6.S062: Mobile and Sensor Computing

Lecture 6: Wireless Sensing of Breathing, Heartbeats, and Emotions

Ubiquitous Health & Comfort Monitoring

Can smart homes monitor and adapt to our breathing and heart rates?

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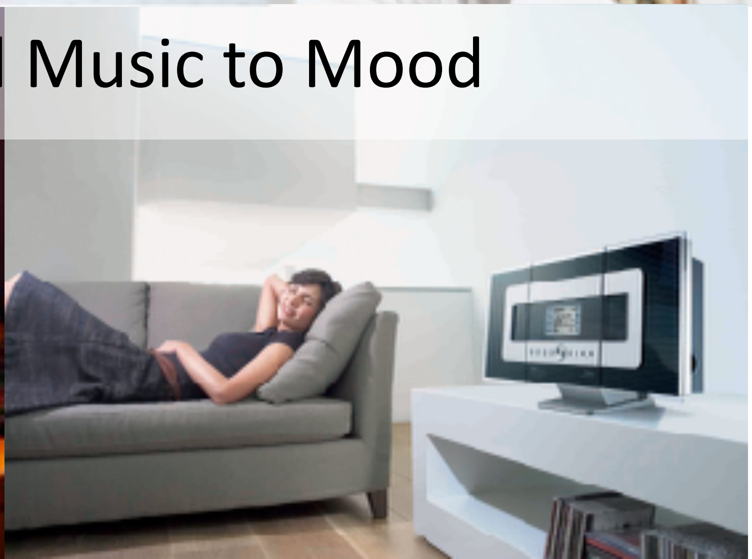
Personal Health

Baby Sleep

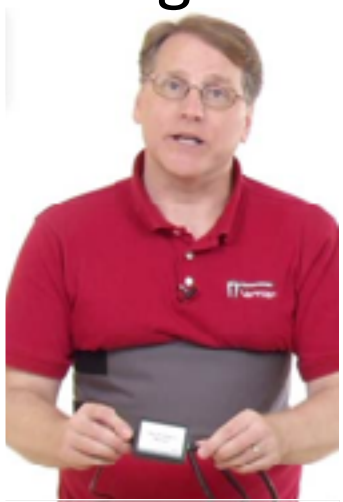
Elderly Health

Adapt Lighting and Music to Mood



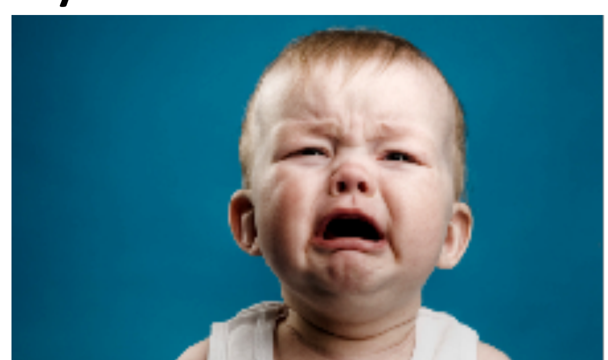
But: today's technologies for monitoring vital signs are cumbersome

Breath Monitoring



Heart Rate Monitoring

Not suitable for elderly & babies



Can we monitor breathing and heart rate from a distance?

Vital-Radio

- Technology that monitors breathing and heart rate remotely with 97% accuracy
- Can monitor multiple users simultaneously
- Operates through walls and can cover multiple rooms

Idea: Use wireless reflections off the human body

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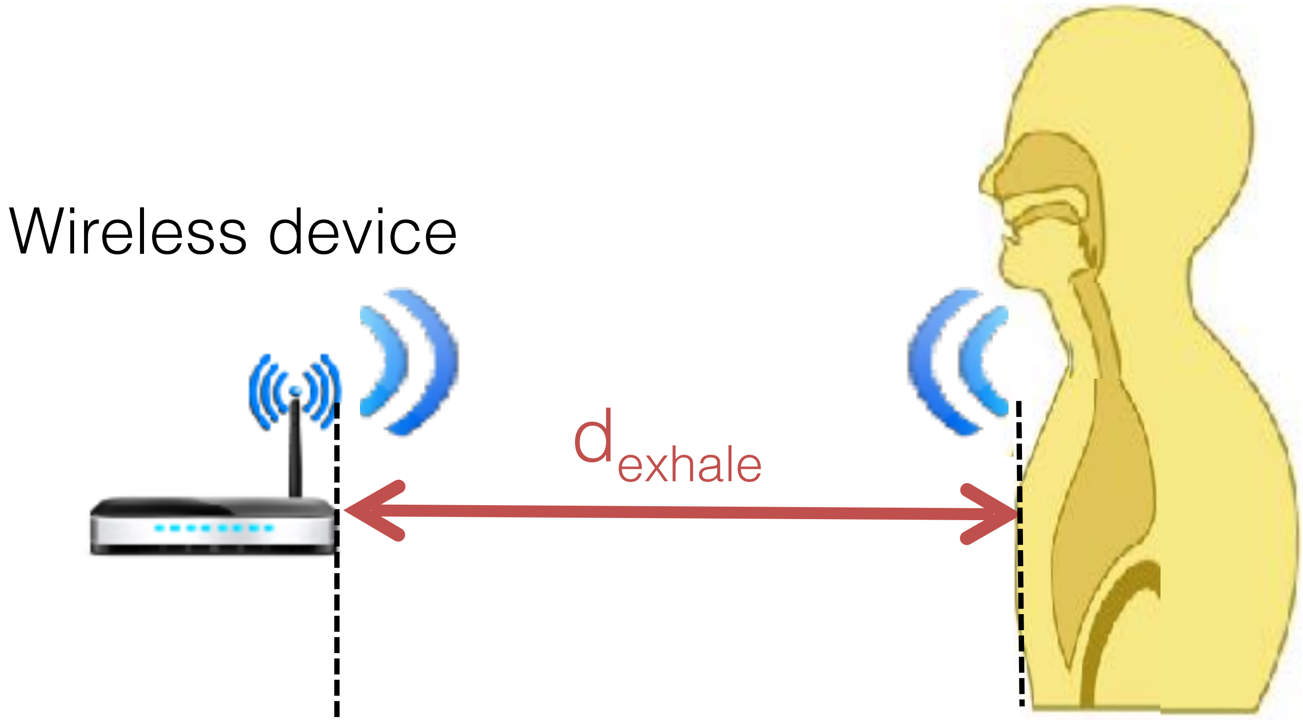
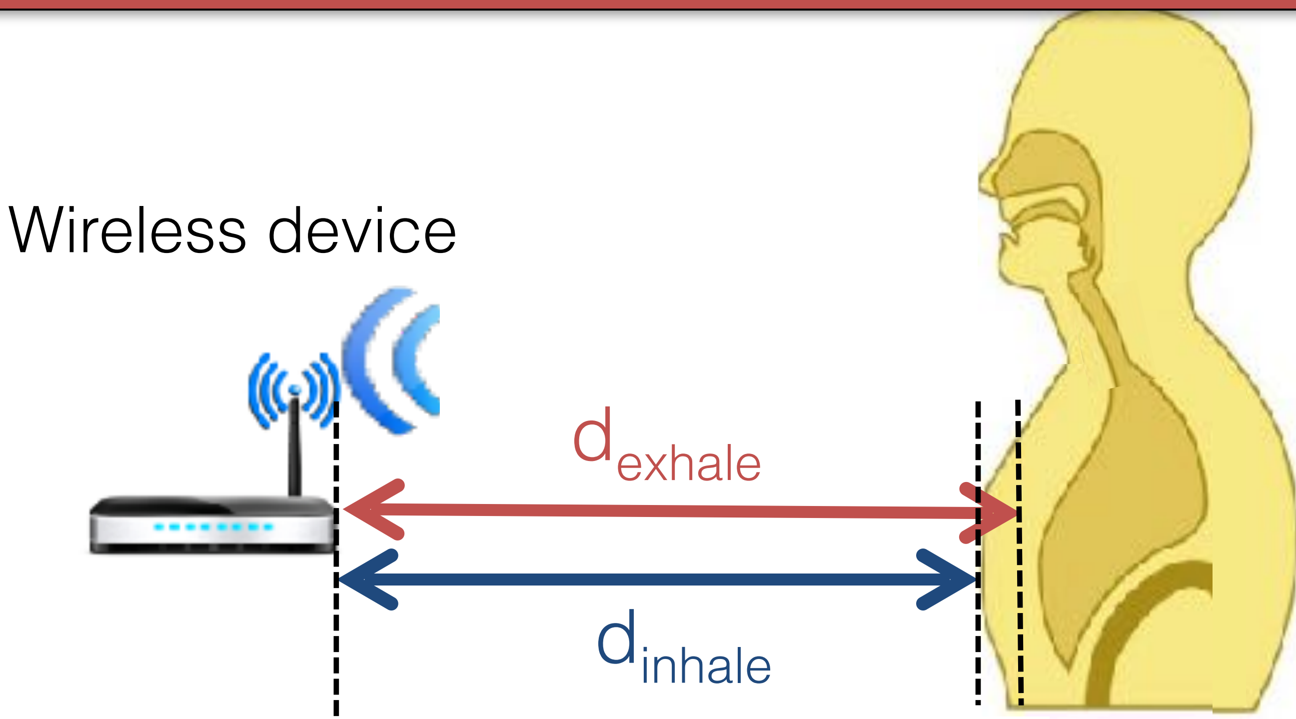
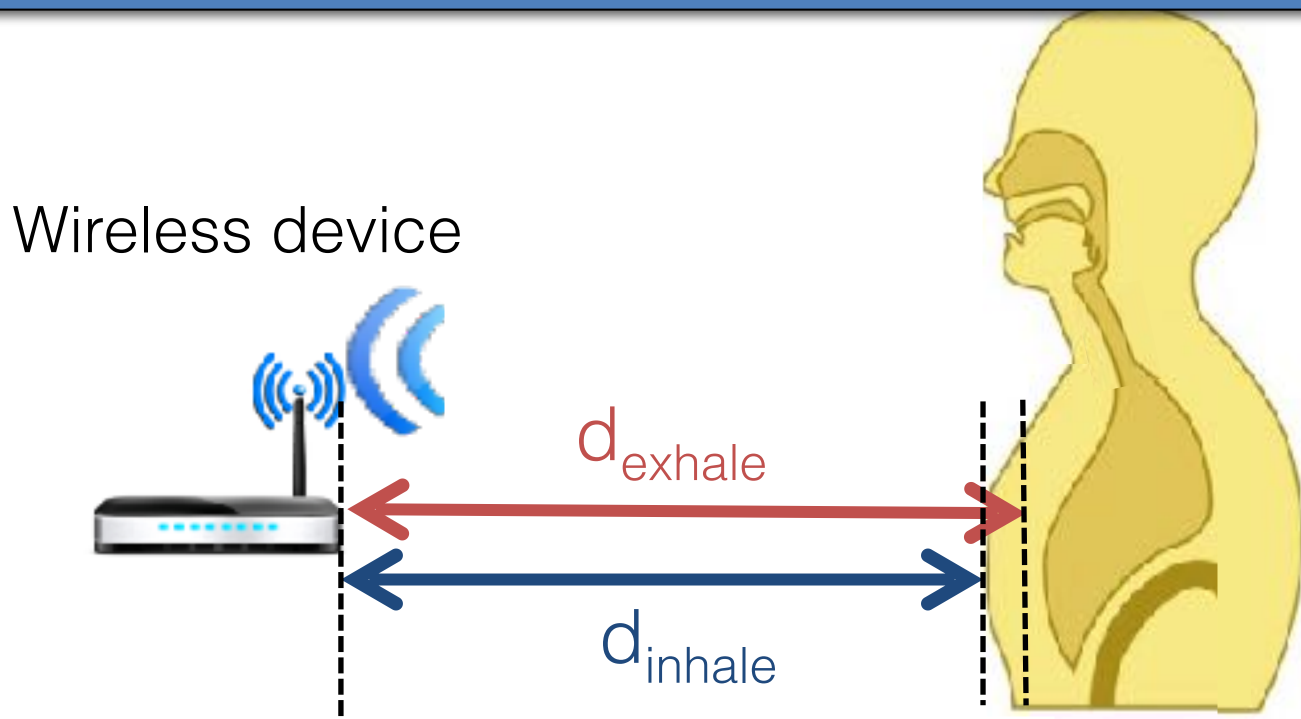


Problem: Localization accuracy is only 12cm and cannot capture vital signs



Why? How did we compute the resolution?

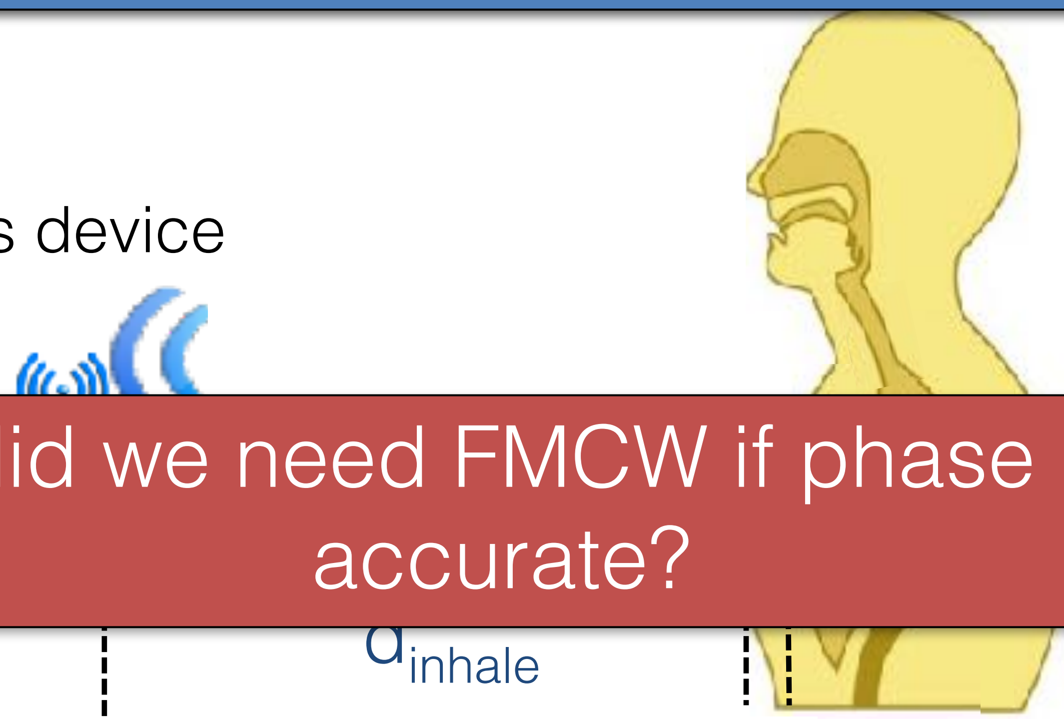
Solution: Use the phase of the wireless reflection



Why does phase allow us to get the distance at higher granularity?

Solution: Use the phase of the wireless reflection

Wireless device



Why did we need FMCW if phase is so accurate?

