Extracting Vitals from Smartphone Accelerometer

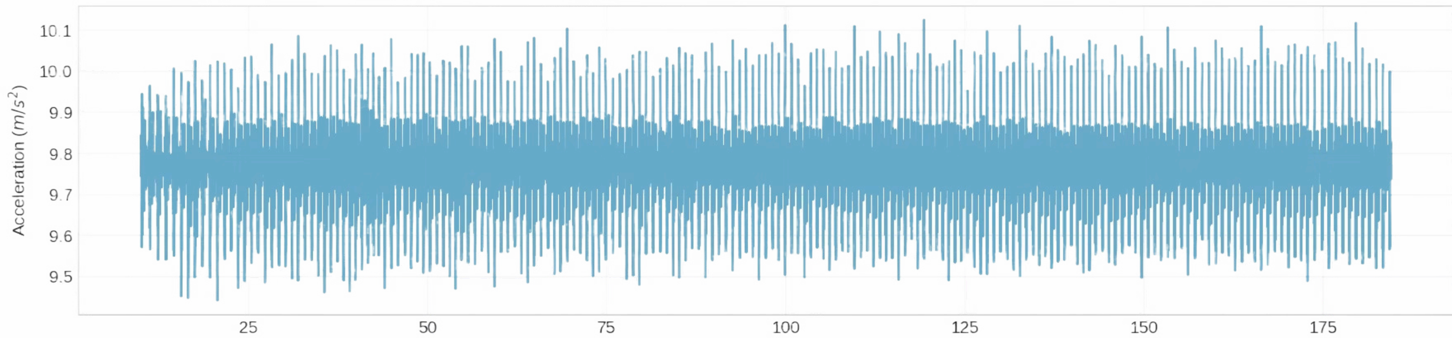
I set out to detect heart rate and respiration using only a smartphone accelerometer. I conducted controlled breathing and spontaneous breathing experiments (2s, 4s, 8s cycles).

Data from an accelerometer is messy

1

Raw Z-axis Data

The raw signal is dominated by gravity, sitting at 9.8.



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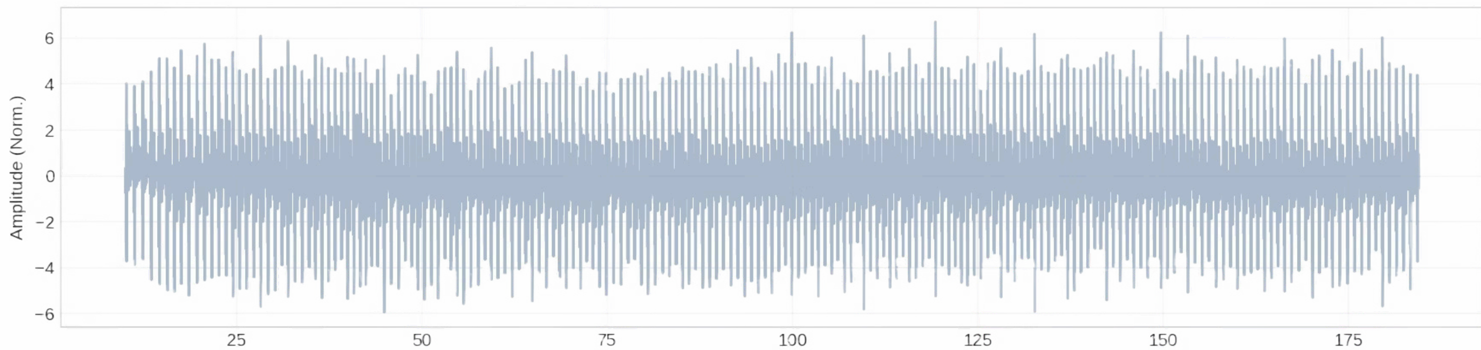
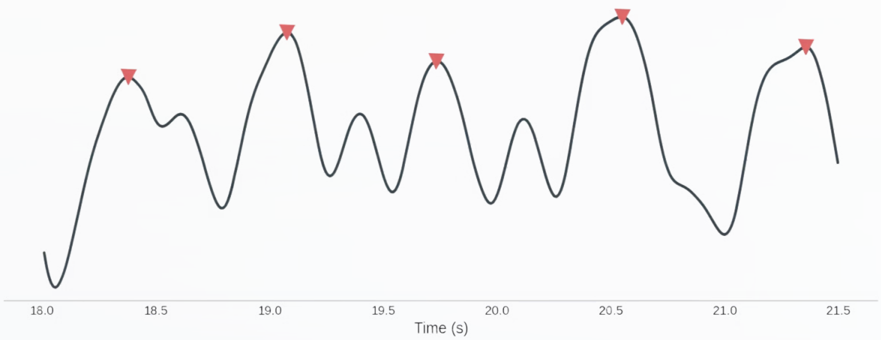
Processed Signal

