TECHNICAL REPORT
BCG HEART RATE ANALYSIS SYSTEM

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Executive Summary

This report presents the development and evaluation of a system designed to estimate heart rate using ballistocardiogram (BCG) signals, with electrocardiogram (ECG) data serving as the reference standard. The system was developed through iterative enhancements in signal processing, peak detection, and statistical analysis. While the results show notable improvements in certain configurations, significant challenges persist—particularly in achieving a reliable correlation between BCG-derived and ECG-derived heart rate measurements.

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1. Methodological Approaches

1.1 Signal Processing Pipeline

1.1.1 Data Acquisition and Preprocessing

- Raw BCG signals were acquired at 140 Hz and resampled to 50 Hz for analysis.
- Noise reduction techniques and movement artifact detection were applied.
- Dynamic correlation-based alignment was used to synchronize BCG and ECG timestamps.

1.1.2 Filtering Techniques

- **Bandpass Filtering**: A second- to third-order Butterworth filter (0.5–8.0 Hz) was applied to isolate cardiac components.
- **Wavelet Filtering**: Wavelet decomposition using Symlet 8 (sym8) at level 5 provided improved cardiac component separation over previous db4 use.
- **Selective Coefficient Reconstruction**: Reconstruction retained approximation and first two detail levels to emphasize cardiac signals.
- **Savitzky-Golay Smoothing**: Noise was further reduced using a window length set to 20% of the sampling frequency.

1.1.3 Movement Detection

- Adaptive windowed standard deviation analysis was implemented for motion artifact detection.
- Threshold formula:
  `threshold = median_std + threshold_factor × MAD`
  where MAD is the median absolute deviation.
- Optimal threshold factor was found between 2.0 and 3.0.
- Approximately 19.8% of the dataset was identified and masked as movement artifacts.

1.2 Heart Rate Detection Algorithms

1.2.1 J-Peak Detection

- Enhanced peak detection with a 5-point verification method.
- Periodogram-based frequency domain analysis was used to estimate dominant cardiac frequencies.
- Applied physiological constraints (40–180 BPM) and adaptive interval validation:
  `min_interval = max(fs × 60 / 180, expected_period × 0.7)`

1.2.2 Windowing Strategy

- Non-overlapping window analysis was used to evaluate heart rate.
- **Window Size Comparison**:
  - **10-second** windows: High granularity but increased noise (567 windows)
  - **60-second** windows: Best performance with stable estimates (95 windows)
  - **30-second** windows: Intermediate size, higher errors, poorer correlation
- **Outlier Rejection**: Used 3σ thresholding based on robust MAD.
- **Weighted Averaging**: Gaussian weighting applied to enhance final HR estimate.

1.3 Statistical Evaluation

1.3.1 Error Metrics

- **MAE**: `mean(|BCG_HR - ECG_HR|)`
- **RMSE**: `sqrt(mean((BCG_HR - ECG_HR)^2))`
- **MAPE**: `100 × mean(|BCG_HR - ECG_HR| / ECG_HR)`
- **Correlation Analysis**: Pearson correlation coefficient and p-values assessed reliability.

1.3.2 Visualization Tools

- Time series overlays for ECG and BCG
- Bland-Altman plots with ±1.96σ agreement limits
- Correlation scatter plots with linear regression

- Histograms of heart rate distributions
- Movement detection plots across time

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2. Results Analysis

2.1 Performance Summary

Configuration	Window Size	Movement Threshold	MAE (BPM)	RMSE (BPM)	MAPE (%)	Correlation
Initial	10 sec	3.0	33.04	35.26	40.98	-0.18
Improved	60 sec	3.0	13.40	17.50	15.81	-0.11
Optimized	**60 sec**	**2.0**	**13.14**	**17.45**	**15.45**	**-0.12**
Rejected	30 sec	4.5	29.13	30.58	34.63	-0.25

2.2 Critical Evaluation

The optimized configuration (60-second window, threshold factor = 2.0) yielded the lowest MAE (13.14 BPM) and RMSE (17.45 BPM), with a reasonable MAPE (15.45%). However, the negative correlation coefficient (-0.12) remains a critical concern, suggesting inconsistent alignment between BCG-derived and ECG-derived heart rate values.

Bland-Altman analysis further revealed:

- **Bias**: -10.20 BPM
- **Limits of Agreement**: [-37.96, +17.57 BPM]

This consistent underestimation by the BCG system highlights a fundamental gap requiring further investigation.

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3. Conclusions and Recommendations

3.1 Current Status

The system demonstrated measurable improvement in accuracy through enhanced filtering, optimized window sizing, and robust motion artifact handling. Despite these efforts, a negative correlation and systemic underestimation persist, limiting the system's reliability for clinical or standalone applications.

3.2 Recommended Enhancements

Signal Quality Enhancement

- Integrate adaptive filtering methods (e.g., Kalman filtering)
- Employ multi-resolution analysis for superior feature isolation
- Develop a real-time **Signal Quality Index (SQI)** to weigh or discard unreliable segments

Advanced Algorithmic Approaches

- Utilize deep learning (e.g., CNNs) for J-peak detection
- Explore transfer learning from ECG-based models
- Incorporate temporal coherence and HR tracking to reduce jitter

Experimental Design Improvements

- Examine physiological delay between ECG and BCG signals
- Evaluate BCG signals primarily in the **frequency domain** to reduce noise sensitivity
- Cross-validate using multiple reference methods beyond ECG

System Integration

- Enable real-time processing and feedback on signal quality
- Support ongoing calibration based on user-specific metrics
- Implement adaptive algorithmic parameter tuning based on demographics or posture

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4. Final Remarks

This project lays the foundation for a promising non-invasive heart rate monitoring solution using BCG. With targeted enhancements in signal quality assessment, algorithmic precision, and system integration, future iterations can move closer to reliable, clinically-viable performance.