Wireless wave has a phase: $\phi = 2\pi \frac{\text{distance}}{\text{wavelength}}$

- Chest Motion changes distance
- Heartbeats also change distance

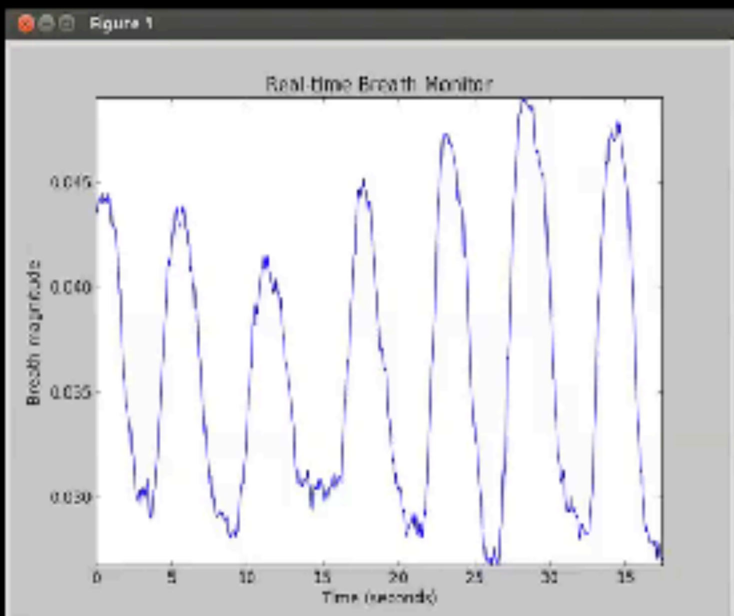
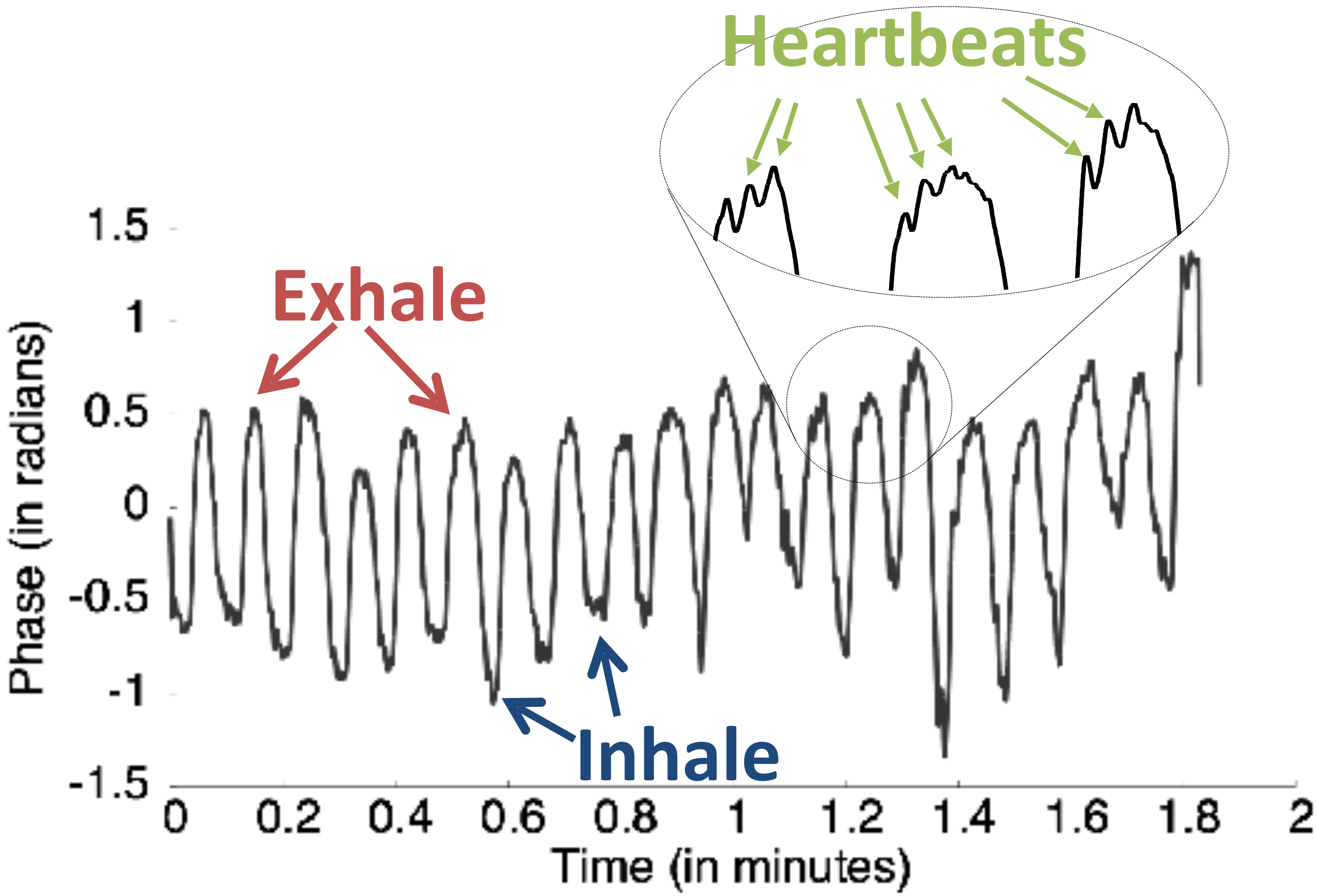


Figure 1
Real-time Breath Monitor
Breath magnitude
0.045
0.040
0.035
0.030
0
5
10
15
20
25
30
Time (seconds)


Let’s zoom in on these signals



How do we get from here to extracting breathing rate and heart rate?

What happens when a person moves his limb?

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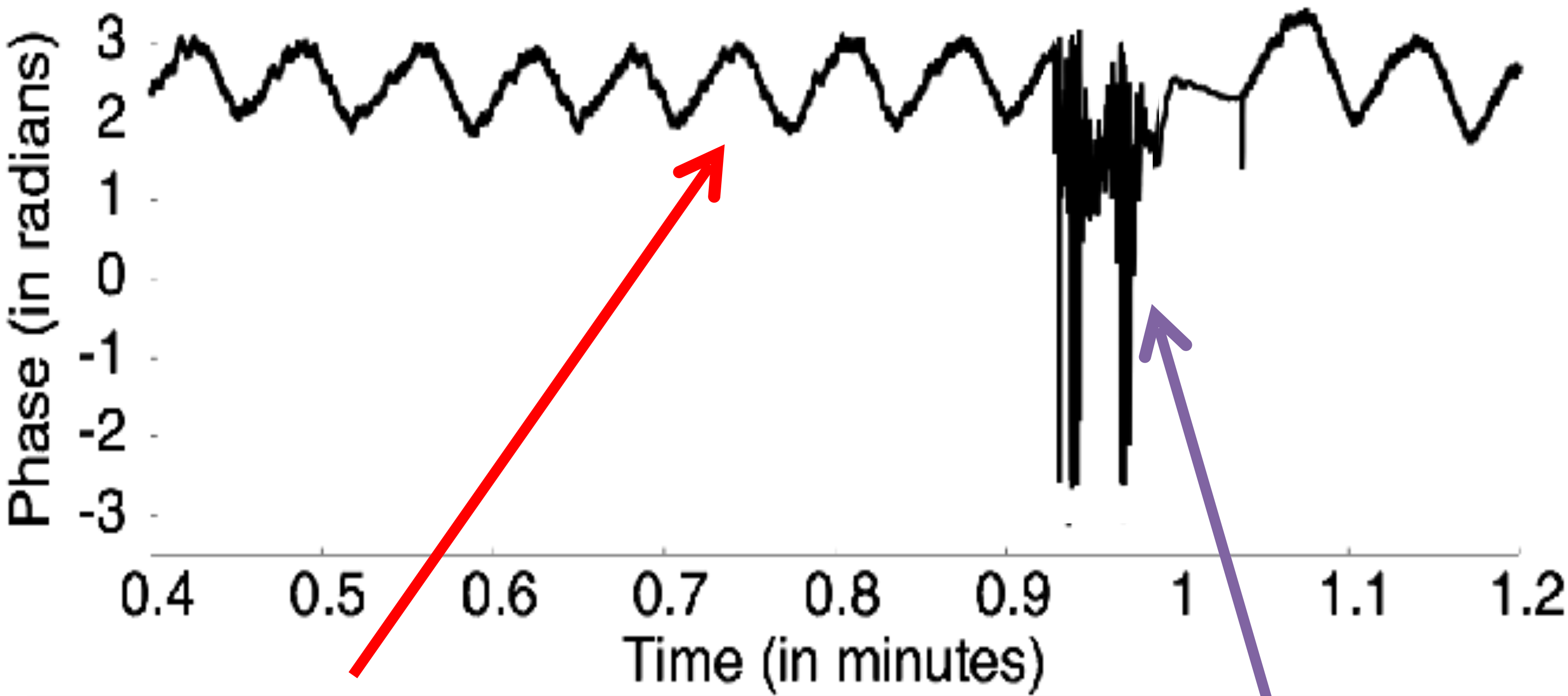
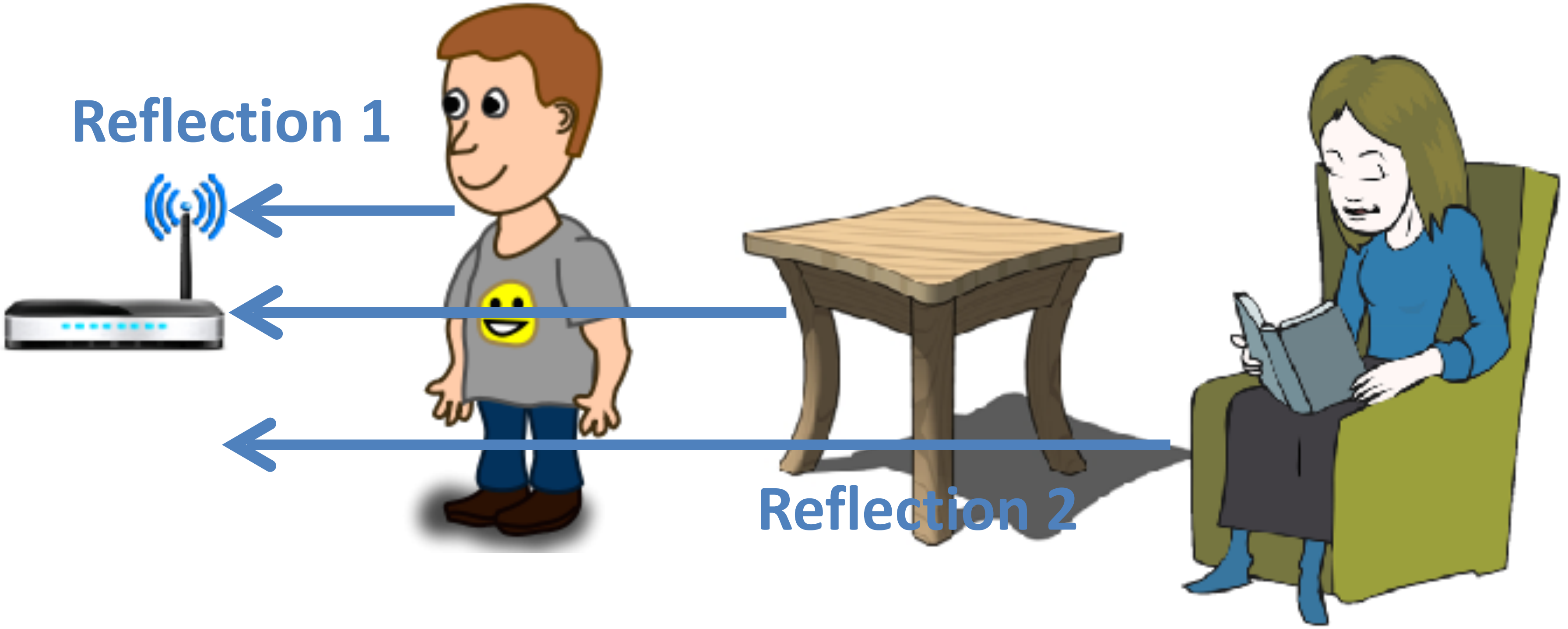


Band-pass filter the cleaned signals to extract breathing and heart rate

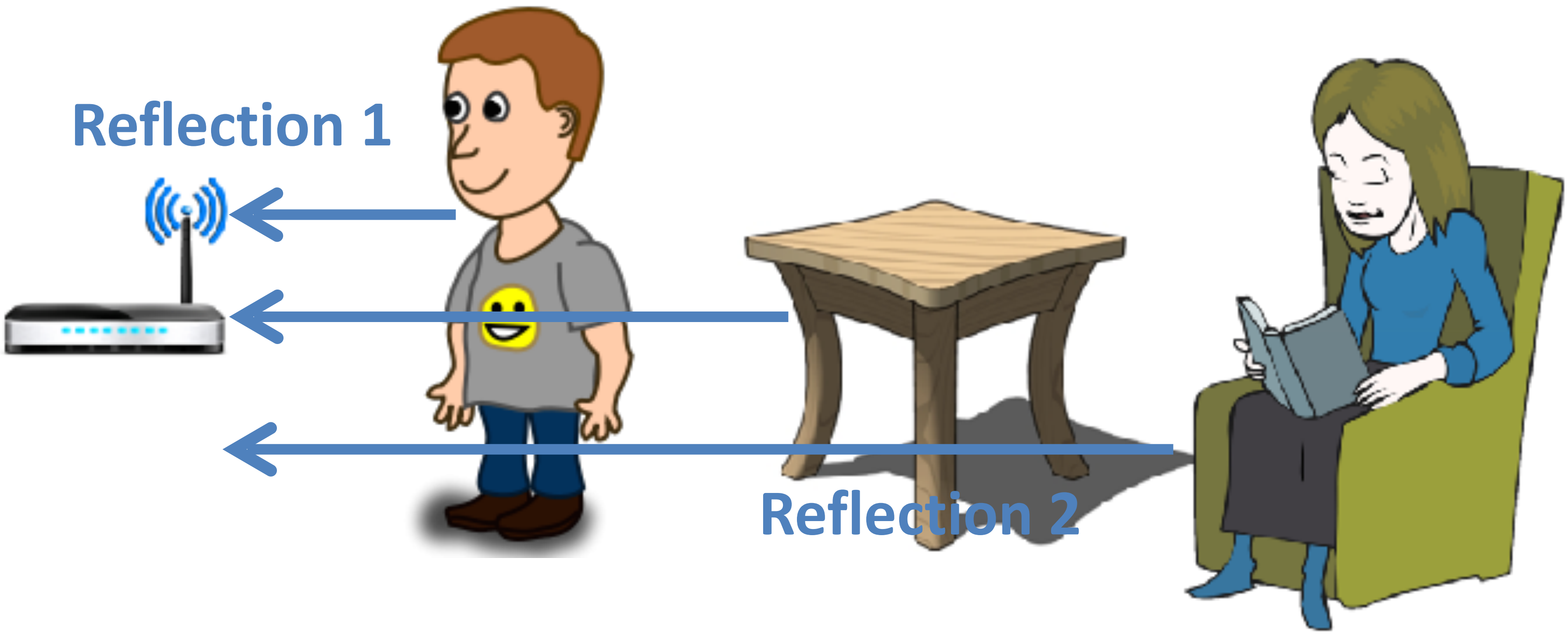
What happens with multiple users in the environment?

