Assessing Signal Quality Impact on Pulse Rate Variability Accuracy from Photoplethysmography

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Abstract

Pulse Rate Variability (PRV) derived from photoplethysmography (PPG) offers a practical alternative to Heart Rate Variability (HRV) from ECG. However, PRV accuracy depends strongly on the quality of the underlying PPG signal. PPG signals from 120 subjects (225 sessions) were analyzed. Data were segmented into 5-minute windows, yielding 1,046 segments. Four Signal Quality Indices (SQIs) were computed: kurtosis, skewness, entropy, and perfusion index. A dynamic quantile-based normalization scaled all SQIs to a 0–1 range. All SQI metrics exhibited significant negative correlations with HRV error (p ¡ 0.001). Perfusion Index showed the strongest association (r = –0.189, R^2 = 3.6%). It also remained predictive in high-quality segments (SQI ¿ 80%, r = –0.151, p ¡ 0.001). In contrast, other SQIs lost discriminative power at high quality levels. Quality distribution varied markedly across metrics: 84.3% of segments exceeded 80% quality for Perfusion Index, while only 32.0% did so for Skewness.

1. Introduction

Heart rate variability (HRV) analysis is a valuable non-invasive tool for assessing autonomic nervous system function and cardiovascular health [1,2]. While electrocardiography (ECG) remains the gold standard, photoplethysmography (PPG) offers significant advantages including ease of use, lower cost, and integration into wearable devices [3, 4]. However, PPG signals are more susceptible to motion artifacts, ambient light interference, and poor sensor contact compared to ECG, leading to potential inaccuracies in HRV parameter estimation [5].

Current PPG signal quality assessment approaches lack standardization and often rely on subjective visual inspection or simple threshold-based methods [6]. While various signal quality indices (SQI) have been proposed, including statistical measures (kurtosis, skewness), information-theoretic measures (entropy), and physiological parameters (perfusion index), no comprehensive study exists for their combined evaluation and standardization. The challenge is further complicated by the need to establish quality thresholds that are sensitive to poor-quality signals while avoiding rejection of acceptable data. Traditional normalization approaches may not adequately account for inter-subject variability and PPG-specific signal characteristics. Recent advances have demonstrated potential for automated quality assessment using multiple complementary metrics, but the relative performance of different SQI metrics and their optimal combination for PPG-based HRV analysis remains unclear.

This study addresses these limitations by performing an analysis that integrates multiple SQI metrics with dynamic normalization. Our objectives were to: (1) evaluate four primary SQI metrics in predicting PRV measurement accuracy; (2) identify the most robust quality metrics for automated PPG signal acceptance in clinical applications.

2. Methods

2.1. Dataset and Signal Processing

This study analyzed PPG signals from 120 subjects in two different sessions stress and baseline. Overall datasets contain 240 sessions. The dataset originates from the ES3 Project, comprising stress induction sessions with a 10-minute baseline relaxation period followed by five stress tasks of varying durations (2-10 minutes). Data were collected from 120 participants across three Spanish universities. Single-lead ECG recordings (X-lead orthogonal configuration) were acquired using standardized equipment and procedures across all sites. Rigorous quality control measures ensured only artifact-free ECG segments were analyzed, minimizing inter-subject and inter-institutional variability. Raw PPG signals were filtered using low-pass filters with cutoff frequency of 10hz.

2.2. Signal Segmentation

PPG signals were initially segmented into 10-second non-overlapping windows for preliminary SQI calculation,

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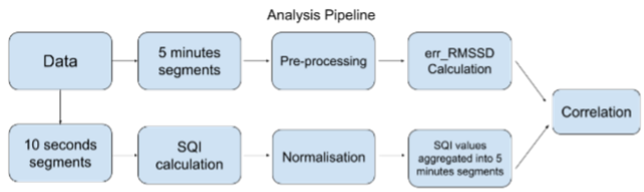

Figure 1. Analysis pipeline for correlation of SQI metrics.

denoted Q(i) where i indicates the i-th window. Subsequently, these 10-second segments were aggregated into 5-minute windows by computing median across constituent 10-second segments within each 5-minute period. Later, we used different normalisation methods to normalise each SQI metrics. This hierarchical segmentation approach enabled both fine-grained and broader temporal analysis of signal quality patterns and robust estimation of RMSSD.

