Impact of Signal Quality on the Accuracy of Pulse Rate Variability Derived from Photoplethysmography

Nayan Wadhwani[1,2], Pablo Armañac[1,2], Raquel Bailon[1,2], Eduardo Gil[1,2]*

[1]BSICoS group, Instituto de Investigación en Ingeniería de Aragón (I3A), IIS Aragón, University of Zaragoza, Spain

[2]CIBER de Bioingeniería, Biomateriales y Nanomedicina (CIBER-BBN), Madrid, España

Abstract

Heart Rate Variability (HRV) analysis from photoplethysmography (PPG) signals requires robust signal quality assessment to ensure accurate Pulse Rate Variability (PRV) measurements. This study introduces an enhanced PPG Signal Quality Index (SQI) analysis incorporating five quality measuring metrics: kurtosis, skewness, entropy, perfusion index, and mean crossing rate. A dynamic quantile-based normalization method standardizes SQI values across diverse physiological conditions.

Methods: *PPG signals from 120 subjects (225 sessions) were processed using hierarchical segmentation (10-second to 5-minute windows) at 250Hz sampling rate. Five SQI metrics were computed with dynamic normalisation method. Correlation analyses assessed relationships between SQI metrics and RMSSD errors compared to reference ECG measurements.*

Results*: Analysis of 1,825 five-minute segments revealed significant negative correlations between all SQI metrics and HRV errors ($p<0.001$). The Perfusion Index demonstrated the strongest correlation ($r=-0.226$, $R^2=5.1\%$), followed by Skewness ($r=-0.152$, $R^2=2.3\%$), Entropy ($r=-0.148$, $R^2=2.2\%$), Kurtosis ($r=-0.109$, $R^2=1.2\%$), and Mean Crossing Rate ($r=-0.077$, $R^2=0.6\%$). Quality distribution analysis showed 83.8% of segments exceeded 80% quality for Perfusion Index, while Mean Crossing Rate provided complementary temporal stability assessment.*

Conclusions: *The enhanced multi-metric analysis with dynamic normalization provides robust PPG signal quality assessment. Perfusion Index offers the consistent quality indicator, while Mean Crossing Rate contributes valuable temporal regularity information for comprehensive quality evaluation in automated PPG-based HRV monitoring systems.*

1. Introduction

Heart rate variability (HRV) analysis is a widely used non-invasive method for evaluating autonomic nervous system activity and cardiovascular health [1,2]. Although electrocardiography (ECG) is considered the gold standard, photoplethysmography (PPG) provides notable benefits, such as simplicity, affordability, and seamless integration into wearable technologies [3,4]. Nevertheless, PPG signals are more prone to motion artifacts, ambient light disturbances, and suboptimal sensor contact than ECG, which can compromise the accuracy of HRV parameter estimation [5].

Existing approaches for assessing PPG signal quality lack standardization and frequently depend on subjective visual inspection or basic threshold-based techniques [6]. Although several signal quality indices (SQIs) have been proposed, ranging from statistical measures (e.g., kurtosis, skewness, mean crossing rate) to information-theoretic metrics (e.g., entropy) and physiological indicators (e.g., perfusion index), a comprehensive evaluation and standardization of these methods has yet to be established.

Recent advances in signal processing have highlighted the importance of temporal regularity assessment for PPG quality evaluation. However, standardized normalization approaches for integrating multiple SQI metrics across diverse physiological conditions remain underdeveloped.

This study addresses these limitations by performing an analysis that integrates multiple SQI metrics with dynamic normalization. Our objectives were to: (1) evaluate five primary SQI metrics in predicting PRV measurement accuracy using RMSSD; (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 across 225 sessions, collected from stress and baseline conditions. Each session consisted of 20-40 minutes of continuous recording.. Raw PPG signals were acquired at 250Hz sampling rate and processed using 10Hz low-pass filtering to optimize the balance between noise reduction and physiological information preservation based on preliminary frequency analysis.

2.2. Hierarchical Signal Segmentation

PPG signals were processed using a two-tier hierarchical segmentation approach:

1. Primary Segmentation: Raw signals were divided into 10-second non-overlapping windows for initial SQI computation (n=51,308 windows).

2. Temporal Aggregation: 10-second segments were aggregated into 5-minute windows using median aggregation across constituent segments (n=1,825 windows). This hierarchical approach enabled both fine-

ISBN: 978-84-09-80259-3

grained temporal analysis and robust quality assessment comparable to standard RMSSD analysis windows.

2.3. Signal Quality Index (SQI) Metrics

Five complementary SQI metrics, $Q_m(i)$, were computed for each 10s signal segment i, where $\boldsymbol{m} \in [\boldsymbol{k}, \boldsymbol{s}, \boldsymbol{z}, \boldsymbol{P}, \boldsymbol{H}]$ denotes the metric:

1. Kurtosis ($\boldsymbol{k}$)*: Measures the "tailedness" of the signal amplitude distribution. Values closer to 3 indicate normal PPG distribution characteristics, while deviations suggest artifacts or noise[6].