Reflections from different objects collide

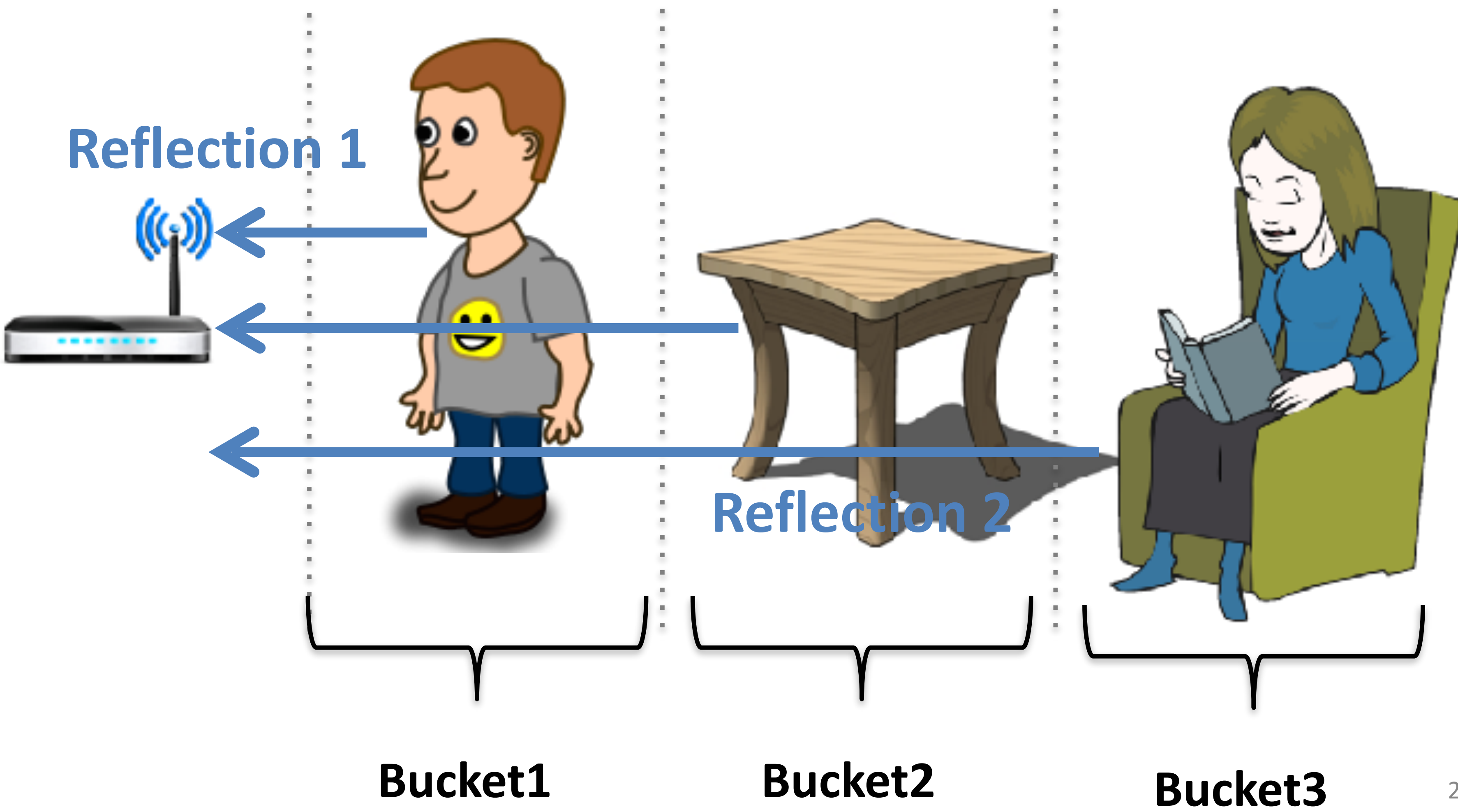
<u>Problem:</u> Phase becomes meaningless!



Solution: Use WiTrack as a filter to isolate reflections from different positions



Solution: Use WiTrack as a filter to isolate reflections from different positions



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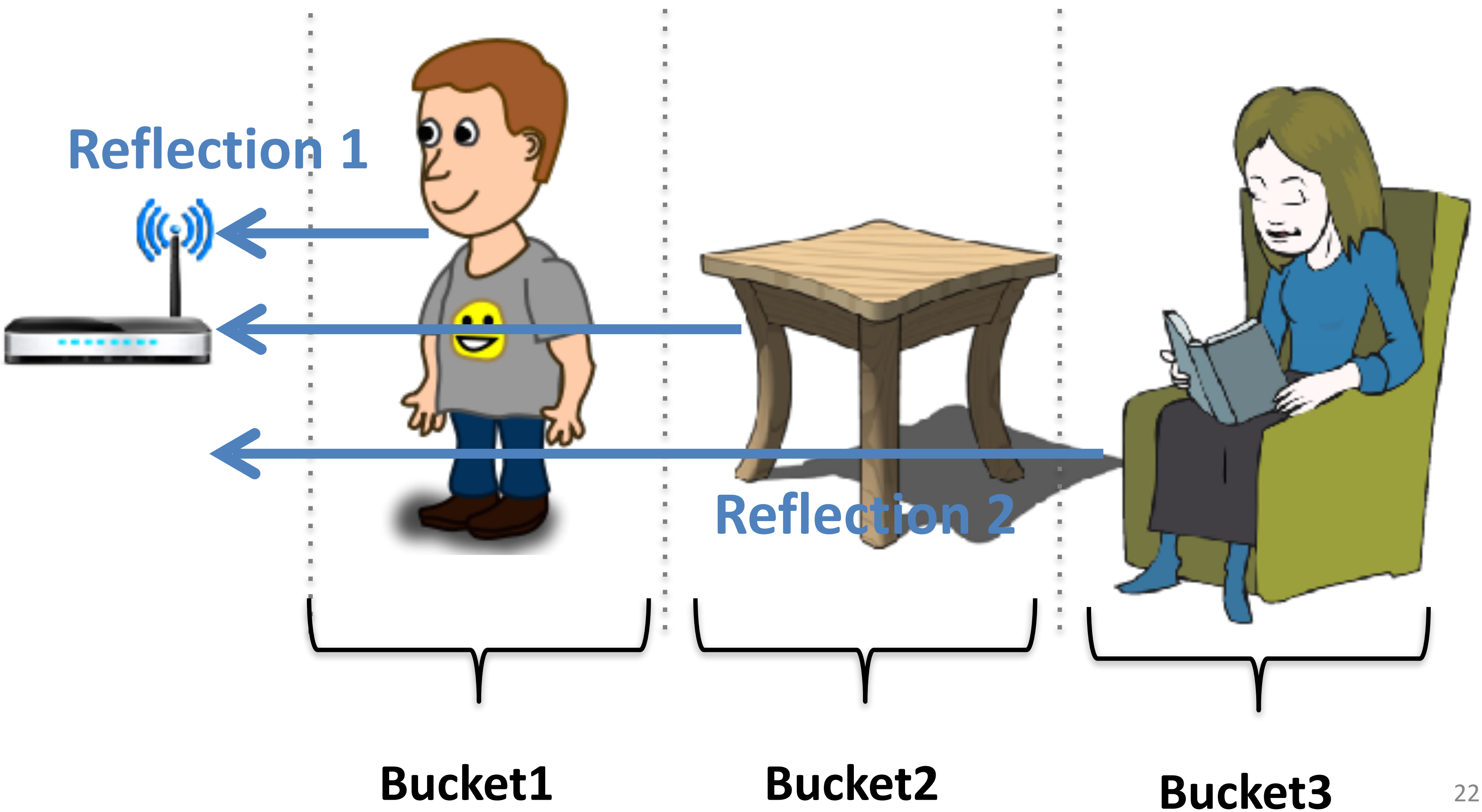


Recall Formulation with FMCW

- Output of FFT with reflectors
- Looked at the amplitude only
- Now will also look at phase

How do we deal with multipath?

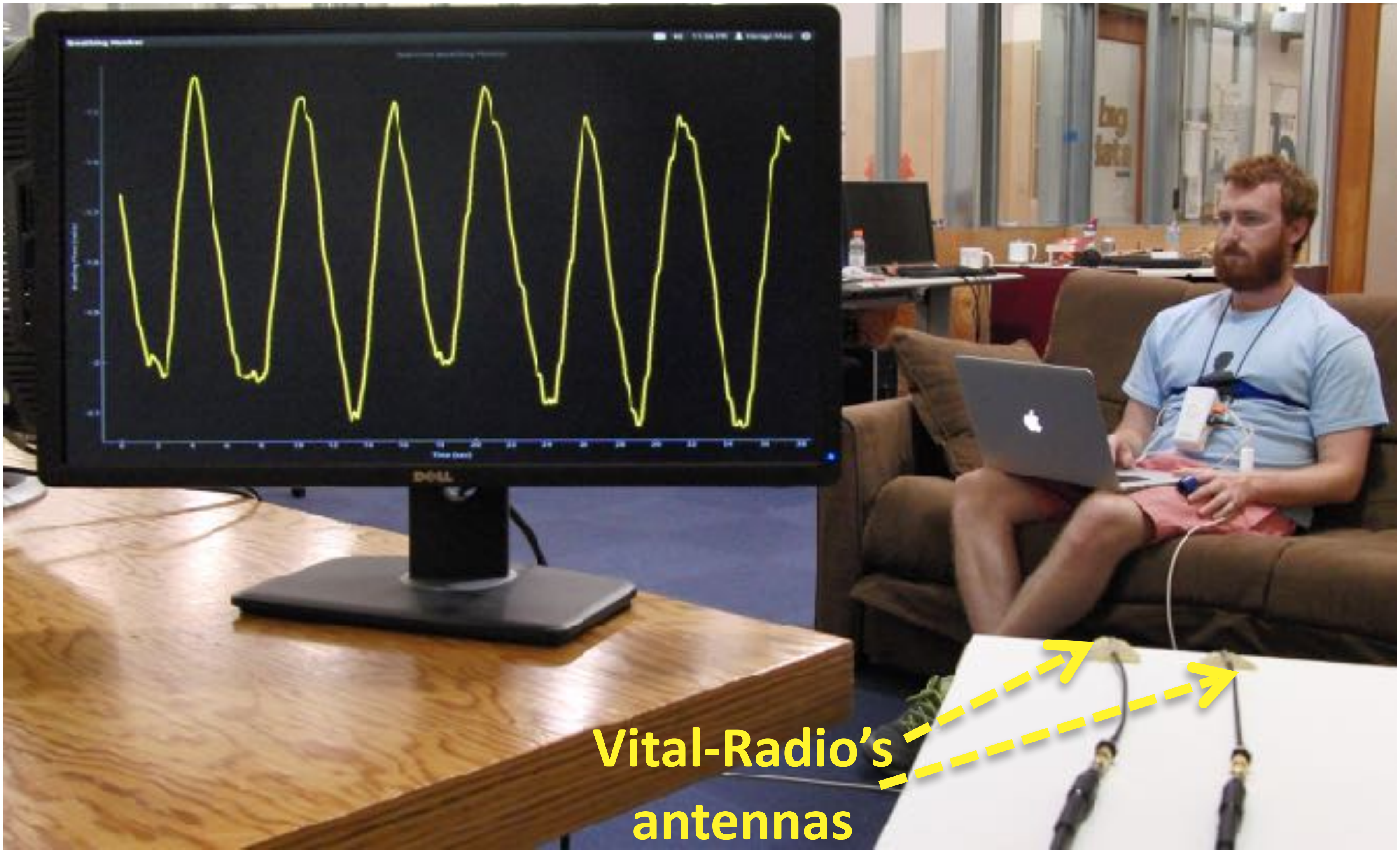
Putting It Together

Step 1: Transmit a wireless signal and capture its reflections

Step 2: Isolate reflections from different objects based on their positions

Step 3: Zoom in on each object's reflection to obtain phase variations due to vital signs

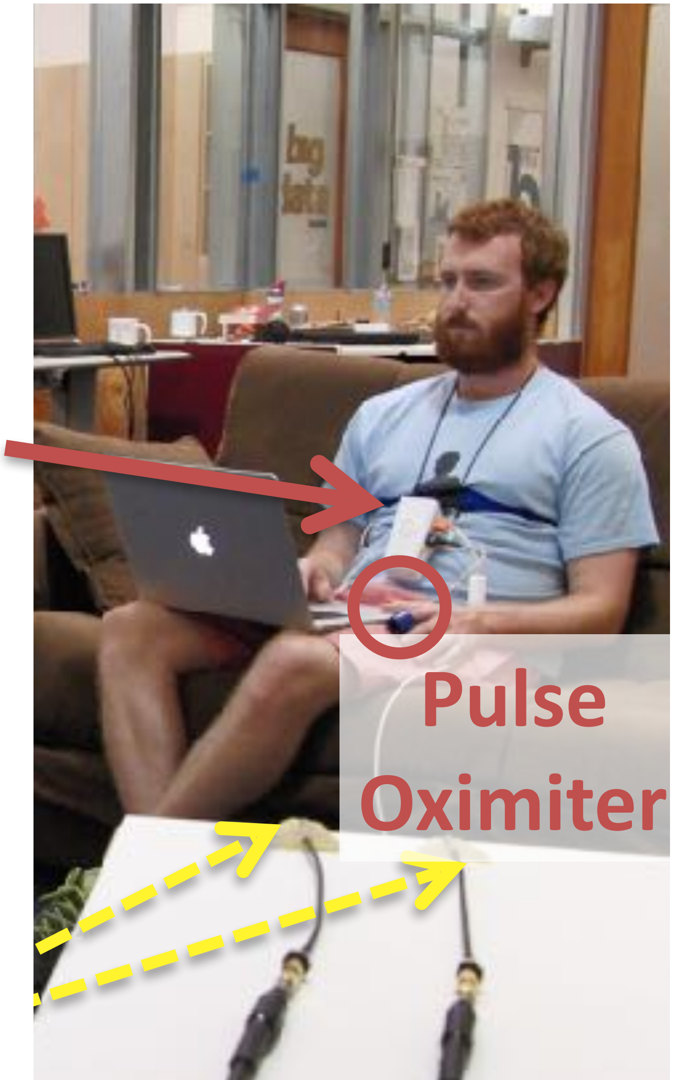
Vital-Radio Evaluation



Vital-Radio Evaluation

Baseline:

- FDA-approved breathing and heart rate monitor

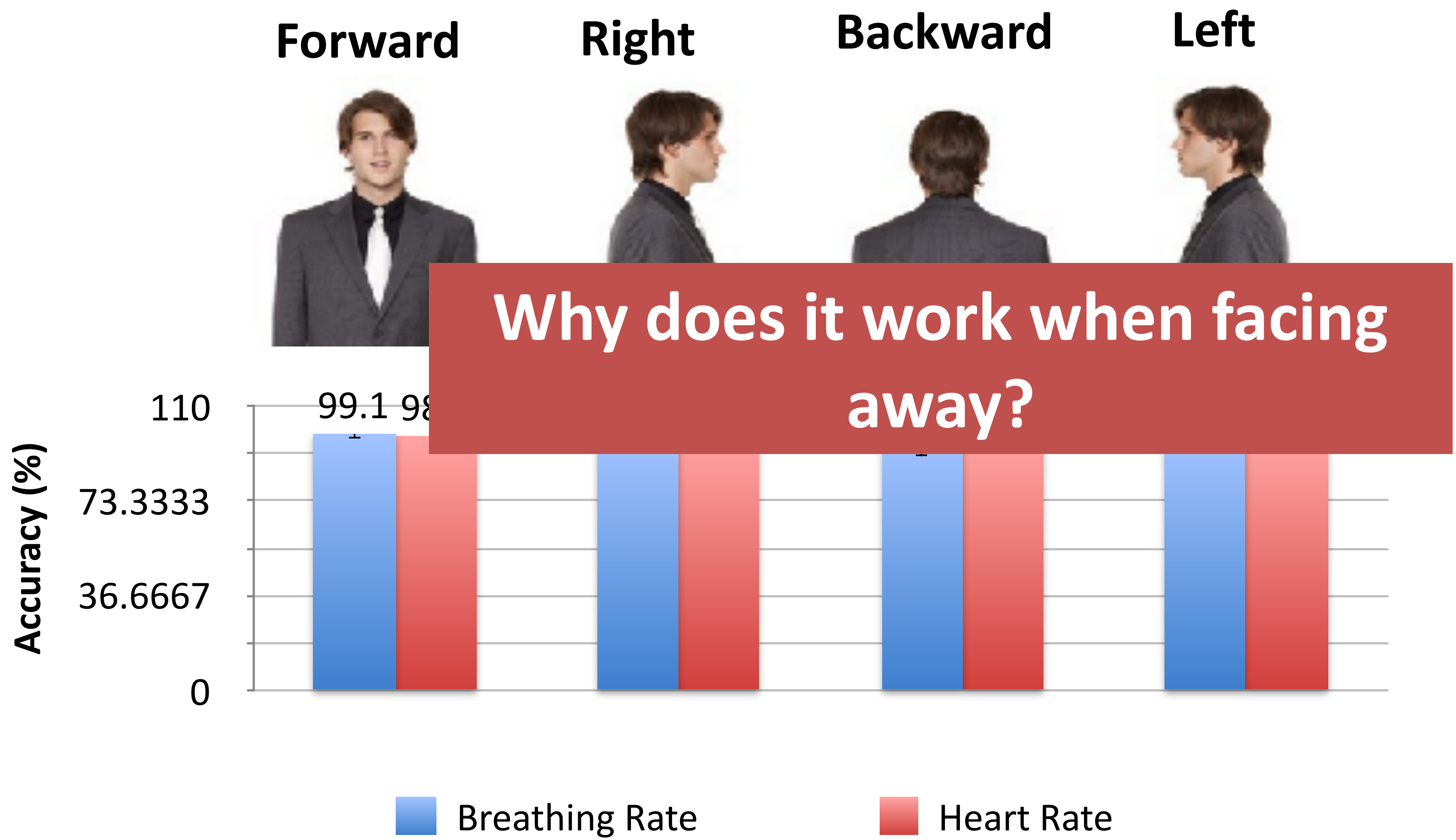


Experiments:

