RespWatch: Robust Measurement of Respiratory Rate on Smartwatches with Photoplethysmography

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Overview: Respiratory Rate (RR) Monitoring

- Rate of breathing
- Important in detecting serious health conditions
- Cases
  - Driving safety
  - Assessing sleep quality
  - Monitoring stress
  - Detecting opioid overdose
- Issue
  - Monitoring outside of clinical setting is difficult
- Solution: wearable sensing systems for RR monitoring using photoplethysmography (PPG) sensors on commercial smart-watches

Related Work

- Smartwatch PPG sensors measure signals reflected from the wrist, which lowers signal quality and introduces noise
- Non-contact sensing approaches developed
  - Radio frequency, waves, wifi signals
  - Constrained to environment
- Inertial measurement unit (IMU) to capture subtle respiration motions
  - Limited to settings with minimum motion
- Deep learning
- PPG-Based RR measurement

Photoplethysmography (PPG) Sensors

- Detects pulsatile blood volume changes in tissues by measuring optical changes
- PPG sensor consists of a light-emitting diode (LED) to illuminate the tissue and a photodiode (PD) to measure the light transmitted through or reflected by the tissue
- Transmission-mode used in fingertip pulse oximeters
- Reflectance-mode used on wrist or forehead for heart rate monitoring

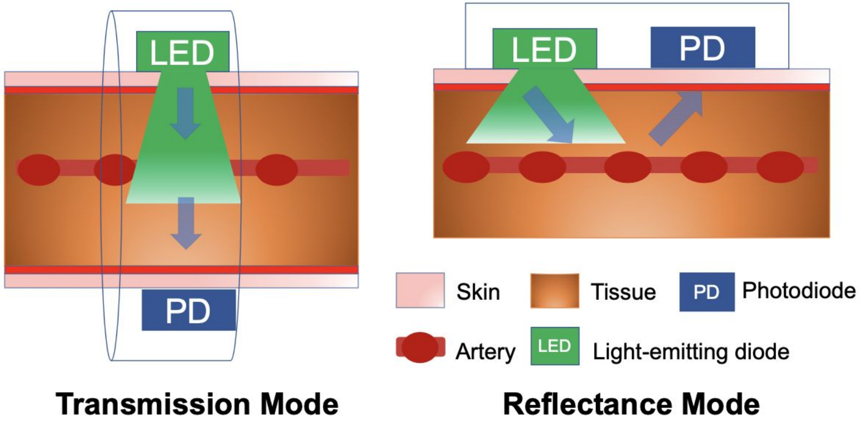

Figure 1: Two modes of the PPG sensor [3].

Respiratory-Induced Variations

- Amplitude (RIAV)
  - Changes in peripheral pulse strength
  - Vertical distances from the peak to the valley for each pulse
- Intensity (RIIV)
  - Intrathoracic pressure variation
  - Peak heights
- Frequency (RIFV)
  - Autonomic response to respiration
  - Horizontal distances between the successive peaks

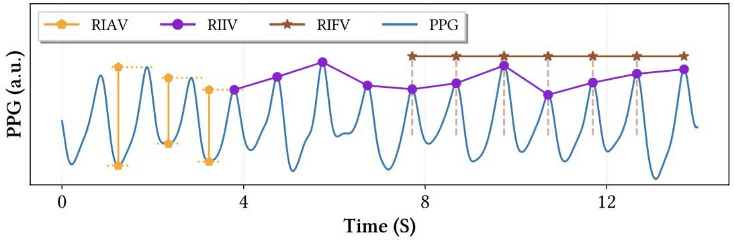

Figure 2: PPG waveform and respiratory-induced variations [22]. RIAV: respiratory-induced amplitude variation; RIIV: respiratory-induced intensity variation; RIFV: respiratory-induced frequency variation.