2. Skewness(s): 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].

5. Mean Crossing Rate: Quantifies the frequency at which the PPG signal crosses its mean value, providing temporal regularity assessment.

2.4. Dynamic Normalization

Quality indices were normalized to [0,1] using dynamic quantile-based scaling, where higher values means better quality.

Kurtosis (κ) and Skewness (s) and Mean Zero Crossings (z):

$$Q^n_{k,s,z}(i) = 1 - \frac{|Q\kappa,s,z(i) - \hat{Q}\kappa,s,z|}{(|Q_{k,s,z,0.05} - \hat{Q}_{k,s,z}|, |Q_{k,s,z,0.95} - \hat{Q}_{k,s,z}|)} \quad (1)$$

Perfusion Index:

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

Entropy:

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

where $\hat{Q}$ denotes the median for the whole signal, and subscripts denote percentiles. Finally, temporal aggregation was done in a 5 minute segment.

2.5 HRV Error Assessment

Reference HRV parameters were computed from simultaneously recorded ECG signals using standard protocols. 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. The error metric (e_{RMSSD}) served as the primary validation criterion for SQI effectiveness.

2.6 Statistical Analysis

Comprehensive correlation analyses were performed using Pearson correlation coefficients to assess relationships between SQI metrics and e_{RMSSD} . Statistical significance was evaluated at $\alpha = 0.05$. Analysis included both complete dataset evaluation and quality-stratified subgroup analyses for high-quality segments (SQI > 0.8).

3 Results

3.1 Dataset Characteristics

The hierarchical processing generated 51,308 initial 10-second windows, which were aggregated into the final analysis dataset. The final enhanced dataset comprised 1,825 five-minute segments from 225 sessions after quality control procedures.

3.2 SQI Correlation with HRV Accuracy

Comprehensive correlation analysis revealed significant negative relationships between all five SQI metrics and RMSSD error, confirming that higher signal quality corresponds to lower HRV estimation errors. All correlations were statistically significant ($p<0.001$), with distinct performance characteristics across metrics, see table 1

SQI Metric	Pearson r	R^2	p-value
Perfusion Index	-0.226	5.1%	<0.001
Skewness	-0.152	2.3%	<0.001
Entropy	-0.148	2.2%	<0.001
Kurtosis	-0.109	1.2%	<0.001
Mean Crossing Rate	-0.077	0.6%	<0.001

***Table 1**: Correlation results*

ISBN: 978-84-09-80259-3



***Figure 1**: Correlation Analysis of Signal Quality Indices vs RMSSD Error. Perfusion Index (blue, r=-0.226), Skewness (orange, r=-0.152), Entropy (green, r=-0.148), Kurtosis (red, r=-0.109), and Mean Crossing Rate (brown, r=-0.077). Data points represent individual 5-minute PPG segments (n=1,825) with trend lines indicating correlations.*

3.3 Enhanced SQI Distribution Analysis

Quality distribution varied significantly across the five SQI metrics, revealing distinct sensitivity patterns and threshold characteristics.

• Perfusion Index: 83.8% of segments exceeded 80% quality threshold.

• Entropy: 66.8% of segments exceeded 80% quality threshold

• Kurtosis: 61.5% of segments exceeded 80% quality threshold.

• Mean Crossing Rate: 60.9% of segments exceeded 80% quality threshold.

• Skewness: 31.8% of segments exceeded 80% quality threshold.