- 200 experiments
- 14 participants
- 1 million measurements

Accuracy vs. Orientation

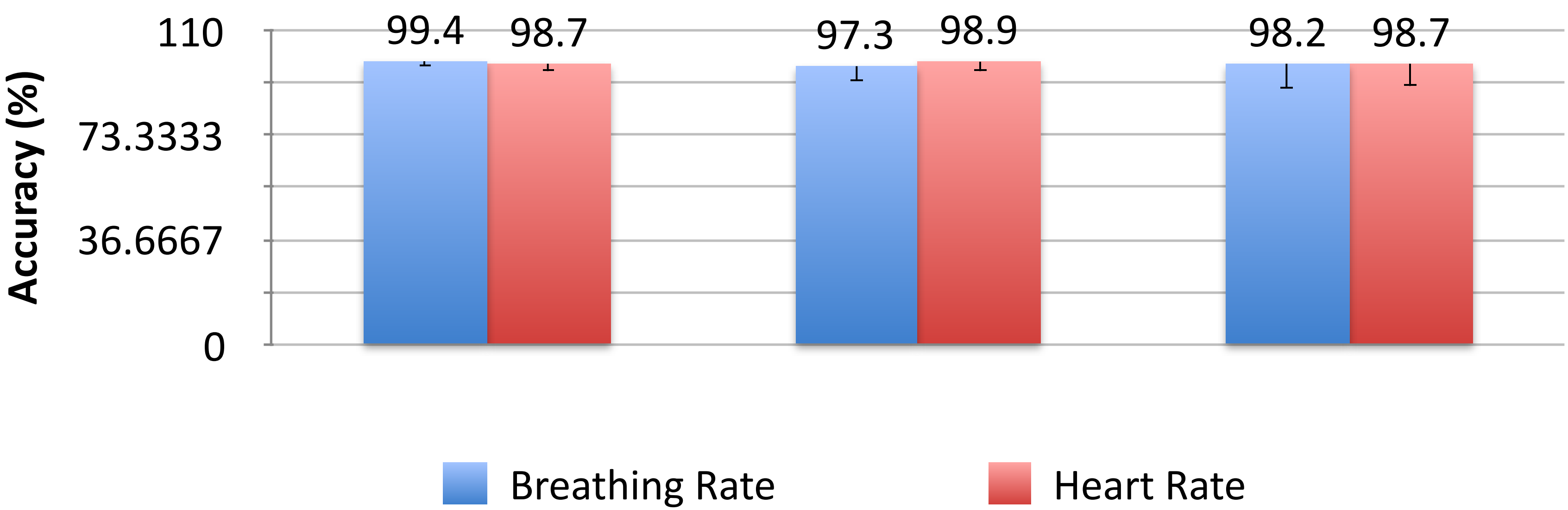
User is 4m from device, with different orientations



Accuracy for Multi-User Scenario

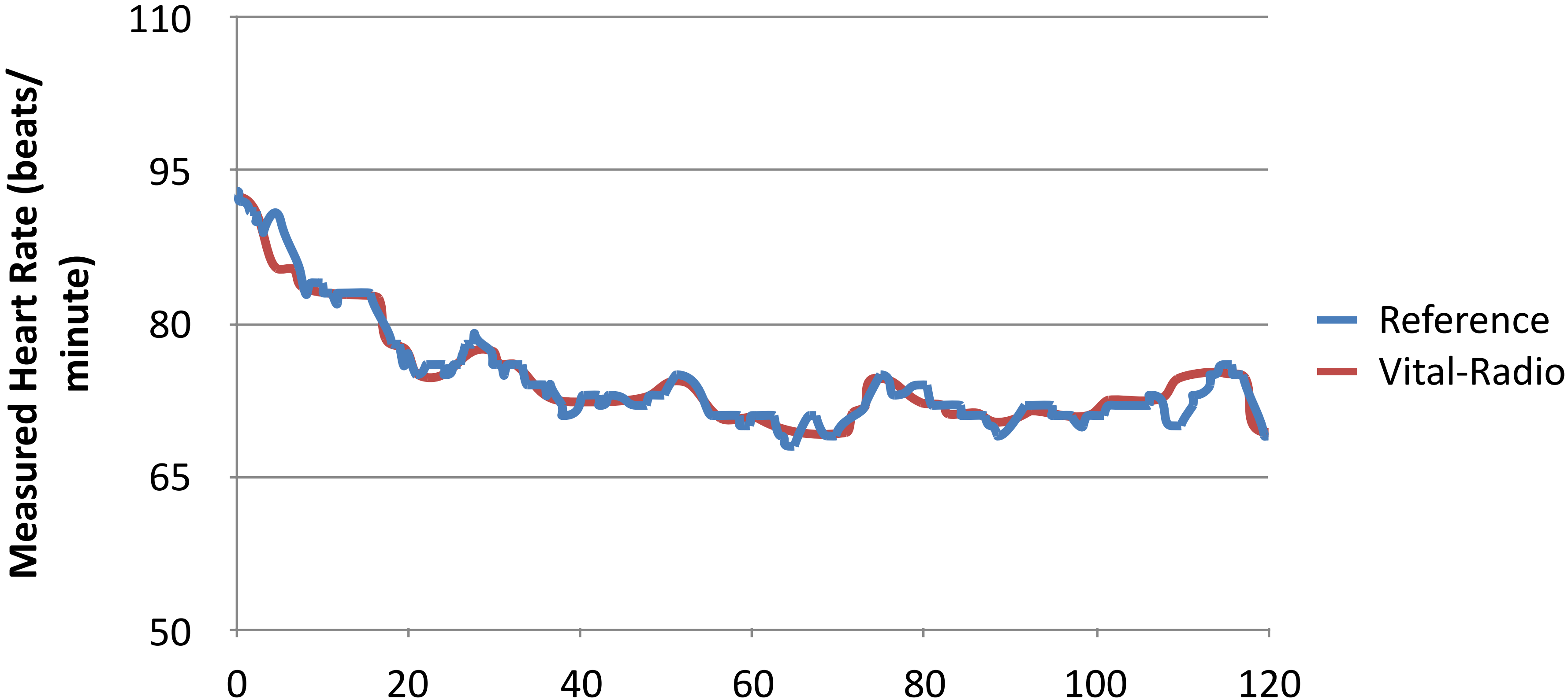
Multiple users sit at different distances

Nearest (at 2m) Middle (at 4m) Furthest (at 6m)



Accuracy for Tracking Heart Rate

Measure user's heart rate after exercising

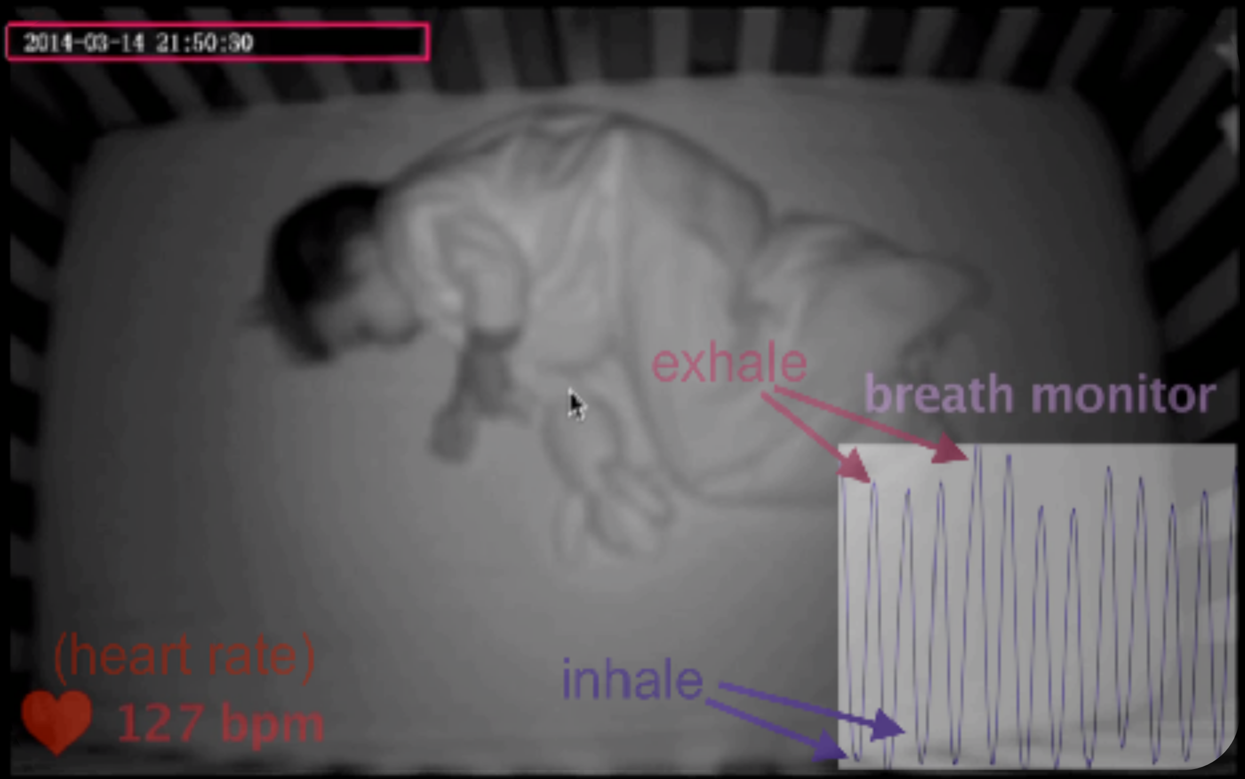


Vital-Radio accurately tracks changes in vital signs

Vital-Radio Limitations

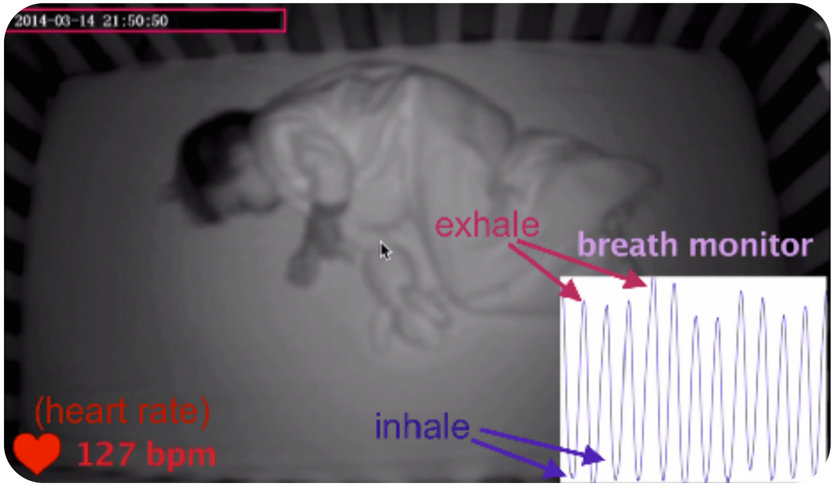
- Minimum separation between users: 1-2m
- Monitoring range: 8m
- Collects measurements when users are quasi-static

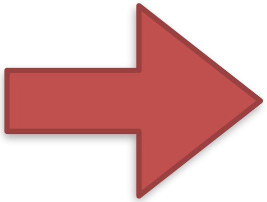
Baby Monitoring



Works for multiple people and through walls

Breathing & Heart Rate



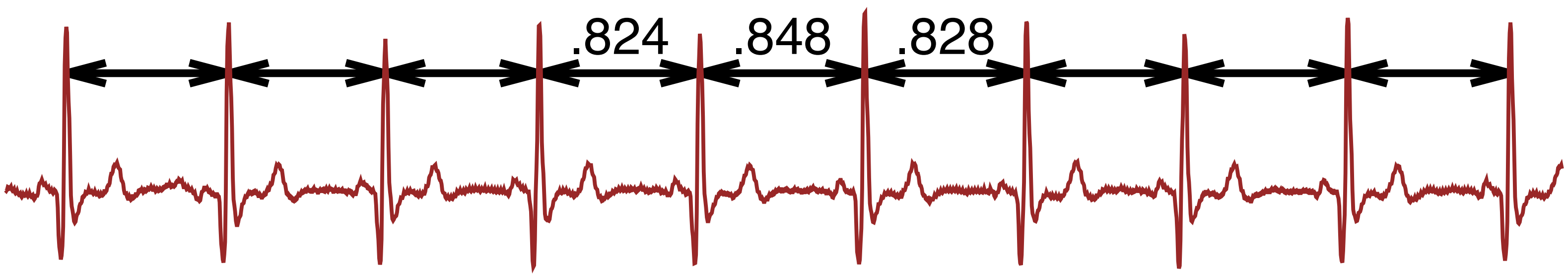


Want Emotions

Recognizing Human Emotions

Key challenge: Inter-Beat Interval (IBI)

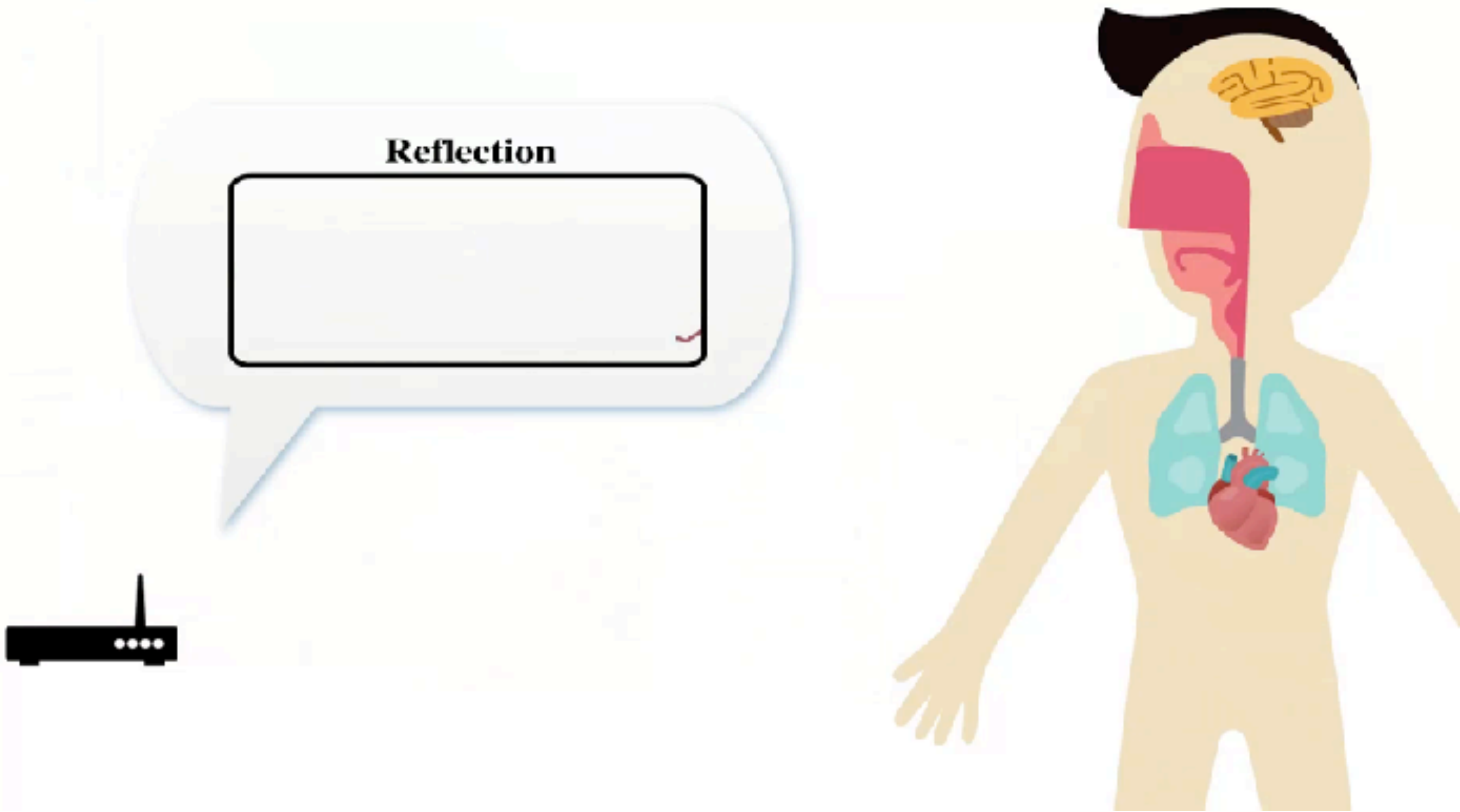
- Emotion recognition needs accurate measurements of the length of every single heartbeat