RespWatch

- RespWatch: RR monitoring system
- Goals
  - Accuracy
  - Robustness
  - Efficiency
- Developed estimators
  - Signal processing estimator
  - Deep learning estimator
  - Hybrid estimator

Signal Processing Estimator

- **Preprocessing Stage**
  - Use bandpass filter to eliminate noise outside the cardiac and respiratory bands from the raw signals
  - Divide the signal waveform into 60-second windows

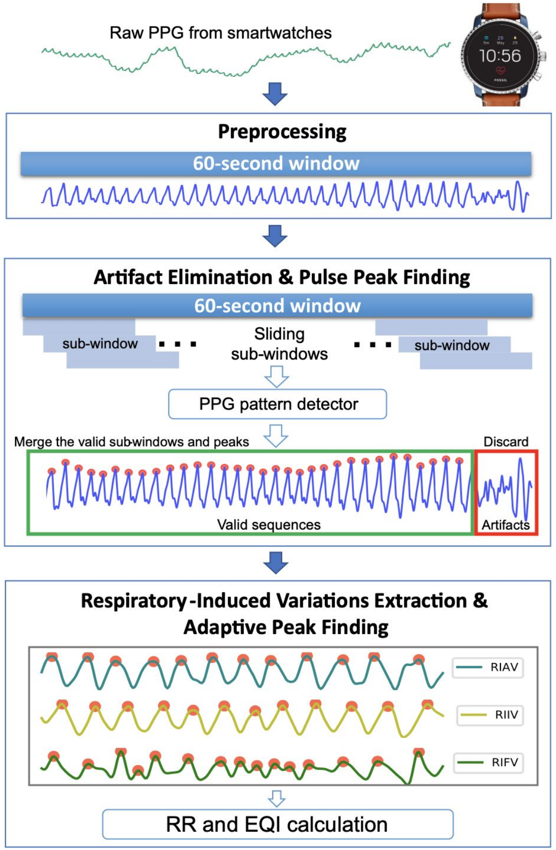

Figure 3: Architecture of the signal processing estimator in RespWatch

Signal Processing Estimator

- **Artifact Elimination and Pulse Peak Finding**

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Algorithm 1: Artifact Elimination & Pulse Peak Finding
Data: 60-second preprocessed PPG waveform
Sliding sub-windows with size of 10s and step of 2s;
for each sub-window do
    /* begin of PPG pattern detector                */
    2nd-order highpass forward-backward filtering;
    Re-scale the waveform with range of [-1,1];
    Find the peaks higher than 0;
    Calculate heart rate, peak intervals, peak-to-valley
     distances;
    // PPG pattern matching
    if heart rate ≤ 180 and heart rate ≥ 40
     STD(peak intervals)<0.4s and
     STD(peak-to-valley distances)<0.4 then
        mark the sub-window as valid ;
    end
end
Merge the consecutive valid sub-windows into valid
 sequences;
Merge the peaks from the valid sequences into peak lists;