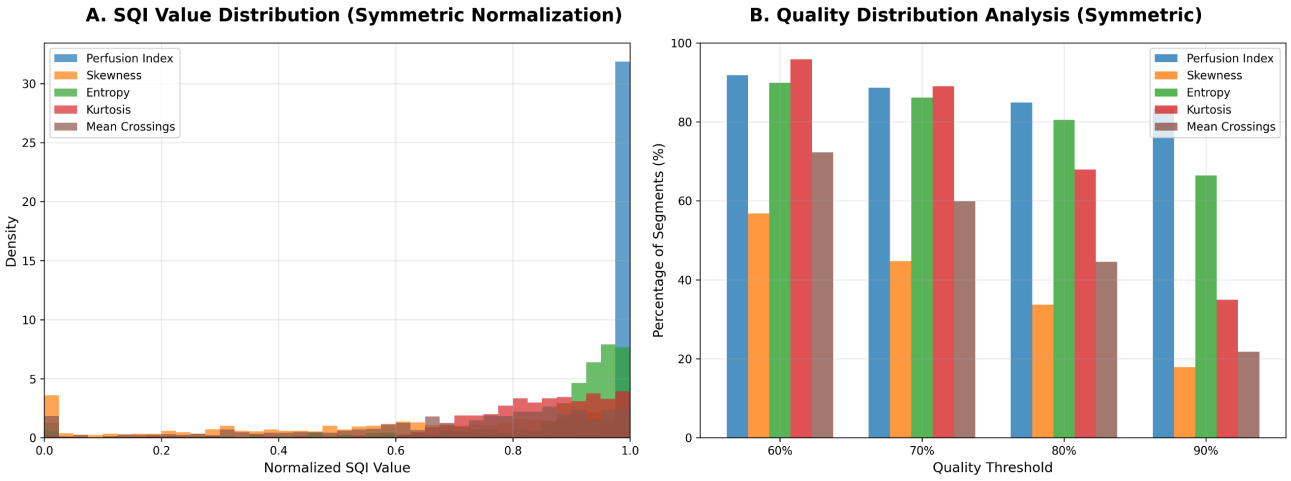


***Figure 2:** Enhanced SQI Framework Distribution Analysis. Panel A shows normalized SQI value distributions using color-coded histograms for each metric. Panel B displays quality threshold analysis across different percentile cut-offs (60%, 70%, 80%, 90%).*

ISBN: 978-84-09-80259-3

3.4 Multi-Metric Analysis Comparison

When analysis was restricted to high-quality segments (SQI>80%), performance patterns revealed the robustness of different metrics:

• **Perfusion Index:** Maintained significant correlation (r=-0.082, p<0.001) with largest sample size (n=1,527).

• **Other metrics:** Showed reduced correlations in high-quality subsets, indicating saturation effects.

• **Mean Crossing Rate:** Demonstrated moderate performance with balanced sensitivity.

4 Discussions

The enhanced five-metric SQI framework provides comprehensive PPG signal quality assessment addressing multiple physiological and technical aspects. Perfusion Index maintains the strongest correlation with HRV accuracy (r=-0.226), establishing it as the primary quality indicator for automated systems. The Mean Crossing Rate contributes complementary temporal regularity information (r=-0.077), particularly valuable for detecting subtle signal irregularities that amplitude-based metrics may miss.

The multi-metric approach addresses different aspects of signal degradation: Perfusion Index captures amplitude adequacy, statistical metrics (kurtosis, skewness) detect distribution anomalies, entropy quantifies signal complexity, and Mean Crossing Rate assesses temporal stability. This comprehensive evaluation enables robust quality assessment across diverse artifact types and physiological conditions.

5 Conclusions

This study establishes an enhanced five-metric SQI framework with dynamic quantile-based normalization for robust PPG signal quality assessment. The novel Mean Crossing Rate provides valuable temporal regularity information while Perfusion Index serves as the most reliable overall quality indicator. The multi-metric approach comprehensively addresses different signal quality aspects, enabling automated PPG signal acceptance with clinical-grade reliability. Dynamic normalization successfully standardizes quality assessment across diverse physiological conditions, facilitating broader adoption of PPG-based HRV monitoring in clinical practice and research applications for reliable cardiovascular health assessment.

Acknowledgments

This work is supported by ‘Ministerio de Ciencia, Innovación y Universidades, Spain’ and ‘European Regional Development Fund (FEDER)’ under project PID2021-126734OB-C21, and by Gobierno de Aragón, Spain (Reference Group BSICoS T39-23R). The computation was performed at the High Performance computing platform of the NANBIOSIS ICTS.

References

[1] Shaffer F, Ginsberg JP. An overview of heart rate variability metrics and norms. Front Public Health. 2017;5:258. doi: 10.3389/fpubh.2017.00258.
[2] Thayer JF, Yamamoto SS, Brosschot JF. The relationship of autonomic imbalance, heart rate variability and cardiovascular disease risk factors. Int J Cardiol. 2010;141(2):122-131. doi: 10.1016/j.ijcard.2009.09.543.
[3] Allen J. Photoplethysmography and its application in clinical physiological measurement. Physiol Meas. 2007;28(3):R1-39. doi: 10.1088/0967-3334/28/3/R01.
[4] Castaneda D, Esparza A, Ghamari M, Soltanpur C, Nazeran H. A review on wearable photoplethysmography sensors and their potential future applications in health care. Int J Biosens Bioelectron. 2018;4(4):195-202. doi: 10.15406/ijbsbe.2018.04.00125.
[5] Charlton PH, Birrenkott DA, Bonnici T, Pimentel MA, Johnson AE, Alastruey J, et al. Breathing rate estimation from the electrocardiogram and photoplethysmogram: A review. IEEE Rev Biomed Eng. 2018;11:2-20. doi: 10.1109/RBME.2017.2763681.
[6] Elgendi M. Optimal signal quality index for photoplethysmogram signals. Bioengineering. 2016;3(4):21. doi: 10.3390/bioengineering3040021.

Address for correspondence

Nayan Wadhwani(nwadhwani@unizar.es)