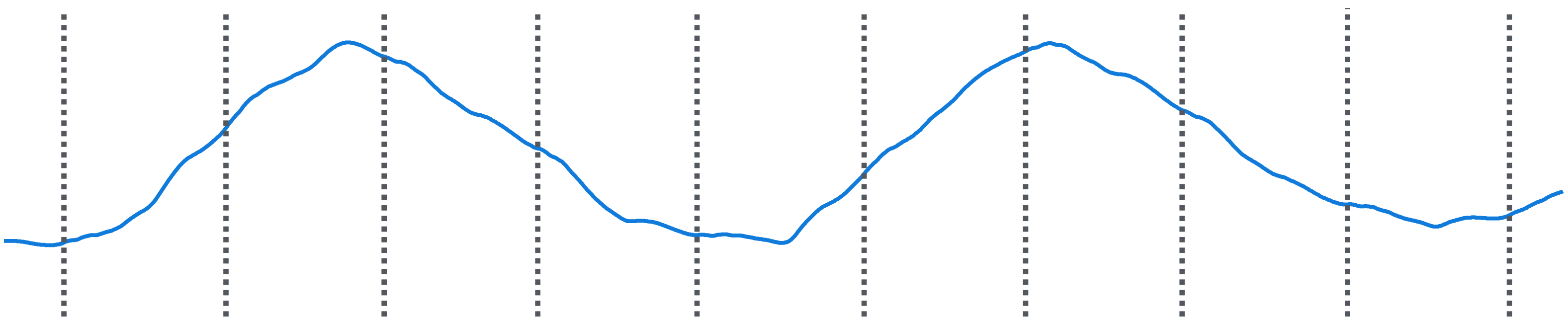
We need to extract IBI with accuracy over 99%

Input signal

Wireless reflection of the human body



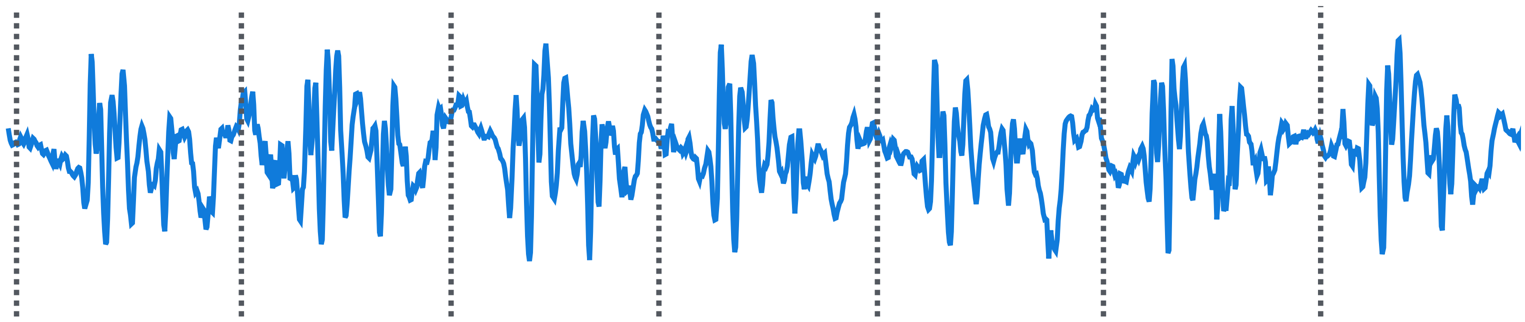
Step 1: Remove breathing signal



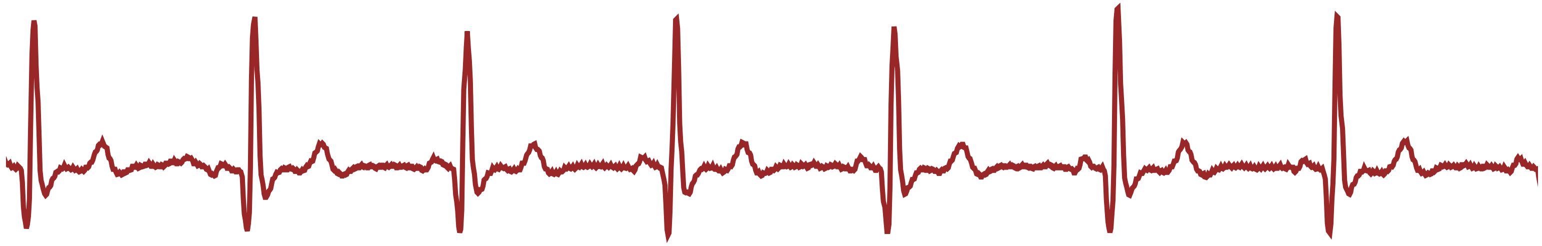
- Breathing masks heartbeats
- We use acceleration filter
    - Heartbeat involves rapid contraction of muscle
    - Breathing is slow and steady

Heartbeat signal

- Output of acceleration filter

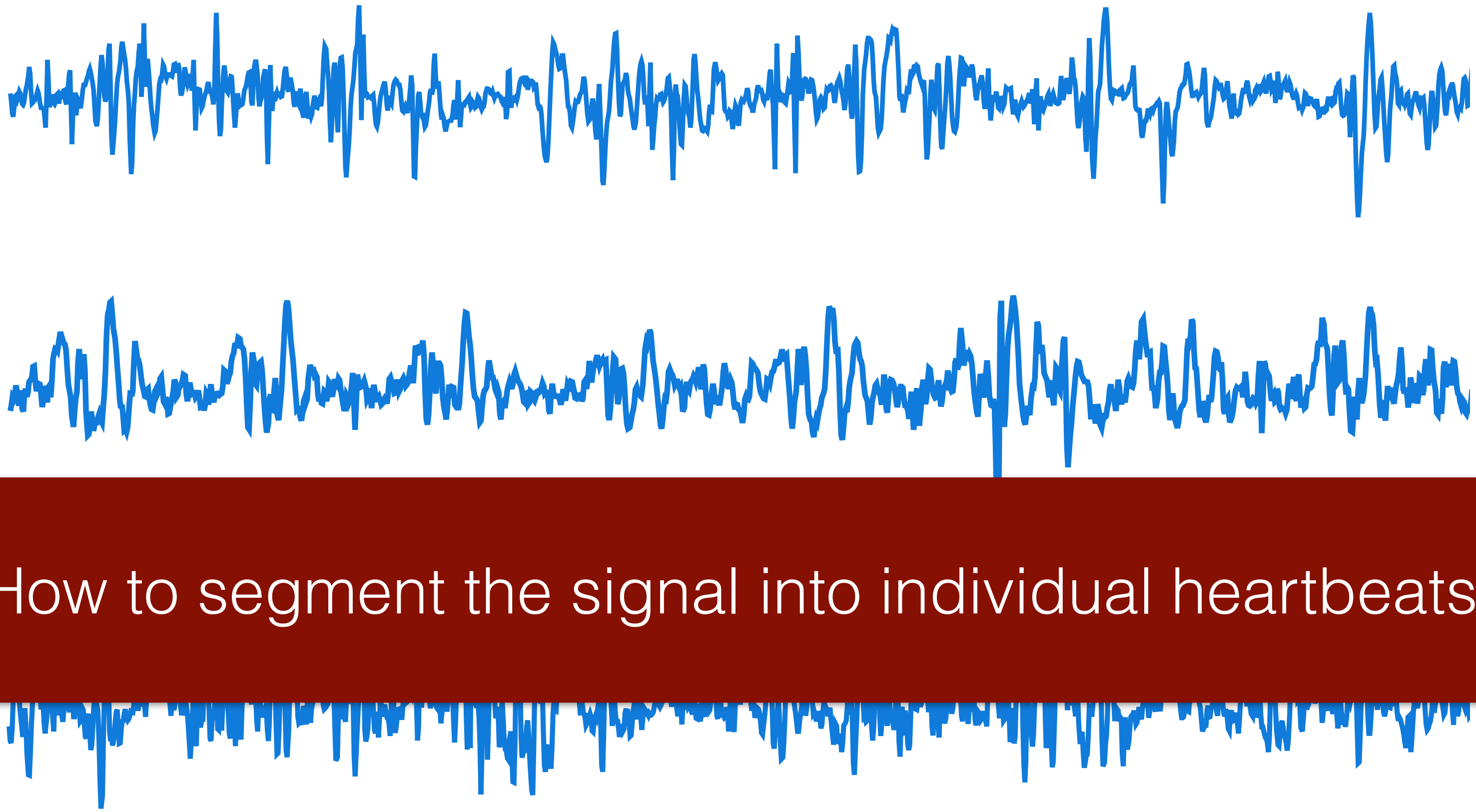


- ECG signal



Heartbeat signal

- Other typical examples:



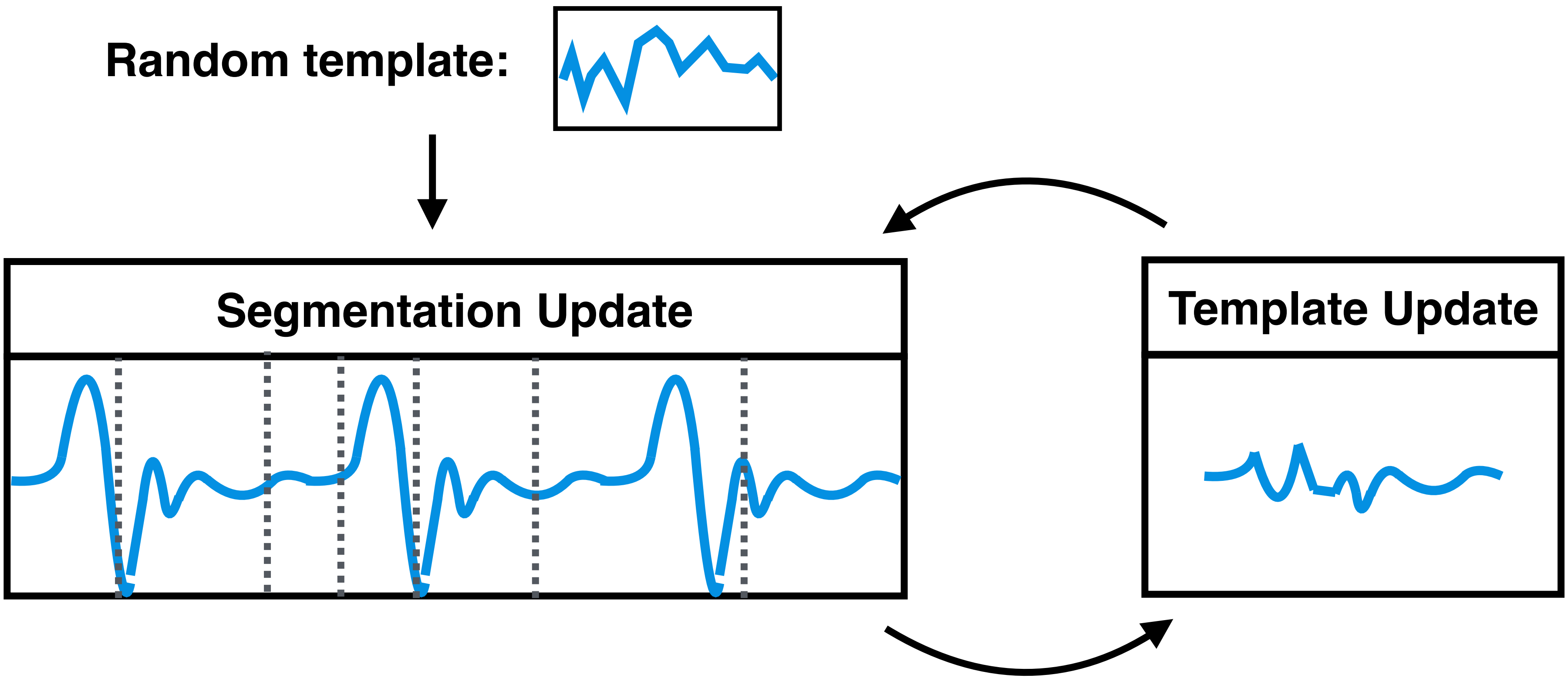
How to segment the signal into individual heartbeats?

Step 2: Heartbeat segmentation

- **Intuition**: heartbeat repeats with certain shape (template)
- If we can somehow discover the template, then we can segment into individual heartbeats

Step 2: Heartbeat segmentation

- **Intuition**: heartbeat repeats with certain shape (template)



Step 2: Heartbeat segmentation

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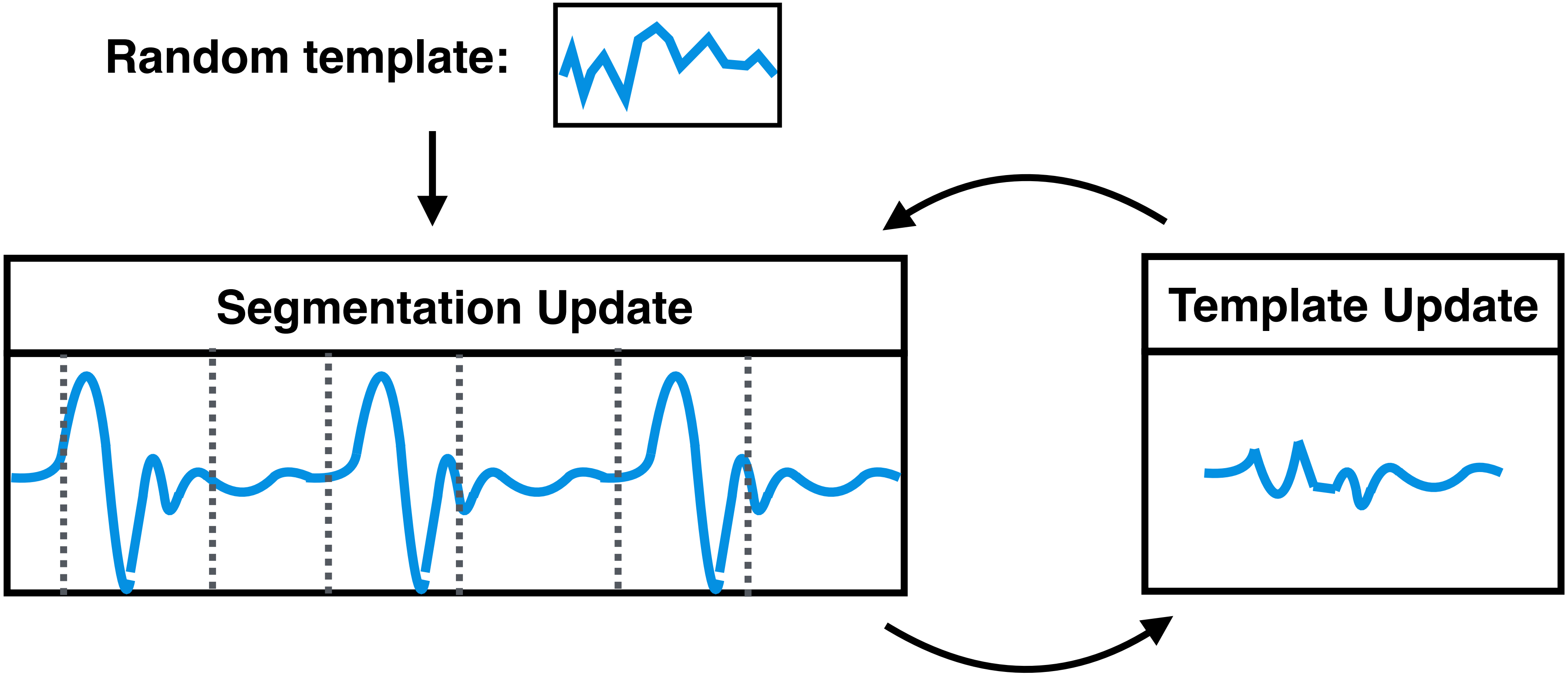