Result: Valid sequences and corresponding peak lists
```

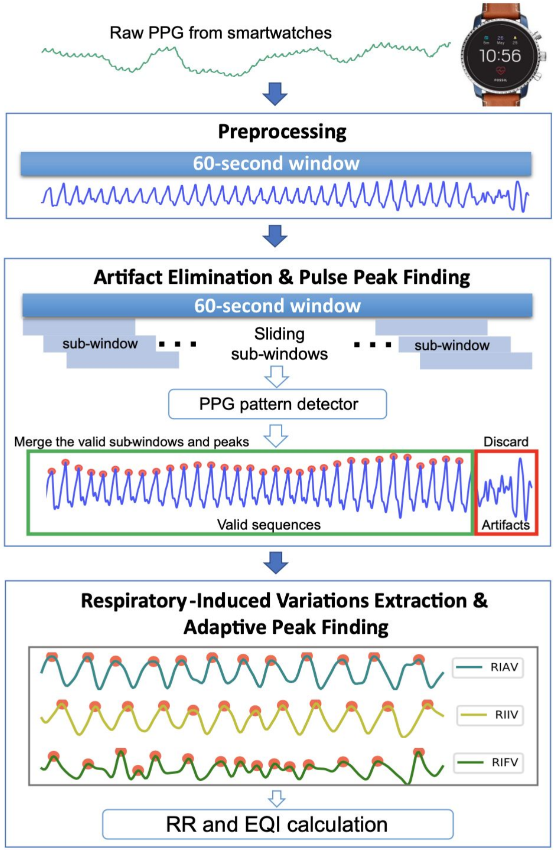


Figure 3: Architecture of the signal processing estimator in RespWatch

Signal Processing Estimator

- **Respiratory-Induced Variation Signals**
  - Map the variation signals to the RR estimations with an adaptive peak finding method to detect respiratory peaks
    - Use to calculate RR for each sequence

$$RR_{RIXV,i} = \frac{60}{MEAN(peak\_intervals_{(i)})/f_s}$$

  - Estimation quality index (EQI): assesses the accuracy of measurements
    - Based on two intuitions
      1. Respiration is rhythmic, so standard deviation of the respiration peak intervals should be small
      2. RR measurement is more accurate on the longer sequence

$$EQI_{RIXV,i} = \alpha \cdot \frac{STD(peak\_intervals_{(i)})}{seq\_length_{(i)}} \qquad (3)$$

where α is a fixed scaling factor, $STD(\cdot)$ is the standard deviation of $\cdot$, $seq\_length_{(i)}$ is the length of the i^{th} valid sequence. The final EQI_{RIXV} is the sum of $EQI_{RIXV,i}$ for each valid sequence:

$$EQI_{RIXV} = \sum_i EQI_{RIXV,i} \qquad (4)$$

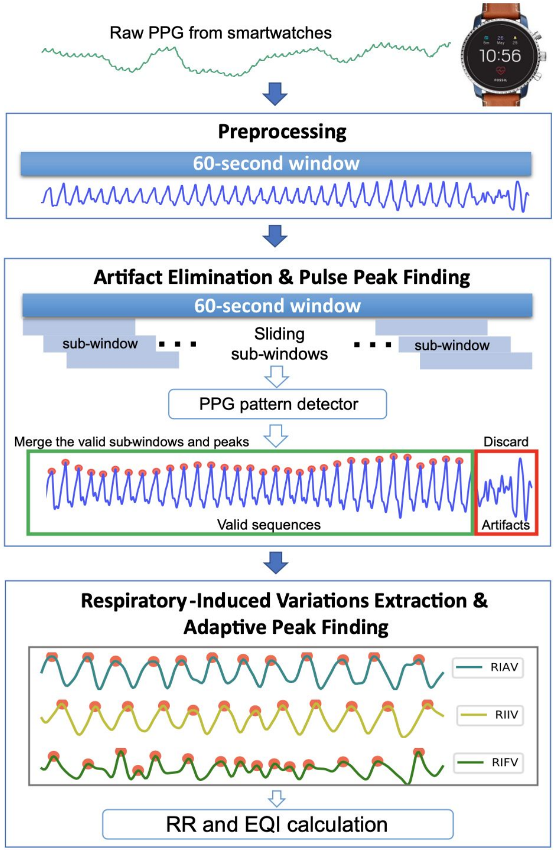


Figure 3: Architecture of the signal processing estimator in RespWatch

Deep Learning Estimator

- CNN model can directly output the estimation of RR using the PPG waveform
- **Preprocessing**