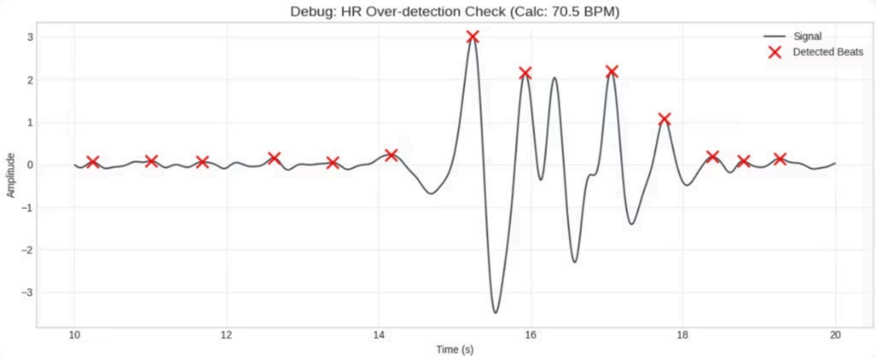
1. Detrend (Remove Gravity).
2. PCA (Combine Axes into Max Variance direction).
3. Bandpass Filter (Isolate Frequencies).





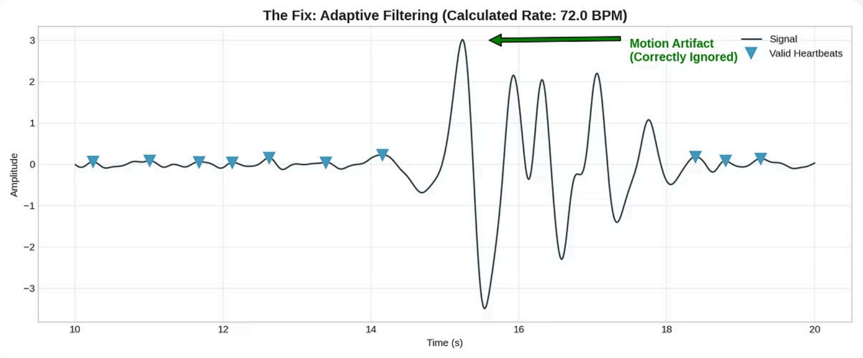
The Standard Pipeline (Time Domain)

- **The Goal:** Identify local maxima (peaks) as heartbeats.
- **The Math:** Calculate the time difference between peaks to derive instantaneous Heart Rate.
- **The Assumption:** "If we filter the signal well, every peak is a heartbeat."
- **The Reality:** "Unfortunately, real-world data isn't this clean..."