3. Signal Quality Index (SQI) Metric

Four primary SQI metrics were computed for each signal segment: (1) Kurtosis: Measures the "tailedness" of the signal amplitude distribution. Values closer to 3 indicate normal distribution characteristics, while deviations suggest artifacts or noise. (2) Skewness: Quantifies the asymmetry of the signal amplitude distribution. Values near zero indicate symmetric distributions, typical of high-quality PPG signals. (3) Entropy: Estimates signal complexity and predictability. Lower entropy values indicate more regular, predictable signals associated with better quality. (4) Perfusion Index: Calculated as the ratio of pulsatile to non-pulsatile components of the PPG signal, representing peripheral perfusion strength and signal amplitude adequacy [6].

Quality indices were normalized to $[0, 1]$ using dynamic quantile-based scaling. For kurtosis (κ) and skewness (γ), normalization was performed as follows:

$$Q^n_{k,\gamma}(i) = 1 - \frac{\left|Q_{k,\gamma}(i) - \hat{Q}_{k,\gamma}\right|}{\max\left(\left|Q_{k,\gamma,0.05} - \hat{Q}_{k,\gamma}\right|, \left|Q_{k,\gamma,0.95} - \hat{Q}_{k,\gamma}\right|\right)}. \tag{1}$$

For the perfusion index, normalized values were computed using:

$$Q^n_P(i) = \frac{Q_P(i) - Q_{P,0.05}}{Q_{P,0.95} - Q_{P,0.05}}. \tag{2}$$

Finally, entropy-based quality indices were normalized according to:

$$Q^n_H(i) = 1 - \frac{Q_H(i) - Q_{H,0.05}}{Q_{H,0.95} - Q_{H,0.05}}. \tag{3}$$

where $\hat{Q}$ denotes the median, and subscripts indicate percentiles.

3.1. HRV Method Assessment

Reference HRV parameters were computed from simultaneously recorded ECG signals. PPG-derived PRV metrics were compared against ECG references, with RMSSD error calculated as the absolute difference between PPG-derived and ECG-derived RMSSD values.

3.2. Statistical Analysis

Correlation analyses were performed using the Pearson correlation coefficient to assess relationships between SQI metrics and $\mathrm{err}_{\mathrm{RMSSD}}$. Statistical significance was evaluated at $\alpha = 0.05$. Analyses were conducted on both the complete dataset and high-quality subsets ($\mathrm{SQI} > 0.8$).

4. Results

4.1. Dataset Characteristics

The final dataset comprised 1,046 five-minute segments from 225 sessions. After removal for 15 sessions from the overall datasets due to the erroneous data.

4.2. SQI Distribution and Quality Assessment

Quality distribution varied significantly across the four SQI metrics: (1) Perfusion Index: 84.9% of segments exceeded 80% quality threshold. (2) Entropy: 80.5% of segments exceeded 80% quality threshold. (3) Kurtosis: 67.9% of segments exceeded 80% quality threshold. (4) Skewness: 33.7% of segments exceeded the 80% quality threshold. (Figure 2).

4.3. Correlation with HRV Accuracy

Overall correlations (all 1,046 segments) revealed significant negative relationships between SQI metrics and RMSSD error, supporting the hypothesis that higher signal quality corresponds to lower $\mathrm{err}_{\mathrm{RMSSD}}$ estimation errors.