  - Standardize data and reduce noise because raw PPG signals exhibit different ranges and amplitudes under different conditions which can lead to overfitting
  - Re-sampled the PPG signal at 50Hz, applied the same bandpass filter used in the signal preprocessing estimator, and normalized the signals to a zero mean and a unit variance

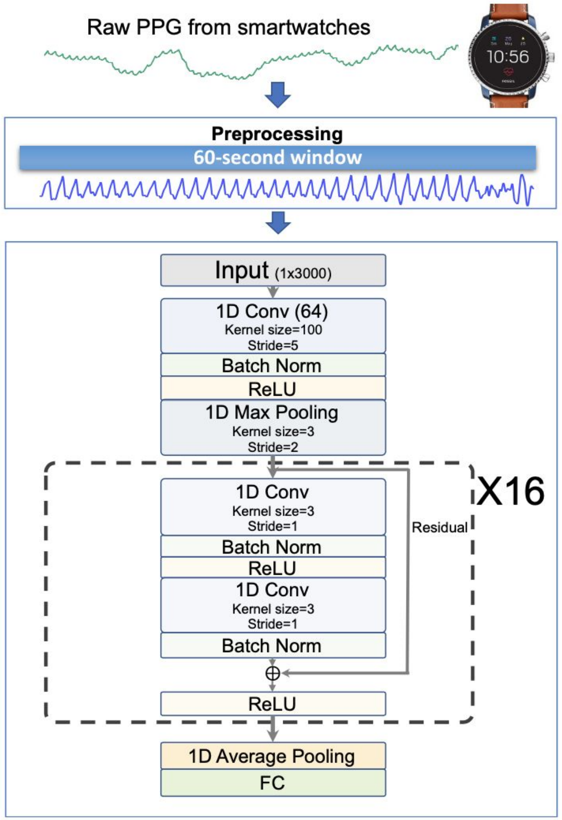
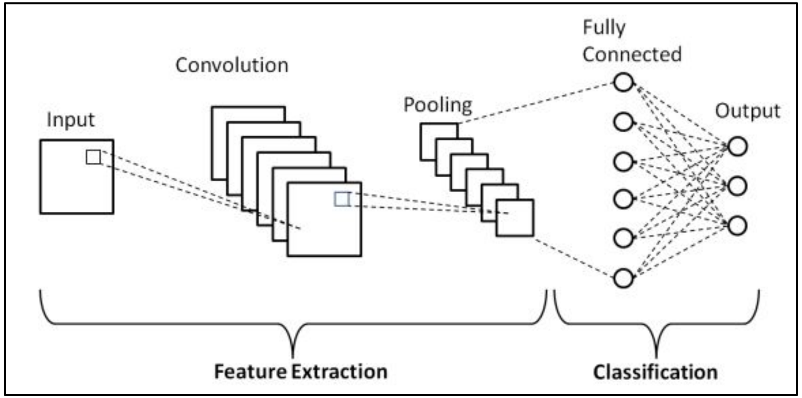


Figure 7: Architecture of the deep learning estimator in RespWatch

Deep Learning Estimator

- **CNN model**
  - 1D convolutional layer down-samples input and reduces computation complexity
  - 16 basic blocks sharing the same topology with residuals bypass and 1D convolutions applied
  - Batch normalization (Batch Norm) and a rectified linear unit (ReLU) activation layer employed after each convolutional layer
  - 16 basic blocks are grouped into 4 stages
  - Lastly, append a 1D average pooling layer and a fully connected layer which performs regression tasks of final RR estimation



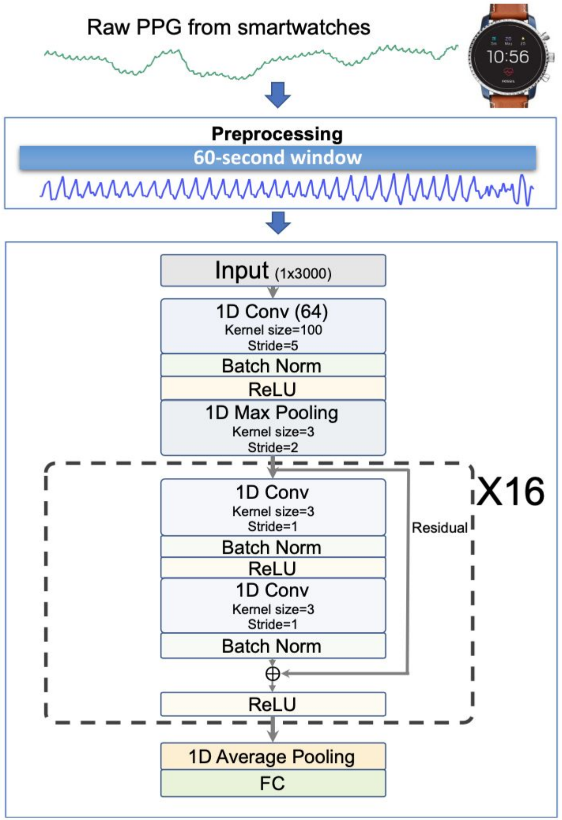


Figure 7: Architecture of the deep learning estimator in RespWatch

Hybrid Estimator

Automatically switches from signal processing to deep learning to take advantage of its higher level of robustness, and switches back to signal processing when noise artifact diminishes to benefit from its higher efficiency and accuracy

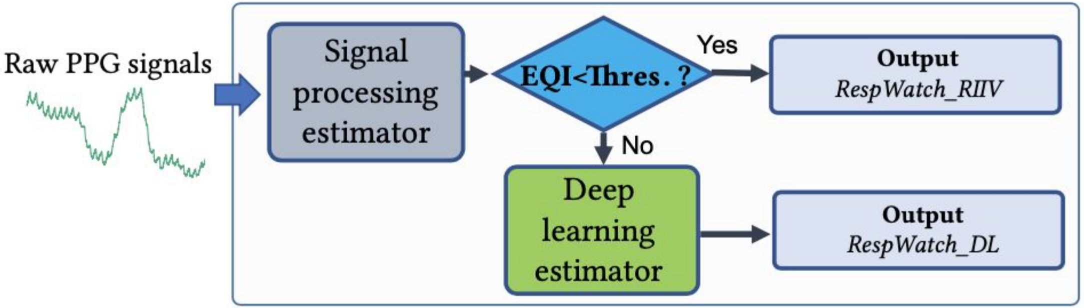


