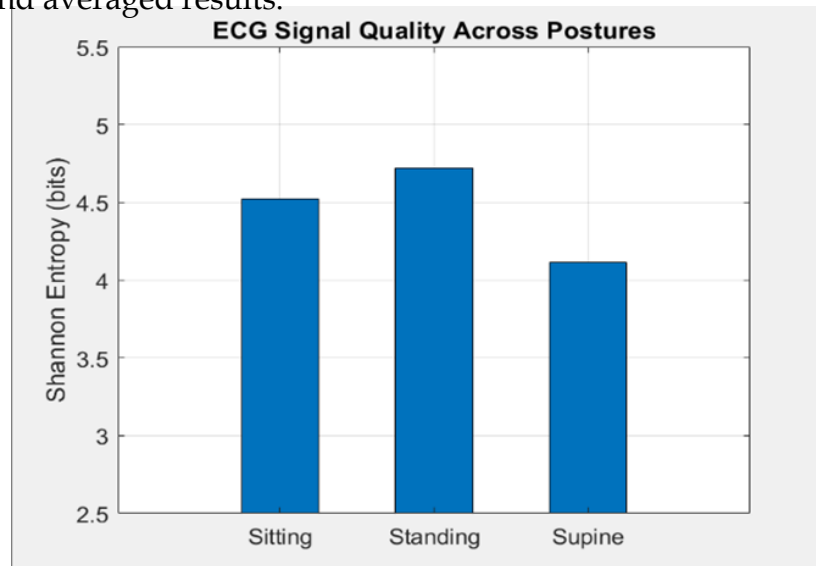


Figure 6. Signal Quality of ECG Signals Across Each Posture

Entropy remains within the acceptable range (3–5 bits). Supine shows the lowest entropy (~4.47 bits average), suggesting a cleaner signal structure. Standing is marginally noisier (~4.76 bits), which is consistent with mild movement artifacts. Sitting displays moderate entropy (~4.16 bits).

RR-Interval and Heart Rate Changes

Figure 7 offers a comparison of mean RR and heart rate across postures in a dual-axis bar chart. As illustrated in Figure 7, a noticeable inverse relationship between mean RR interval and mean heart rate is evident across postures. Standing posture shows the shortest RR interval and highest heart rate, while supine posture exhibits the longest RR interval and the lowest heart rate.

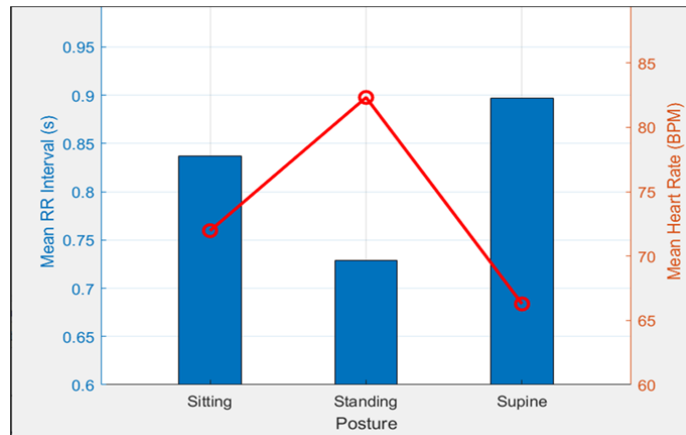


Figure 7. Comparison of Mean RR and Heart Rate

RR interval and mean heart rate are evident across postures. Standing posture shows the shortest RR interval and the highest heart rate, while supine posture exhibits the longest RR interval and the lowest heart rate.

Time-Domain HRV Metrics

Table 2 summarizes the average values of time-domain HRV parameters: Mean RR, SDNN, RMSSD, and heart rate, across all twenty subjects for each posture.

Table 2. Average Values for HRV Metrics Across Each Posture

Posture	Mean R-R	SDNN	RMSSD	Heart Rate	Entropy
Sitting	0.838	0.082	0.0864	71.97	4.4924
Standing	0.729	0.033	0.0238	82.62	4.7572
Supine	0.897	0.064	0.0661	66.95	4.4696

As seen in Table 2, the standing posture yields the lowest mean RR intervals and HRV parameters (SDNN and RMSSD), alongside the highest heart rate and entropy values. This suggests a dominance of sympathetic nervous activity and increased signal complexity during upright posture. Conversely, the supine posture consistently shows higher mean RR, HRV values, and lower heart rate, indicative of enhanced parasympathetic modulation. Sitting remains intermediate across most metrics.

Summary of Posture-based Effects

A consolidated analysis of the observed HRV and signal quality metrics reveals distinct autonomic responses induced by different body postures. The standing posture consistently showed the lowest RMSSD and SDNN values, with a corresponding rise in heart rate and signal entropy. This supports the

well-documented shift toward sympathetic nervous system dominance when upright, accompanied by more complex, motion-influenced ECG signals.