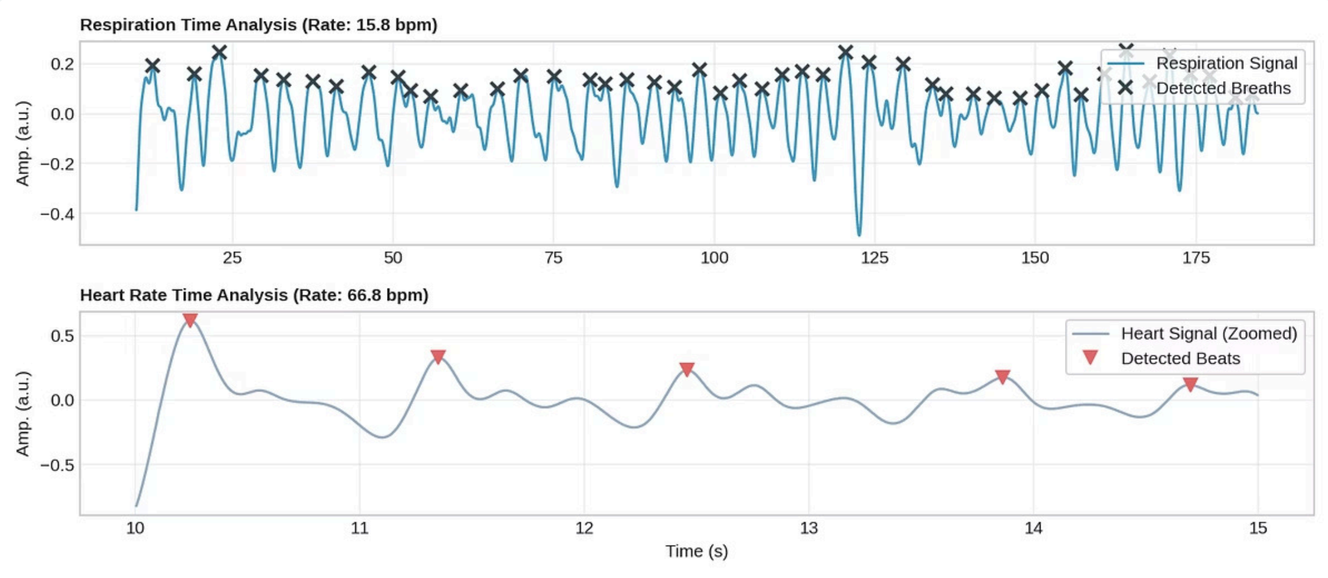
The Limitations of Static Thresholds

- **Method:** Standard peak detection with fixed amplitude.
- **Failure:** Motion artifacts are miscounted as heartbeats.
- **Result:** Massive over-estimation of Heart Rate.

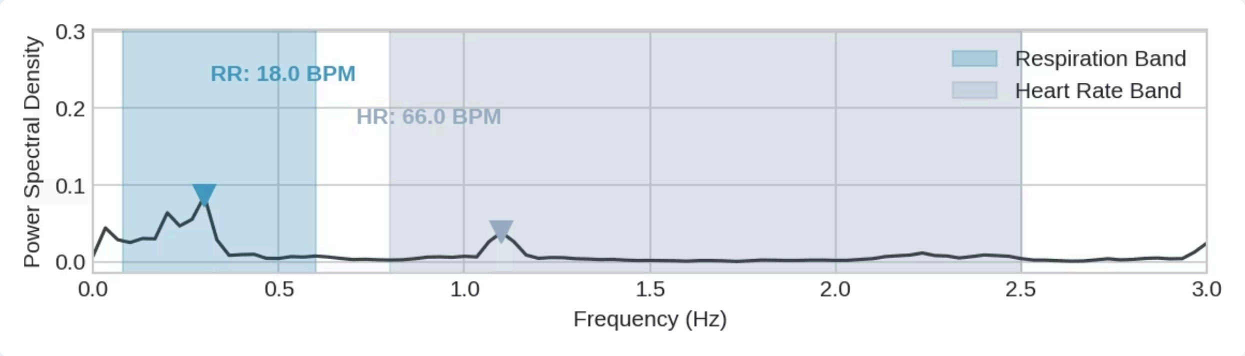


The Fix: Dynamic Thresholding

- **Median-Based Rejection:** I switched to **Median** filtering to calculate the "typical" heartbeat height, ignoring massive motion spikes.
- **Physiological Constraints**: I implemented a **Minimum Peak Distance.** The algorithm now "knows" that a heart cannot physically beat twice in 0.2 seconds, preventing double-counting.