Figure 8: Architecture of hybrid estimator. *RespWatch_RIIV* is the output from signal processing estimator with RIIV; *RespWatch_DL* is the output from deep learning estimator.

User Study

- 30 participants

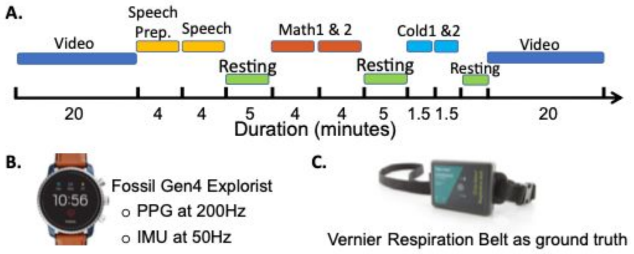


Figure 9: (A). Sequence of activities of the collecting procedure. (B). Fossil Gen4 Explorist smartwatch instrumented for this study. (C). Vernier Respiratory Go Direct Respiration Belt as ground truth.

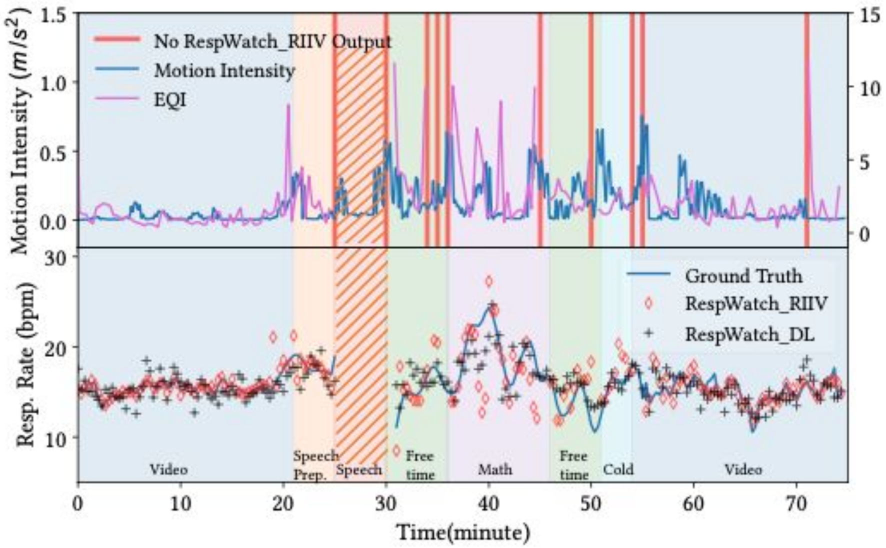


Figure 10: RR measurements, motion intensity, and EQI of one user participating in the study.

RespWatch Evaluation

- Accuracy - mean absolute error

$$MAE = \frac{1}{n}\sum_{i=1}^{n} |\hat{y}_i - y_{ref,i}|$$

n is the number of data windows, $\hat{y}_i$ is the estimated RR and $y_{ref,i}$ is the reference RR from ground truth

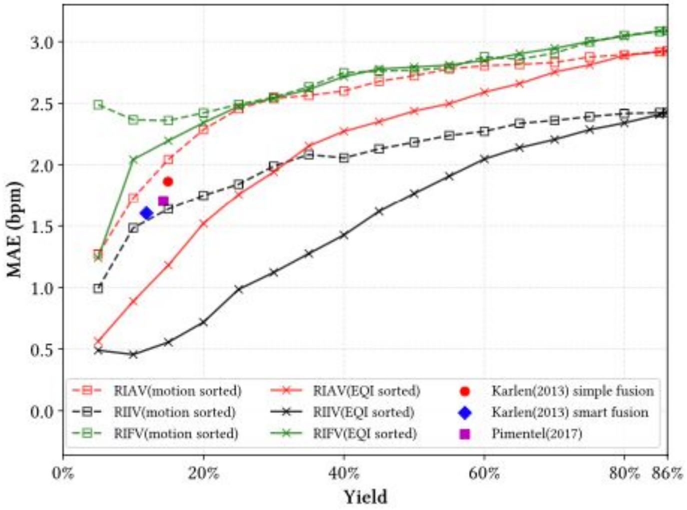


Figure 11: MAE vs. Yield. Different colors represent the estimations from RIAV, RIIV and RIFV, respectively. The line styles indicate different sorting criterion (Motion, EQI). The baselines are illustrated as dots with different shapes and colors.

Results - Accuracy & Robustness

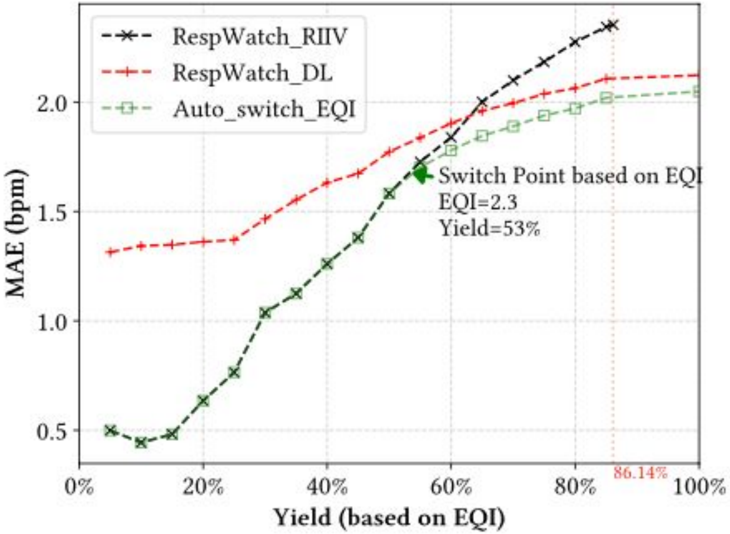


Figure 12: MAE vs. Yield based on EQI ranking.

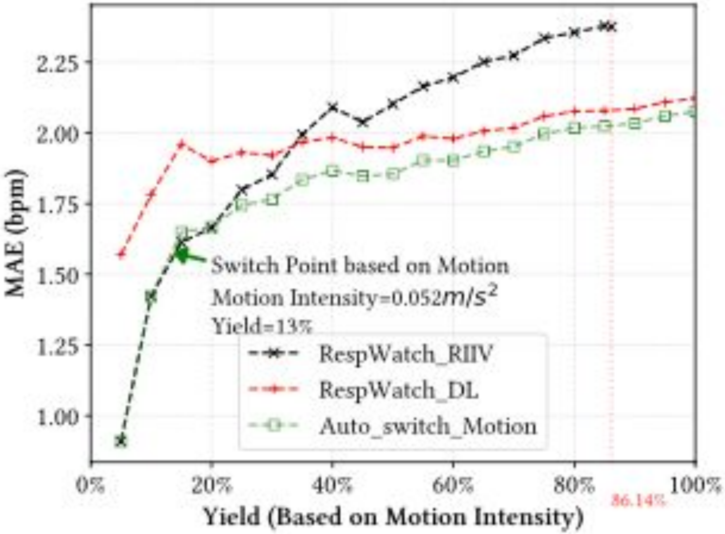


Figure 13: MAE vs. Yield based on Motion ranking.

Results - Efficiency