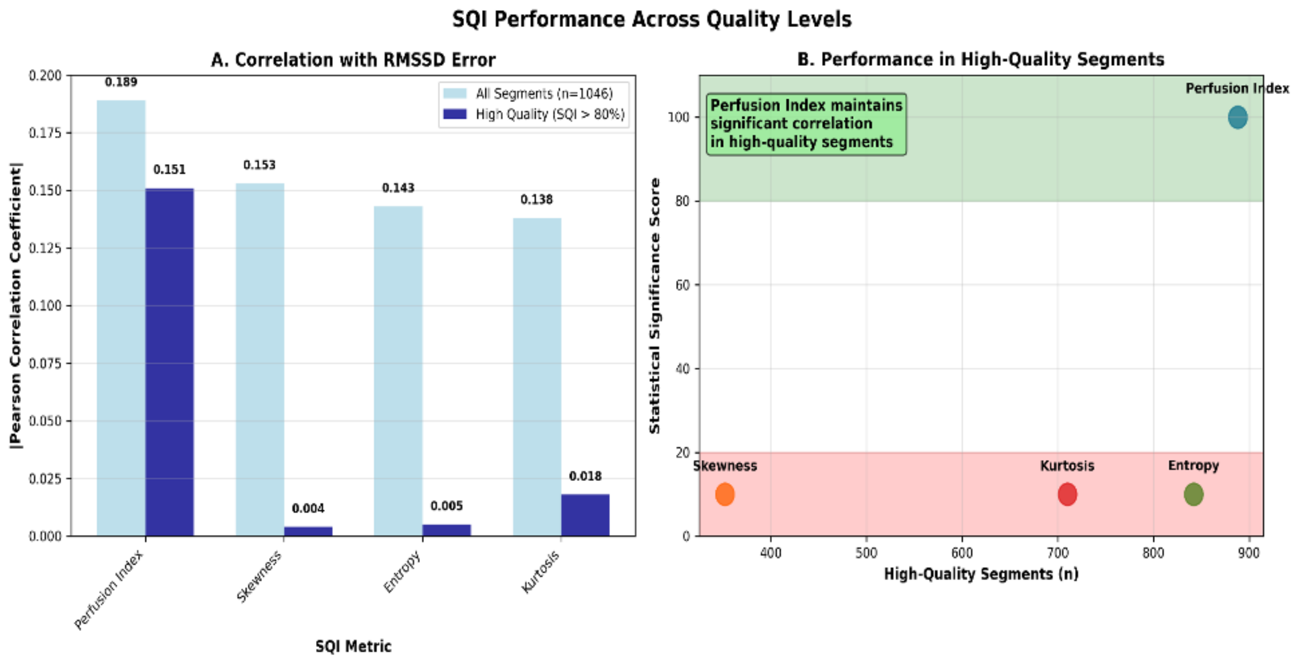

Figure 2. Evaluates SQI performance consistency across different quality levels. Panel A compares absolute correlation coefficients between all segments (n = 1,046) versus high-quality segments (SQI ¿ 80%), revealing that most metrics lose discriminative power when restricted to high-quality signals. Panel B illustrates the relationship between ample size and statistical significance for high-quality segments.

All correlations were statistically significant (p ¡ 0.001), with Perfusion Index demonstrating the strongest relationship with HRV accuracy (Figure 3).

4.4. High-Quality Signal Analysis

When restricting analysis to high-quality segments (SQI ¿ 80%), most SQI metrics lost predictive power, except for Perfusion Index (Table 1).

4.5. Dynamic Normalization Effectiveness

The normalization method successfully standardized SQI values across the 0-1 range while preserving relative quality relationships. Mean normalized SQI values were: Perfusion Index(0.847), Entropy(0.823), Kurtosis(0.765), Skewness(0.542).

5. Discussion and Conclusions

Results demonstrate that Perfusion Index provides the most robust and consistent assessment of PPG signal quality for HRV analysis. Unlike other metrics that lose discriminative power at high quality levels, Perfusion Index maintains significant correlation with HRV accuracy across the entire quality spectrum (r = -0.151, p ¡ 0.001 for high-quality segments). The weak but significant correlations (R^2 = 1.9-3.6%) indicate valuable information for automated quality assessment in clinical and research applications, and automated PPG signal acceptance in cardiovascular monitoring applications.

This study focused on 5-minute segments which may not capture shorter-term quality variations. Future work should investigate real-time quality assessment and adaptive filtering approaches. Additionally, the correlation strengths, while statistically significant, indicate that other factors beyond these SQI metrics contribute to HRV measurement errors.

