Estimating Personal Resting Heart Rate from Wearable Biosensor Data

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Collaborators

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Motivation

- Resting heart rate (RHR) is a biomarker for cardiovascular diseases, type 2 diabetes, cognitive decline, and more
- Gold standard ECG measurements vs PPG-based wearable device measurements
  - Frequency
  - Temporal continuity
- **How can we transform PPG-based wearable device heart rate (HR) data into RHR estimations?**
  - How can we evaluate this estimation?

Background

Stanford's STRONG-D Study: Strength Training Regimen for Normal Weight Diabetics

- Goal: determine the best exercise regimen for normal weight participants with Type 2 Diabetes
  - Manipulated variables: strength vs aerobic vs combined exercises
  - Response variable: indirect measures of blood sugar levels (hemoglobin A1c)

Background

Table 1: Strong-D features used for RHR estimation.

Data Set	Features
Fitbit/Fitabase: HR*	Participant ID, timestamp (seconds), HR (bpm)
Fitbit/Fitabase: Steps	Participant ID, timestamp (minutes), num. steps
Clinic	Participant ID, timestamp (date), supine HR (bpm), sitting HR (bpm), standing HR (bpm)

- Fitbit data: 423 days of measurements for 78 participants from August 1, 2017 to September 28, 2018
- *: Sampled first 85-day (20%) contiguous block of measurements for each participant, excluding night-time measurements

Methods: Model Design

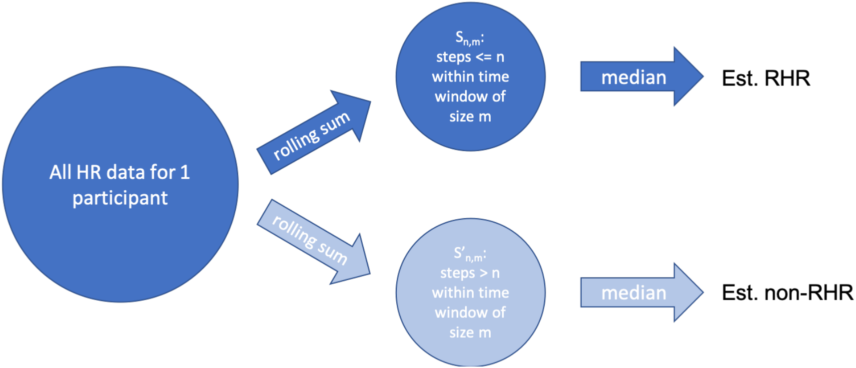


Figure 1: RHR Estimation Model.

Methods: Optimization

Motivation: *deviation* of HR is positively correlated with exercise intensity $\Rightarrow$ RHR has *lower deviation*

$$n^*, m^* = \underset{n,m}{\arg\min}\, SD(S_{n,m})$$

$$n \in \{x \in \mathbb{Z} : 0 \leq x \leq 1000 \text{ and } x \bmod 10 = 0\}$$

$$m \in \{x \in \mathbb{Z} : 1 \leq x \leq 120\}$$

Results: Sensitivity Analysis

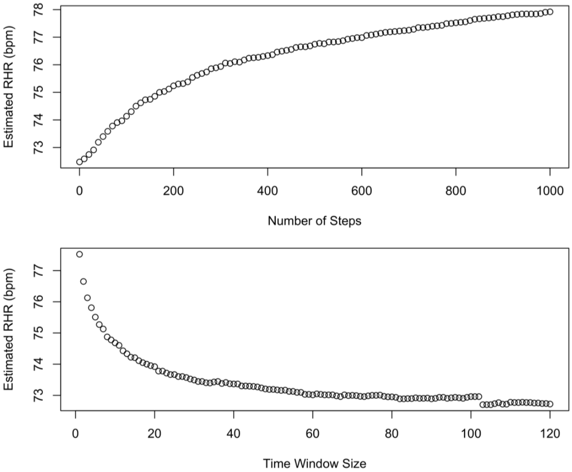
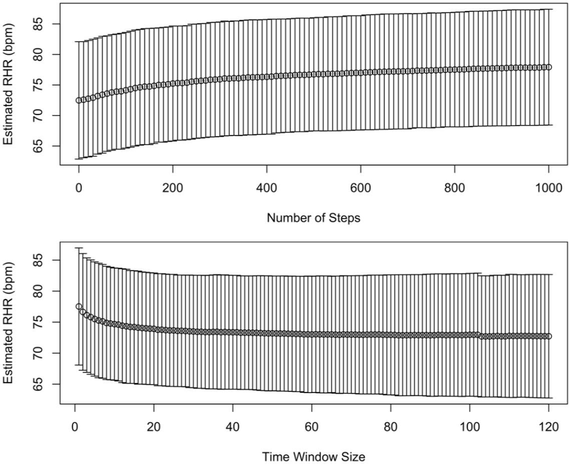


Figure 2: Sensitivity analysis of the mean RHR estimates over all participants for each step value (top) and time window size (bottom) while respectively holding the optimum window size and optimum step value constant.

Results: Sensitivity Analysis



Results: Evaluation

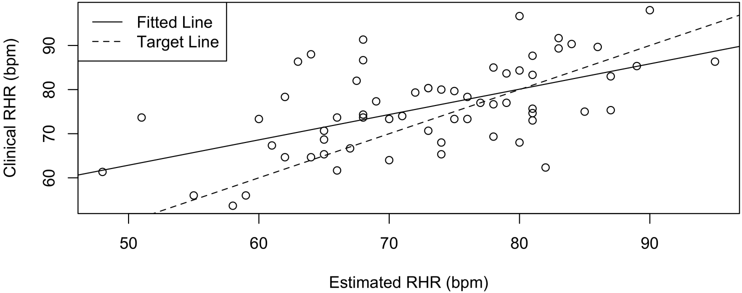


Figure 3: Linear regression of RHR_{est} versus RHR_{clinic} values for the deviation penalty. Each data point represents a participant. The solid line compares the clinical RHR with the estimated RHR ($R^2 = 0.32$, $P = 1.32 \times 10^6$). The dashed line represents the target scenario, where RHR_{est} perfectly recapitulates RHR_{clinic}.

- $RHR_{clinic} = mean$(supine/sitting/standing RHRs)
- Mean (all participants): Est. RHR = 73.02bpm; Est. non-RHR = 84.33bpm; Clinic RHR = 76.09bpm

Discussion

Timestamp Discrepancies

- Dates of the clinical RHR measurements vs 85-day sample period
- Joining HR measurements (seconds) and steps (minutes)
- Inconsistent Fitbit wear

Conclusion

- **How can we transform PPG-based wearable device heart rate (HR) data into RHR estimations?**
  - Optimization model based on HR and steps.

Future Work

- Additional penalty functions
- Predictive model for classifying types of exercise, especially strength exercise
- Refine plots