Table 3: Profile of Signal Processing Estimator

Devices	Preprocessing	Art. Elim.* & Pulse Peak Finding	RIXV* Extraction & Adaptive Peak Finding	Total Time	Ave. CPU(%)	Ave. Energy Consumption
Fossil Gen4 (H)	5.836ms	19.139ms	19.919ms	44.895ms	53.53%	Light to Medium
Fossil sport (H)	5.385ms	16.058ms	16.621ms	38.064ms	50.25%	Light to Medium

*Art. Elim.: Artifact Elimination

*RIXV: Respiratory-Induced Variations (RIAV, RIIV, RIFV).

Table 4: Profile of Deep Learning and Hybrid Estimator

Devices	Preprocessing	CNN model	Deep learning Total Time	Ave. CPU (%)	Ave. Energy	Hybrid with EQI*	Hybrid with Motion Intensity*
Fossil Gen4 (H)	8.856ms	6504.262ms	6592.828ms	85.34%	Above Medium	2879.811ms	5780.655ms
Fossil sport (H)	8.472ms	7934.962ms	7943.434ms	70.23%	Around Medium	3453.740ms	6948.851ms

*The running time of hybrid estimator is the expected running time based on our dataset with the corresponding best switching threshold.

Positives

- Able to handle noise
- Multiple approaches used
- Non-invasive

Negatives

- 30 participants in user study
- Further elaboration of their evaluations

Discussion

- Are there other major applications that PPG sensing could be applied to?
- What factors could be contributing to noise?
- Are there any other metrics for accuracy that could be used?
- The method is mathematically dependable with low error rate, but does it match real-life experiences?