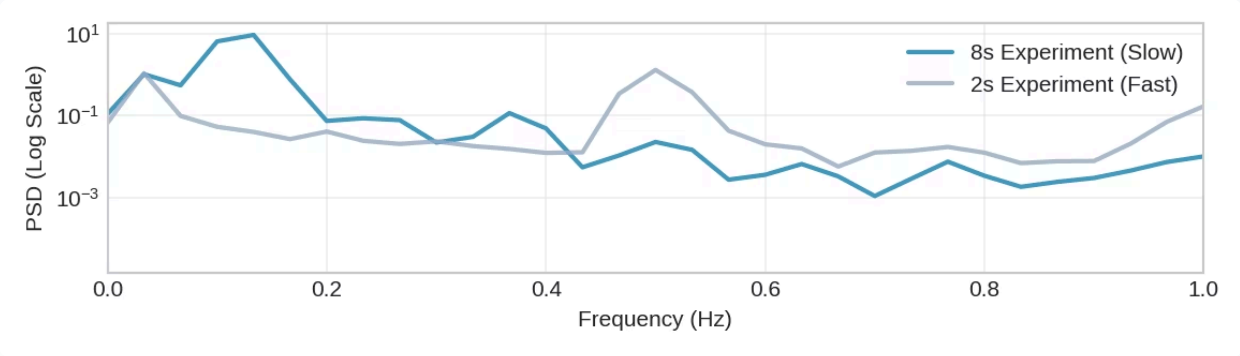


Final Vitals Extraction



The Robust Solution: Welch's Periodogram

Switching to Frequency Domain analysis, specifically **Welch's** method, provided a breakthrough. This technique focuses on identifying dominant, repeating patterns across the entire signal rather than isolated spikes.



Proof of Robustness: Controlled Breathing Experiments

To prove this wasn't a fluke, I compared my 'Fast Breathing' (2s) experiment against my 'Slow Breathing' (8s) experiment.

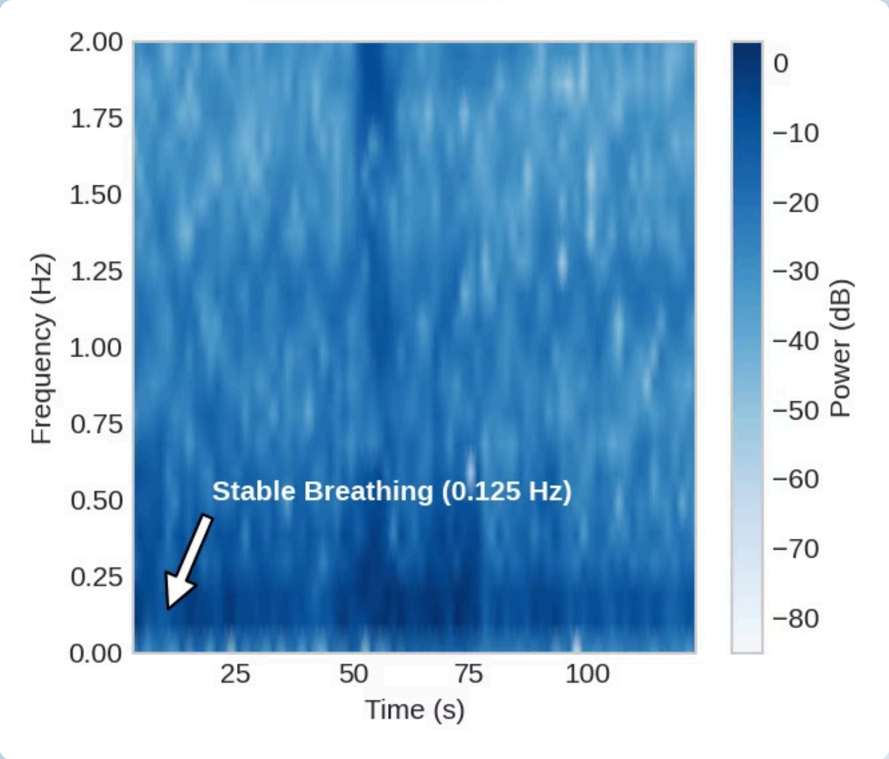
Slow Breathing (8s cycle)

The blue line clearly shows a peak at approximately **0.125 Hz**, corresponding precisely to the 8-second breathing cycle (1/8 Hz).