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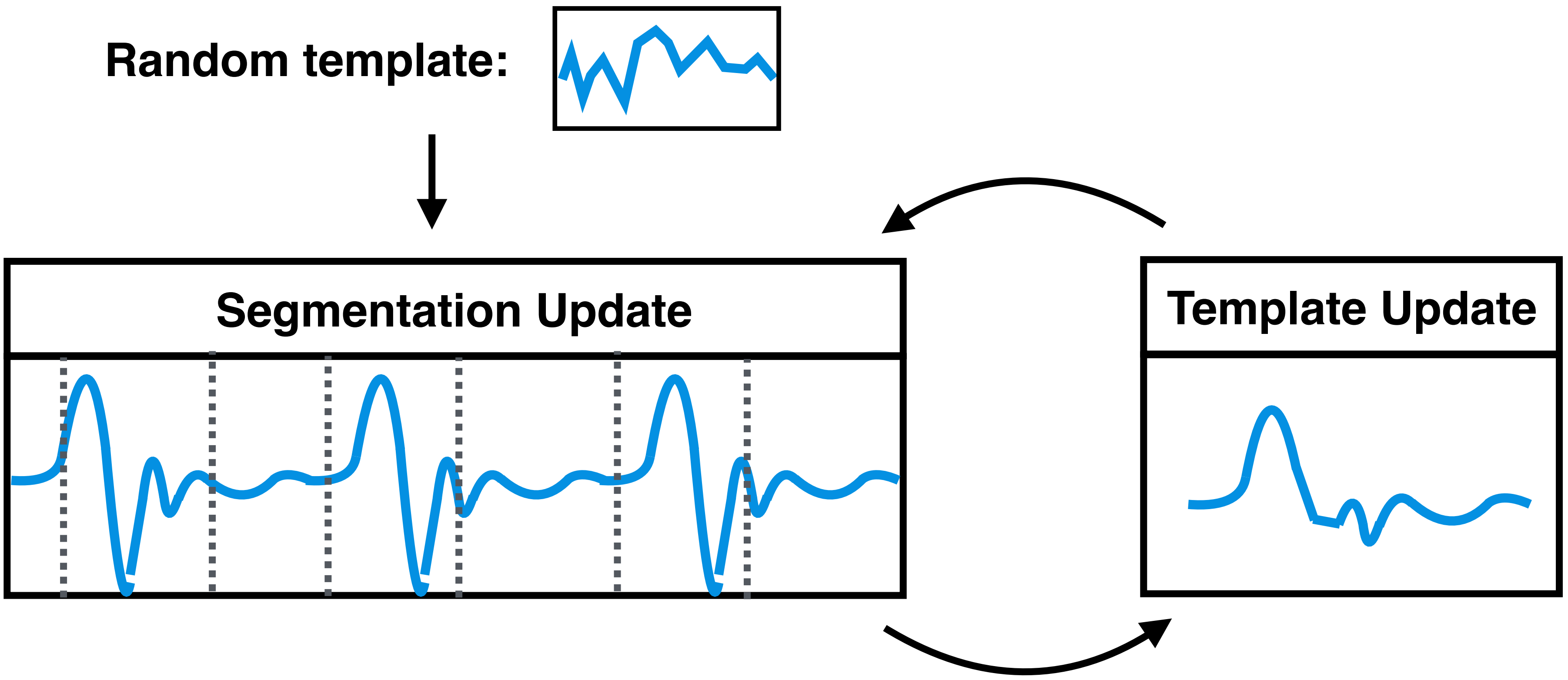

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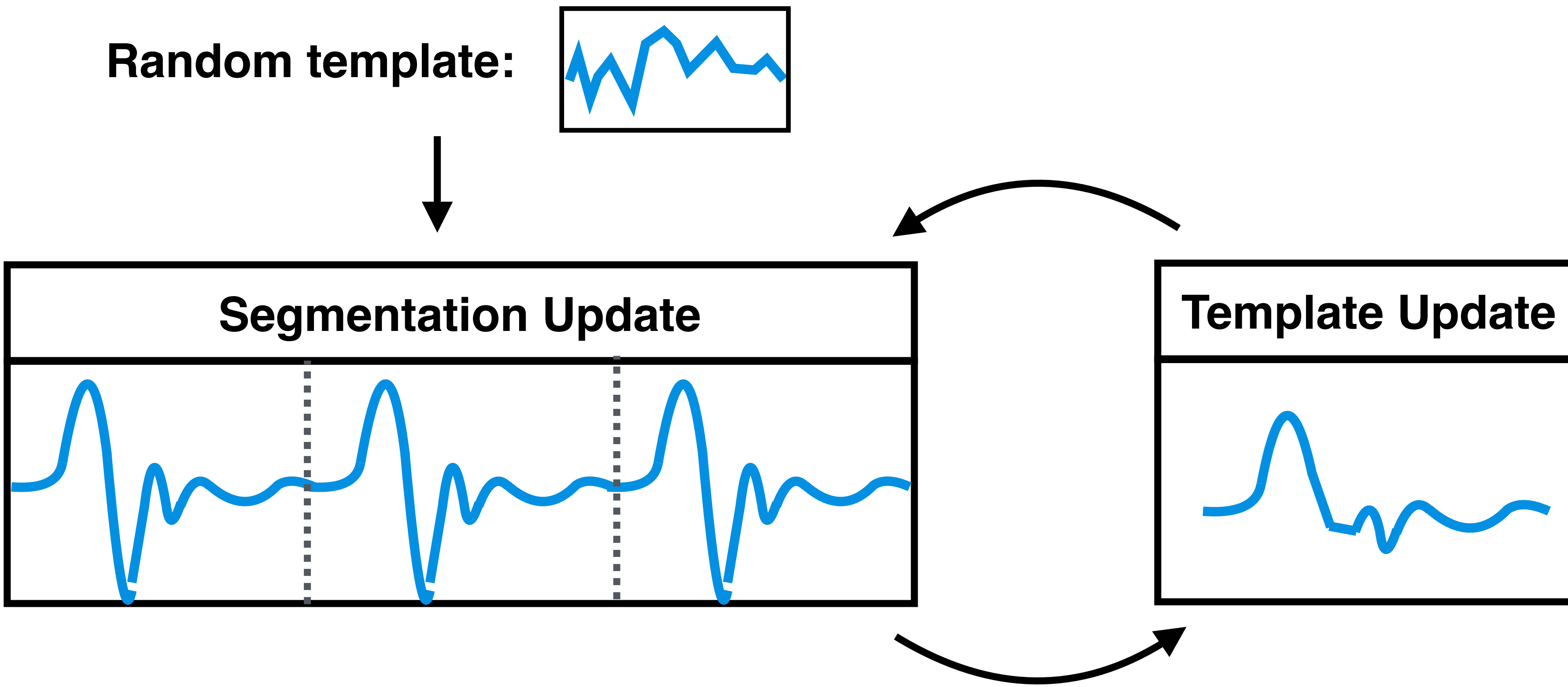

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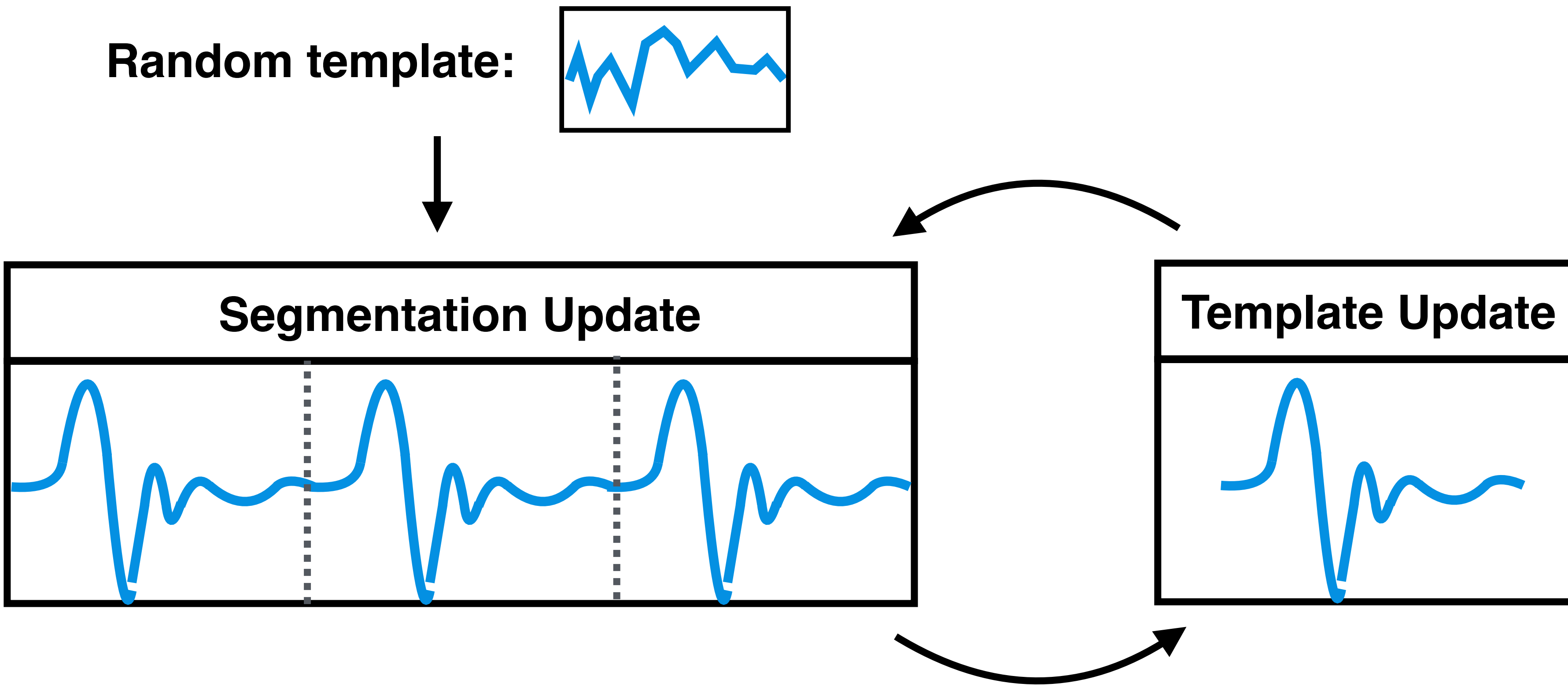
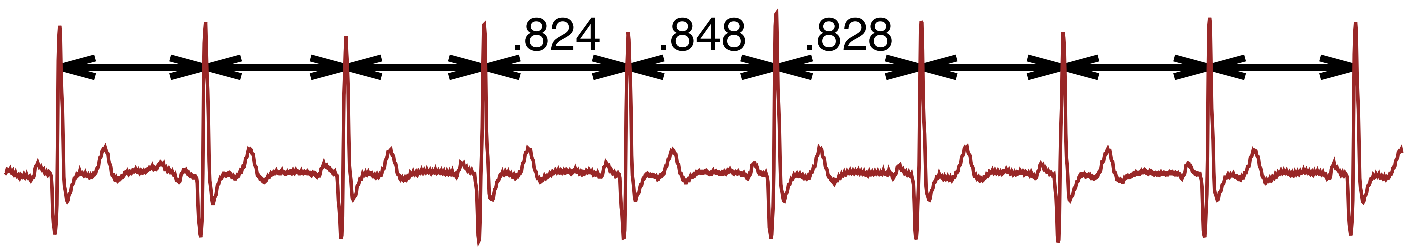


Caveat: Shrinking & Expanding

- IBI are not always the same



- Template subject to shrink and expanding
    - Linear warping

Algorithm

Need to recover both segmentation and template

- Joint optimization: $$\underset{\mathcal{S},\boldsymbol{\mu}}{\text{minimize}} \sum_{s_i \in \mathcal{S}} \|s_i - \omega(\boldsymbol{\mu}, |s_i|)\|^2$$

segmentation (→ $\mathcal{S}$), template (→ $\boldsymbol{\mu}$), warping (→ ω)

Segmentation Update
$\mathcal{S}^{l+1} = \arg\min_{\mathcal{S}} \sum_{s_i \in \mathcal{S}} \|s_i - \omega(\boldsymbol{\mu}^l, |s_i|)\|^2$
(dynamic programming)

Template Update
$\boldsymbol{\mu}^{l+1} = \arg\min_{\boldsymbol{\mu}} \sum_{s_i \in \mathcal{S}^{l+1}} \|s_i - \omega(\boldsymbol{\mu}, |s_i|)\|^2$
(weighted least squares)

Algorithm

Need to recover both segmentation and template

- Joint optimization: $$\underset{\mathcal{S},\boldsymbol{\mu}}{\text{minimize}} \sum_{s_i \in \mathcal{S}} \|s_i - \omega(\boldsymbol{\mu}, |s_i|)\|^2$$

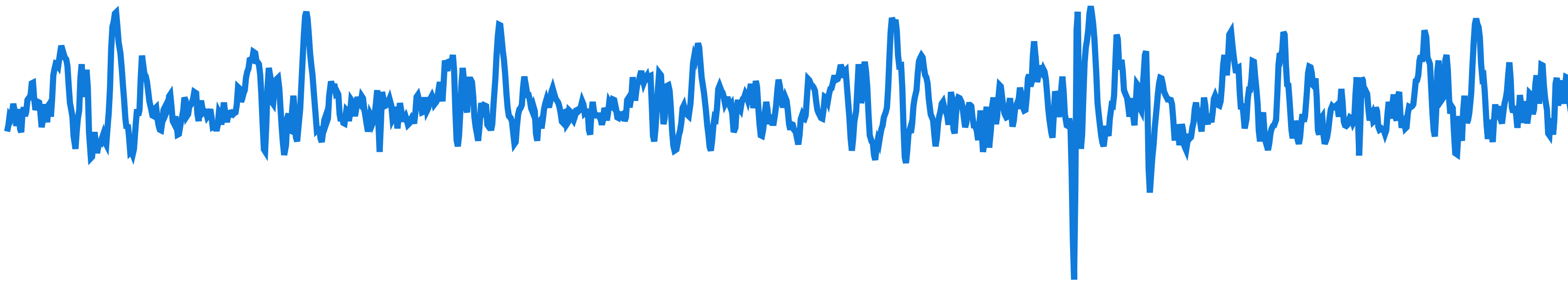
segmentation → $\mathcal{S}$; template → $\boldsymbol{\mu}$; warping → ω