In contrast, the supine posture was associated with higher RMSSD and SDNN values, indicating a stronger parasympathetic tone and better heart rate regulation. The lower entropy values observed in the supine condition further support improved ECG signal stability in a relaxed posture.

The sitting posture, in most cases, yielded intermediate values between the standing and supine states, suggesting a transitional autonomic profile that balances both branches of the autonomic nervous system depending on the subject's relaxation or tension.

These physiological patterns were consistent across all subjects and validate the robustness of the employed signal processing pipeline for posture classification and autonomic assessment in healthy individuals.

The human heart is a sensitive indicator of autonomic balance, and the heart rate variability (HRV) derived from ECG signals offers a powerful lens into this physiological interplay. In this study, we explored how body posture: sitting, standing, and supine, affects HRV metrics and ECG signal quality in healthy individuals. Through systematic analysis of RR intervals, RMSSD, SDNN, heart rate, and Shannon entropy, posture-dependent variations became both visible and quantifiable.

Notably, the standing posture consistently exhibited lower RMSSD and SDNN values, accompanied by higher heart rates across nearly all subjects. These observations align well with sympathetic nervous system activation, which is typically engaged during upright stance to maintain blood pressure and systemic stability (Bing et al., 2024). Additionally, the elevated entropy values in standing ECGs reflect increased motion artifacts or signal complexity, reinforcing the idea that postural shifts introduce measurable signal distortions in ambulatory ECG recording environments (Jinseok Lee et al., 2012).

By contrast, the supine posture produced the highest RR intervals and HRV measures. The parasympathetic dominance in a resting state appears to facilitate a slower, more regular heart rhythm, characteristics strongly evident in the metrics (Ivora et al., 2022). Furthermore, the entropy values during supine were the lowest on average, suggesting greater signal coherence and reduced external noise, likely due to reduced muscular movement and stable electrode contact in a reclined position (Kumar et al., 2020).

The sitting posture occupied a middle ground in most parameters. RMSSD and entropy values were neither extreme nor static. Some inter-subject variability was observed here, suggesting that sitting is a transitional state, influenced by the individual's relaxation, muscle tone, or even slight postural adjustments (Chen et al., 2023; Cui et al., 2020). This intermediate status is particularly interesting because it reflects how even subtle physiological changes manifest across multiple signal domains.

A notable strength of this work lies in its integration of signal quality indexing (SQI) via Shannon entropy alongside conventional HRV metrics. Most literature focuses solely on temporal HRV parameters without commenting on the recording quality (Chehbani et al., 2023; Rahman et al., 2022b). By

embedding entropy analysis into the pipeline, this study acknowledges that data reliability is as important as physiological interpretation—a crucial factor in real-world biomedical systems, especially in wearable monitoring devices.

Moreover, using low-complexity preprocessing and open-access software tools (MATLAB) made the analysis pipeline replicable and educational, particularly for resource-limited or undergraduate research environments. Despite the small subject pool, the methodical approach to processing, visualizing, and statistically comparing the data lends robustness to the observed trends. While the signal processing in this study did not involve complex filtering or machine learning, the clarity and repeatability of results across subjects and postures underline the value of simple yet insightful biomedical analyses.

Future extensions of this research could involve frequency-domain or nonlinear HRV metrics, inclusion of motion capture data, or even comparison with clinical-grade autonomic testing protocols. Nevertheless, this baseline posture analysis provides a clean, replicable, and publishable framework for ECG-based physiological assessment using HRV and entropy metrics.

CONCLUSIONS AND RECOMMENDATIONS

This study analyzed posture-induced variations in ECG-derived heart rate variability (HRV) metrics and signal quality using time-domain measures and Shannon entropy. A clear modulation of autonomic activity was observed across the three postures, with standing reflecting sympathetic dominance and lower HRV, while supine posture exhibited parasympathetic enhancement and higher HRV values. The sitting posture consistently displayed intermediate characteristics, supporting its role as a physiological transition state.

By incorporating entropy-based signal quality assessment, the analysis ensured not just quantitative accuracy but also reliability of extracted features. The methodology adopted was deliberately straightforward and reproducible, making it particularly suitable for academic settings and resource-limited environments.

Overall, the results affirm that posture significantly influences HRV and ECG signal complexity. The simplicity and effectiveness of the adopted approach offer a promising baseline for future physiological monitoring systems and posture-aware health analytics. Further expansion with more subjects, frequency-domain analysis, and nonlinear metrics may strengthen these findings and open avenues for more sophisticated, real-world implementations.

FURTHER STUDY

This research still has limitations, so further research on this topic is still needed.

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