Fast Breathing (2s cycle)

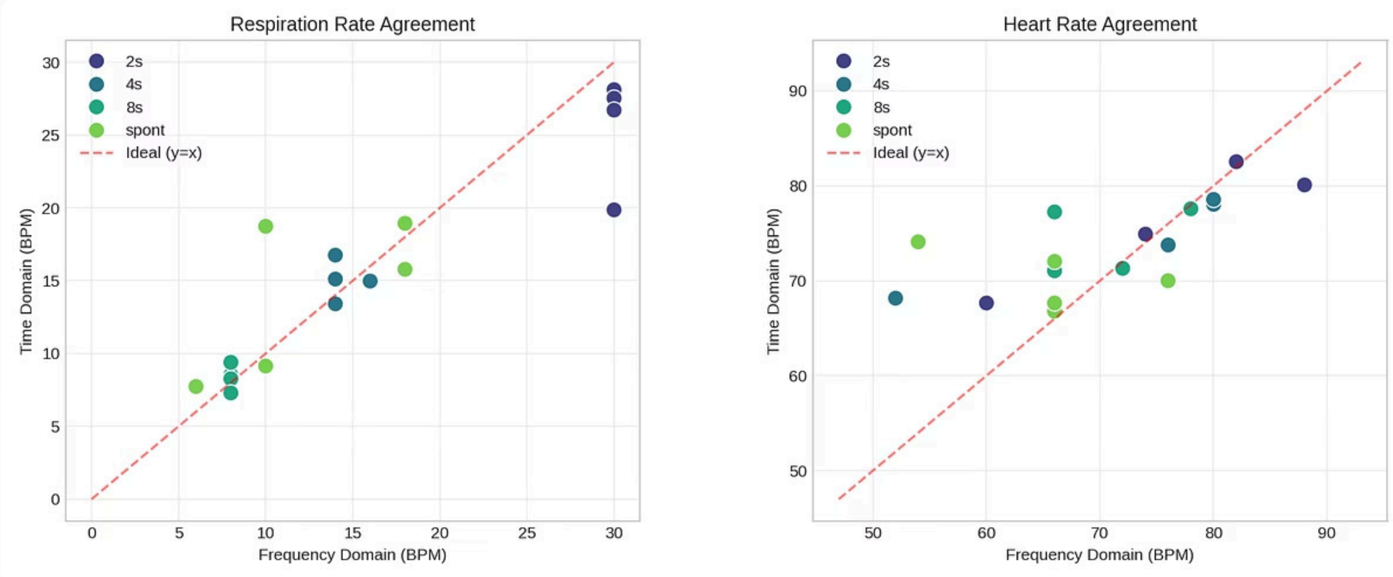
The grey line demonstrates a distinct peak at **0.5 Hz**, aligning perfectly with the 2-second breathing cycle (1/2 Hz).

The **precise alignment** of these peaks with the expected frequencies proves that the algorithm accurately and reliably fulfils its purpose.



Visualising Stability: The Spectrogram

- **Unbroken Horizontal Line:** The spectrogram displays a consistent, continuous high-energy band across the entire 2-minute recording.
- **Experimental Control:** This visually confirms that the breathing rate **did not drift or fluctuate**, validating the quality of the controlled experiment.



Validation: Method Agreement

- **General Trend:** Both methods successfully distinguish between Resting and Active states.
- **Heart Rate Bias:** Time Domain is slightly higher. Likely caused by residual false positives from noise artifacts increasing the count.
- **Respiration Bias:** Time Domain is lower during fast breathing. Shallow breaths sometimes fall below the detection threshold (false negatives). Even with dynamic thresholds some human intervention seems to be still necessary to adjust their parameters to ensure accuracy.

Conclusion: Key Takeaways

- **Frequency Domain** is excellent for average rates (Stable)
- **Time Domain** is viable *if* adaptive thresholds are used.
- **Future Work**: Real-time implementation would require a sliding window to minimize lag vs. accuracy trade-offs.