Segmentation Update

Template Update

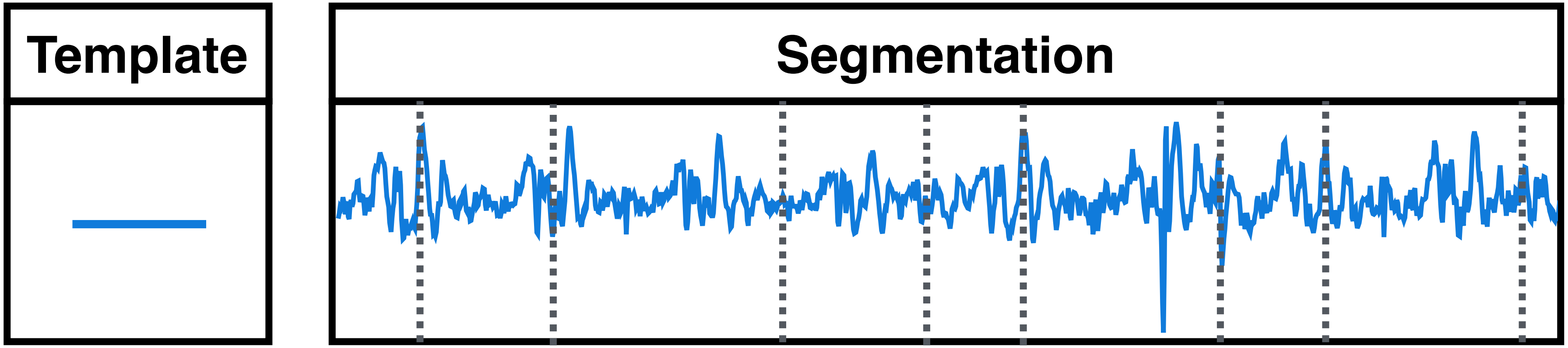
- Both updates have linear complexity
- Each update achieves global optimum
- Iterative algorithm is guaranteed to converge

Example run



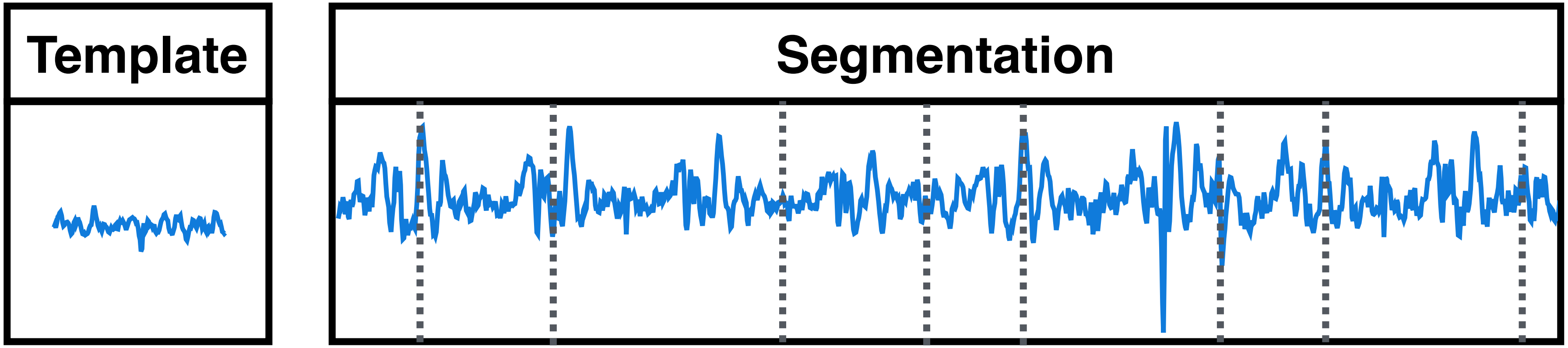
Example run

Iteration 1:



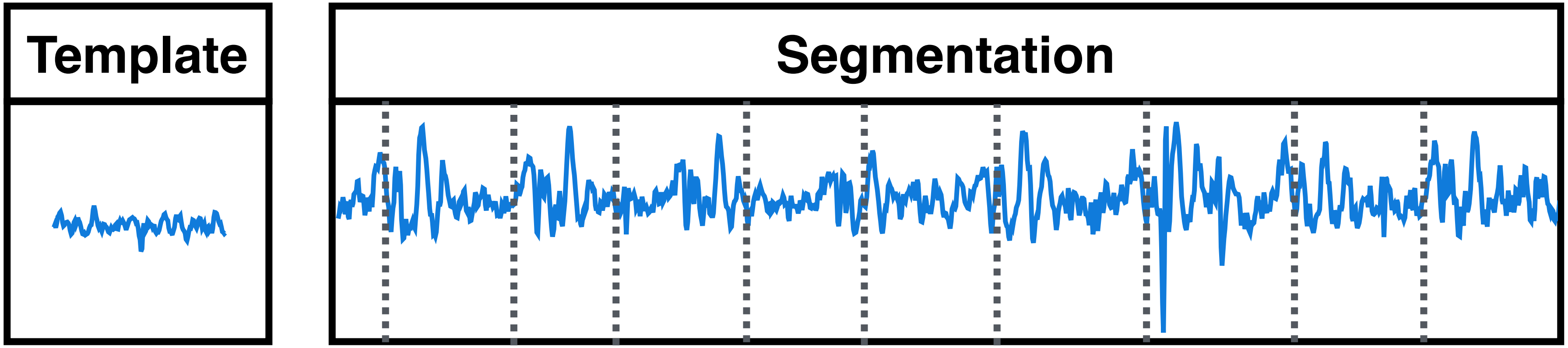
Example run

Iteration 2:



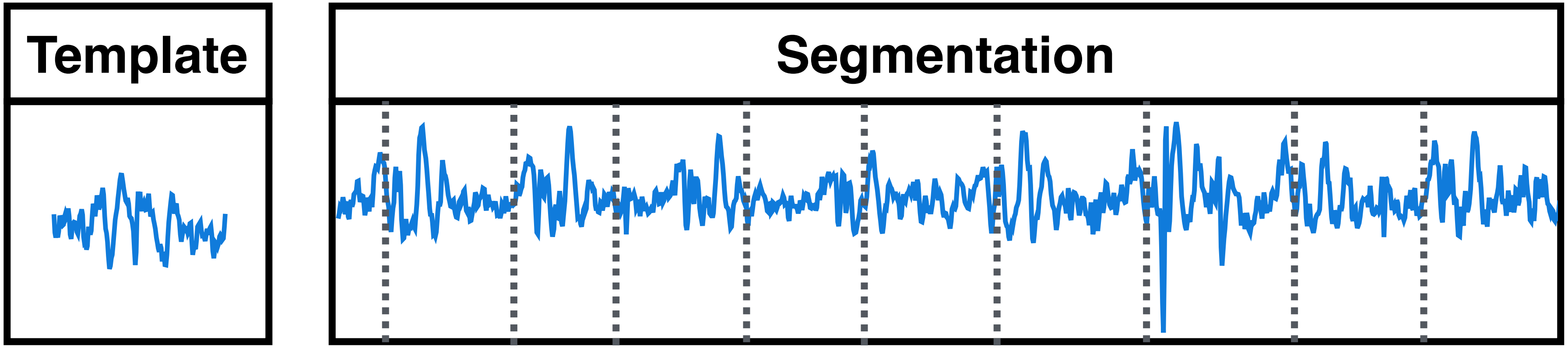
Example run

Iteration 2:



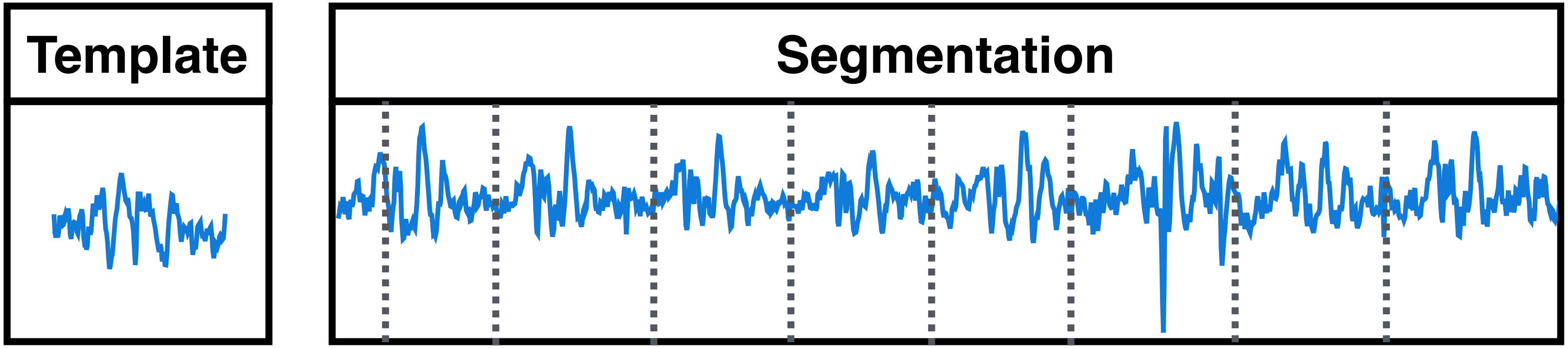
Example run

Iteration 3:



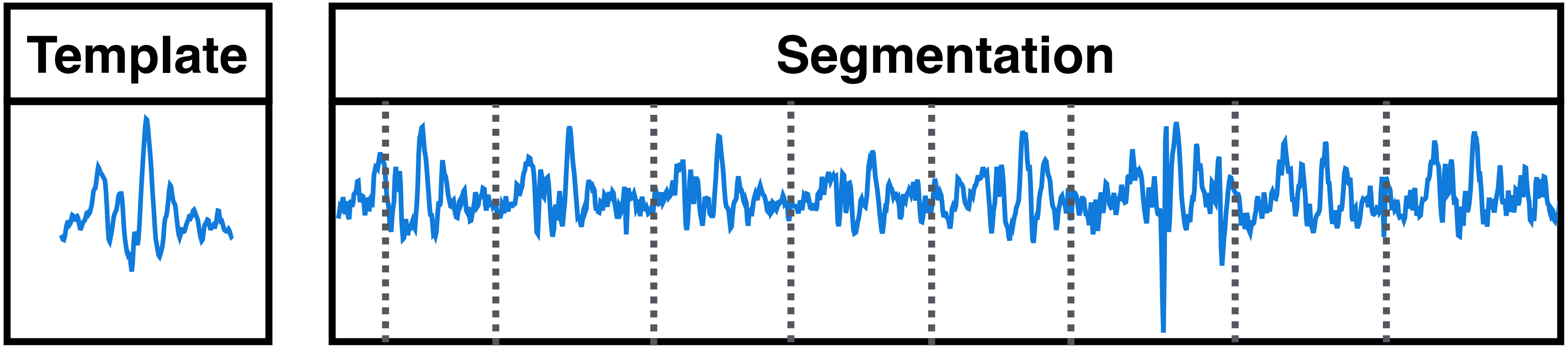
Example run

Iteration 3:



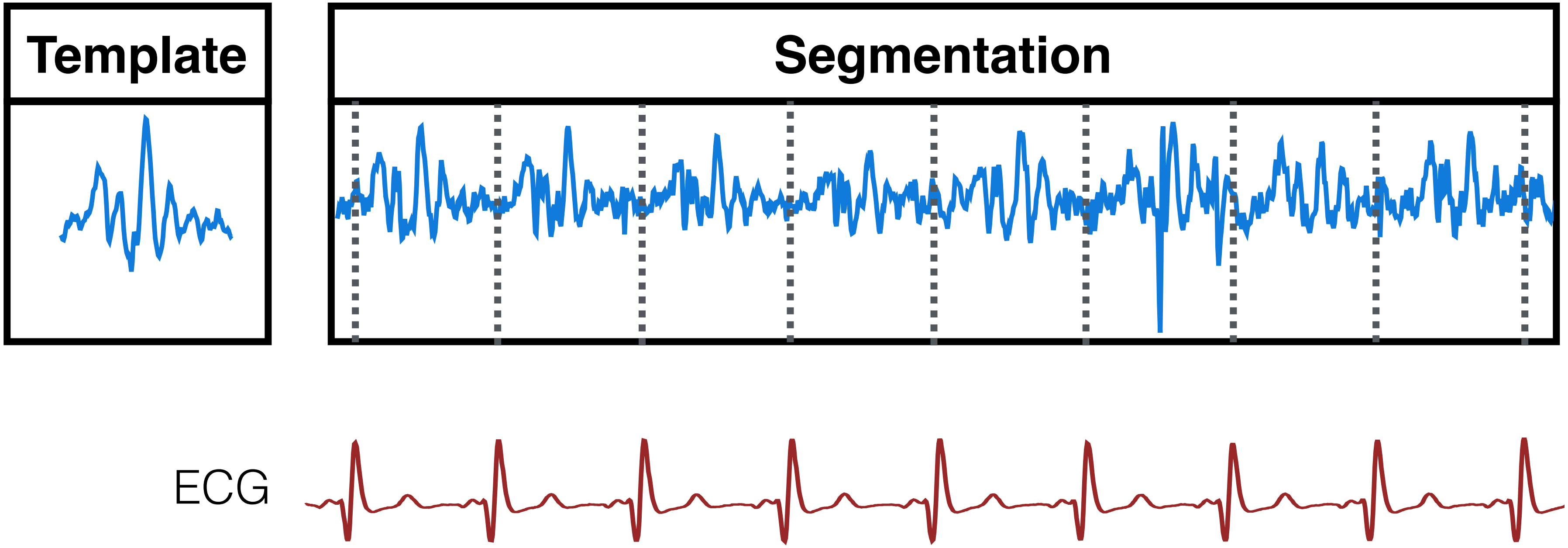
Example run

Iteration 7:



Example run

Iteration 7:



From vital signs to emotions

Physiological Features for Emotion Recognition

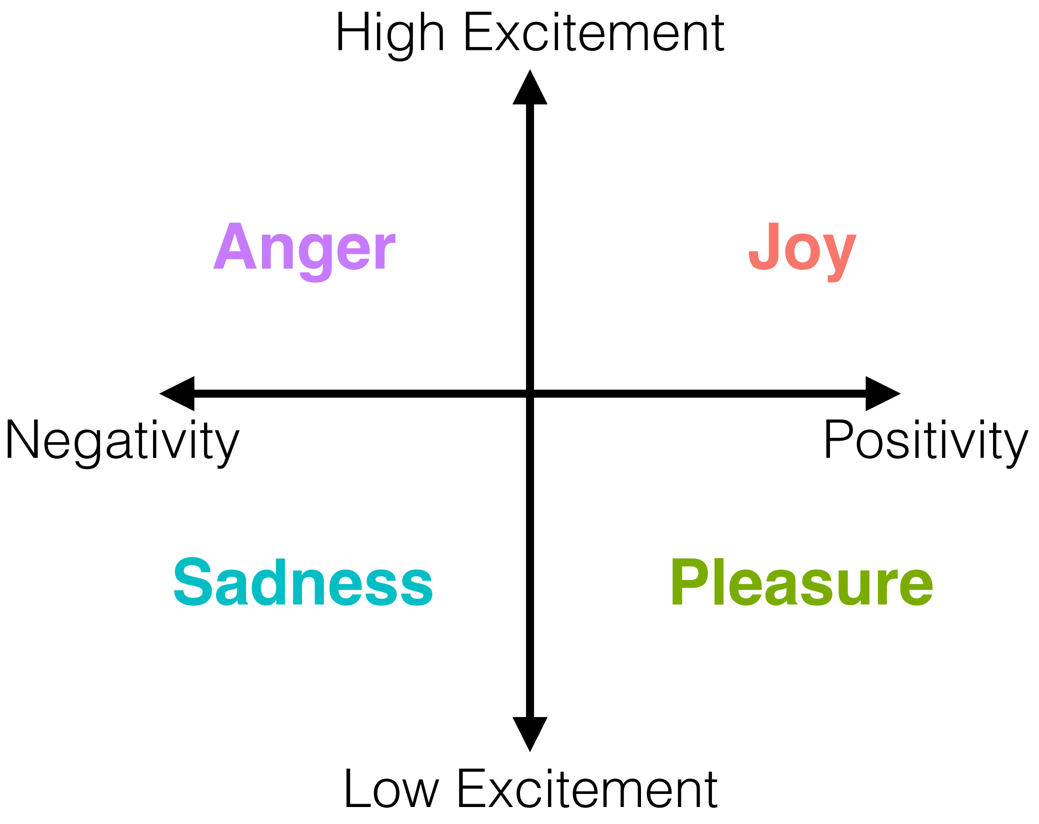
- 37 Features similar to ECG-based methods
  - Variability of IBI
  - Irregularity of breathing