The proposed analysis provides a foundation for developing automated PPG quality assessment systems. Integration with machine learning approaches and real-time implementation in wearable devices represents promising avenues for clinical translation.

This study establishes a comprehensive analysis for PPG signal quality assessment using dynamic normalization of multiple SQI metrics. Perfusion Index emerges as the most reliable quality indicator.

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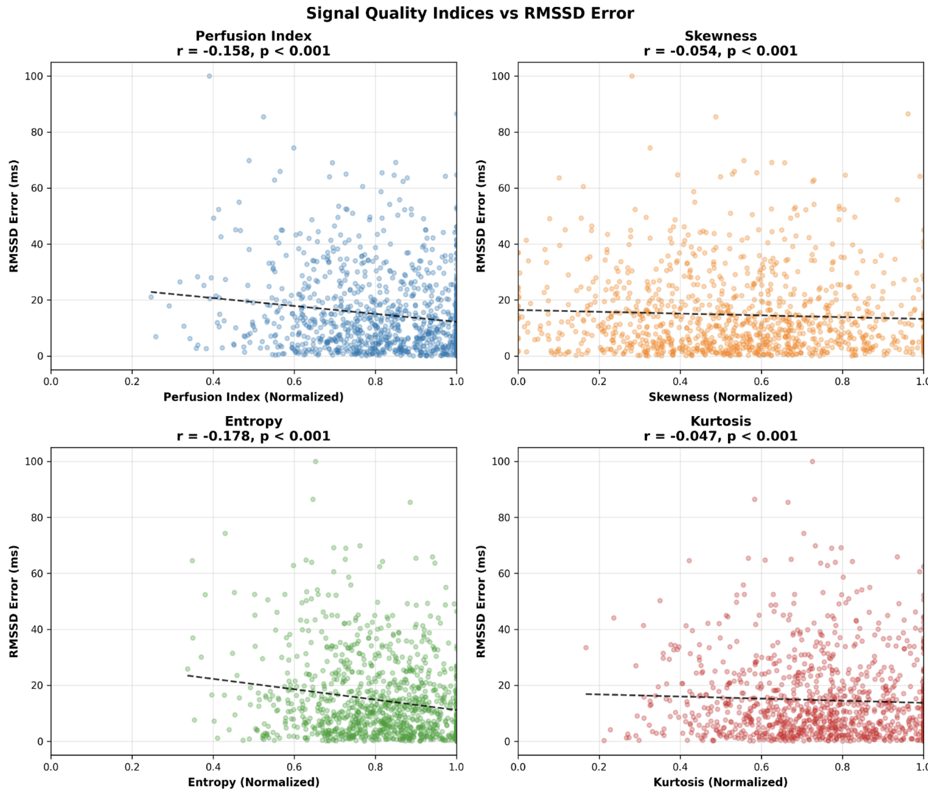

Figure 3. Signal Quality Indices vs RMSSD Error Correlation Analysis. Scatter plots comparing the relationship between normalized Signal Quality Index (SQI) metrics and RMSSD estimation errors. Each panel shows: (A) Perfusion Index (r=-0.189, p¡0.001), (B) Skewness (r=-0.153, p¡0.001), (C) Entropy (r=-0.143, p¡0.001), and (D) Kurtosis (r=-0.138, p¡0.001). Data points represent individual 5-minute PPG segments (n=1,046) with line.

Table 1. Correlation Analysis

SQI Metric	n	Pearson r	p-value	HQ segments (n¿80%)	Pearson r	p-value
Perfusion Index	1046	-0.189***	<0.001	888	-0.151*	<0.001
Skewness	1046	-0.153***	<0.001	842	-0.005	0.887
Entropy	1046	-0.143***	<0.001	710	0.018	0.639
Kurtosis	1046	-0.138***	<0.001	352	0.004	0.943

“PRE-C-2022-0096”. Computations were performed on the HPC cluster provided by University of Zaragoza.

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