Emotion Classification

- Recognize emotion using physiological features
- Used L1-SVM classifier
  - select features and train classifier at the same time

Emotion Model

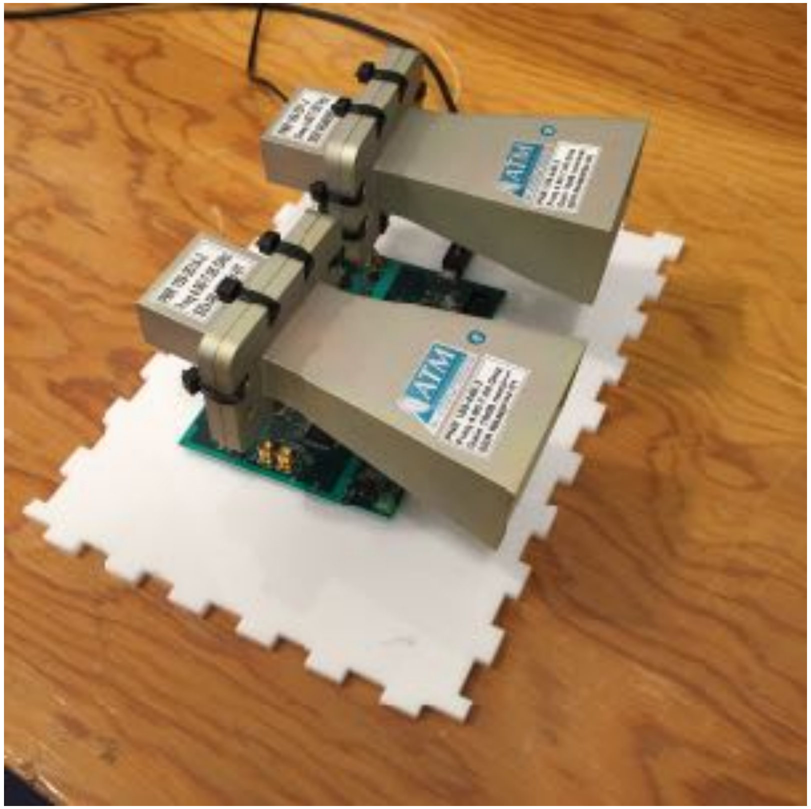
- Standard 2D emotion model
- Classify into **anger**, **sadness**, **pleasure** and **joy**



Evaluation

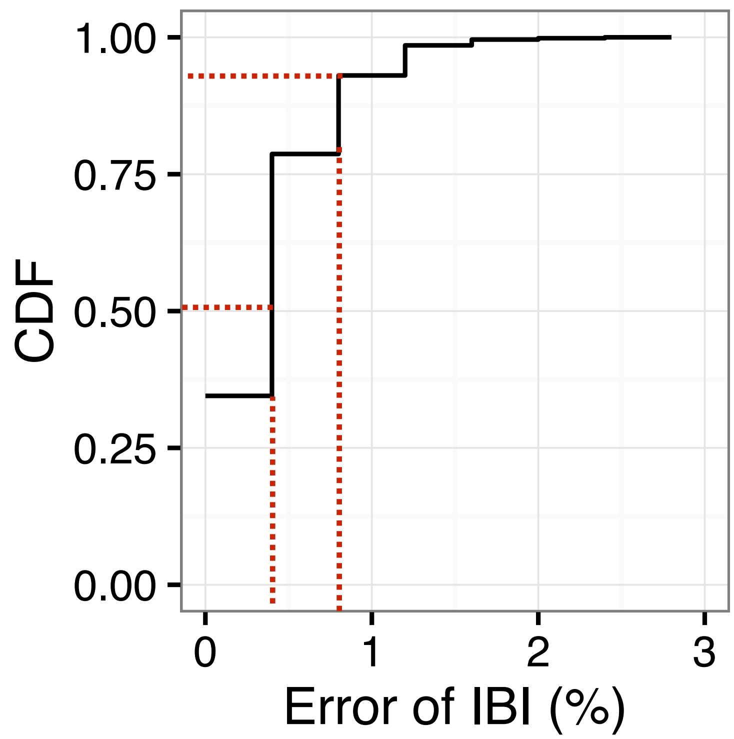
Implementation

- FMCW radio
- 5.5 GHz to 7.2 GHz
- sub-mW power



Median IBI estimation error: 0.4%
90th percentile error: 0.8%

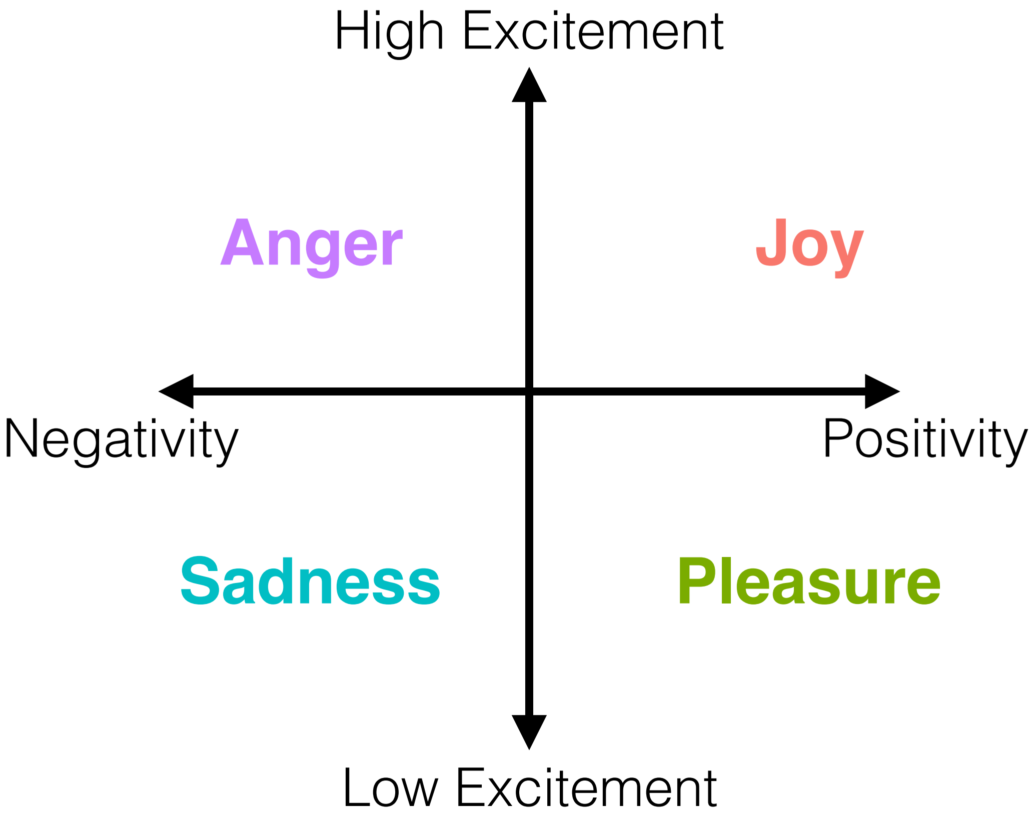
- Ground truth: ECG
- 30 subjects, over 130,000 heartbeats



Can we detect emotions accurately?

- **Experiment:**
  - 12 subjects (6 female and 6 male)
  - Prepare personal memories for each emotion
  - Elicit certain emotion with prepared memories
  - classify every 2 minutes to an emotional state
- **Ground truth:** self-reported for each 2-min period

Can we detect emotions accurately?



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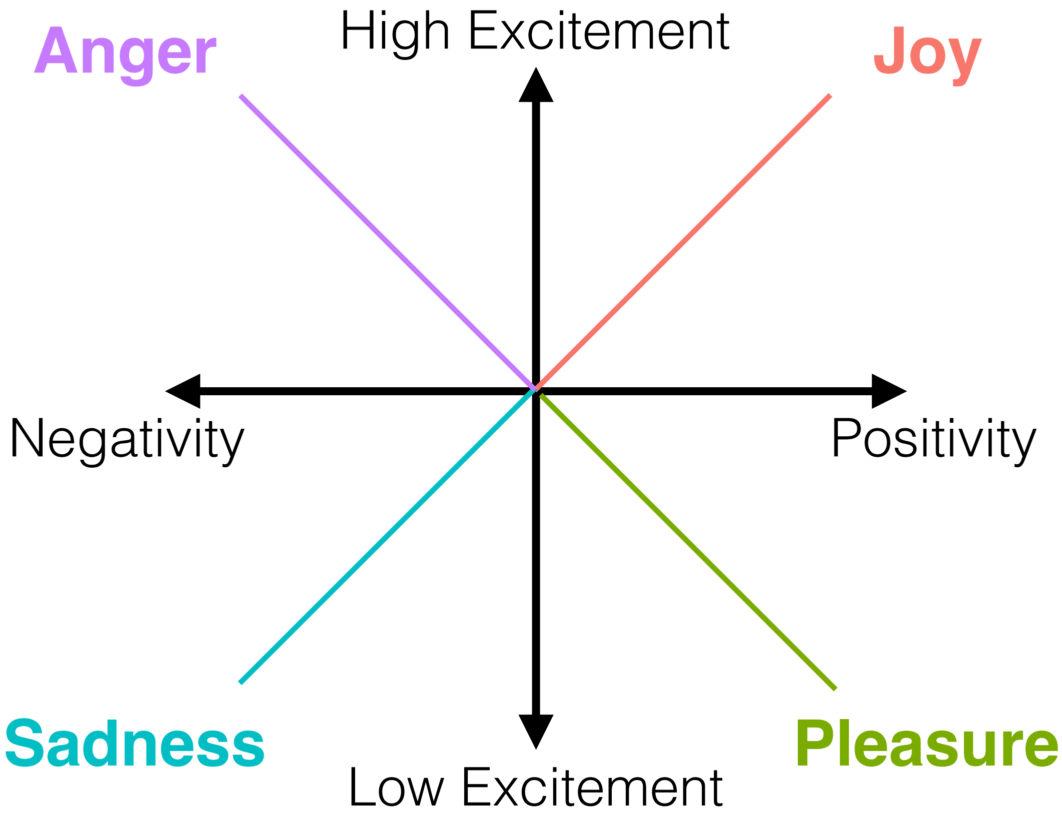
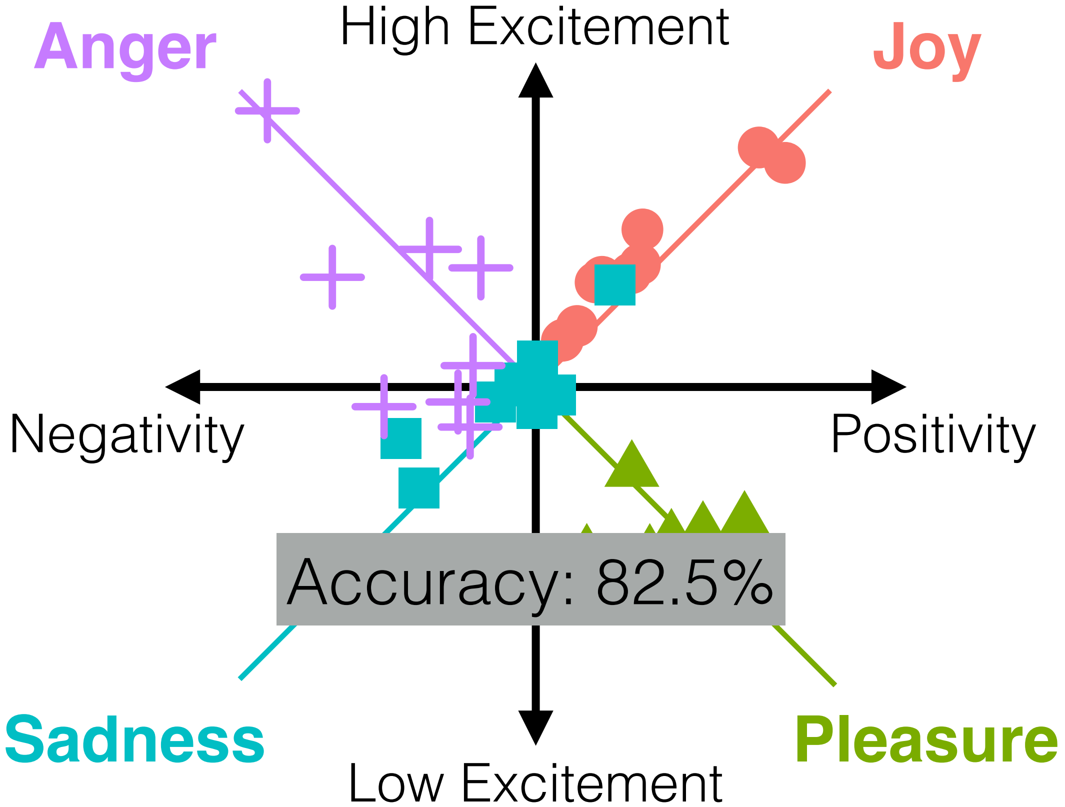


Person-dependent Classification

- Train and test on the same person



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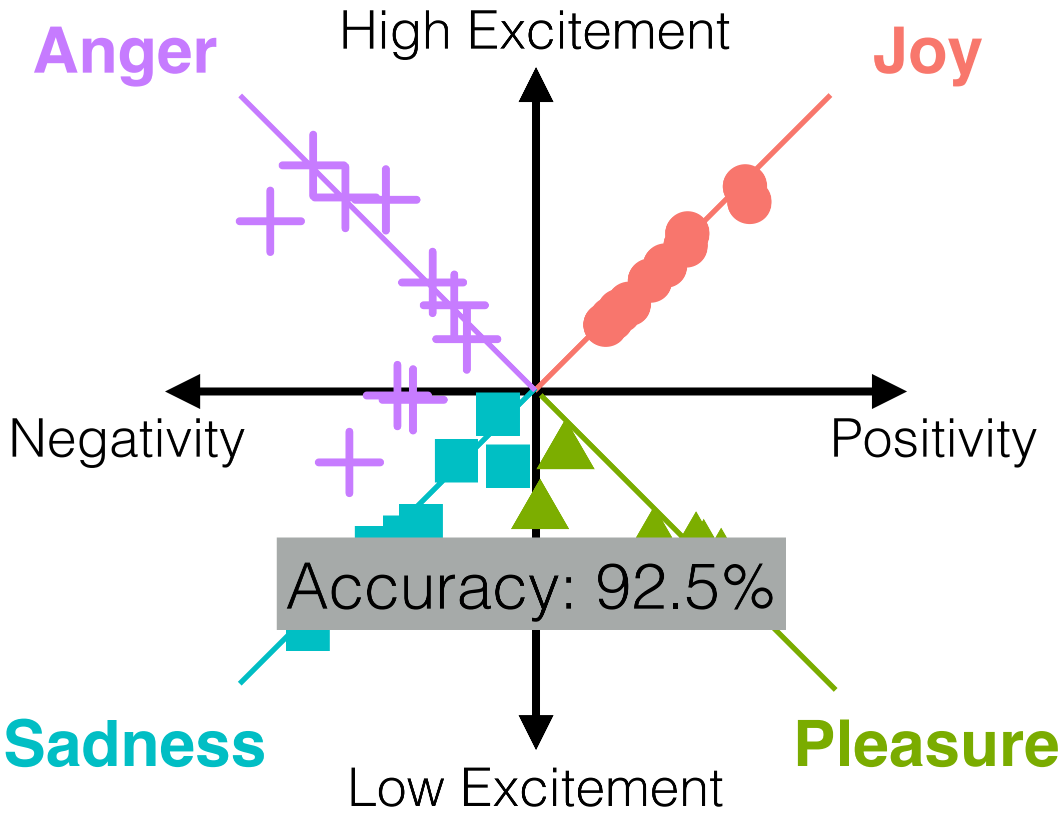
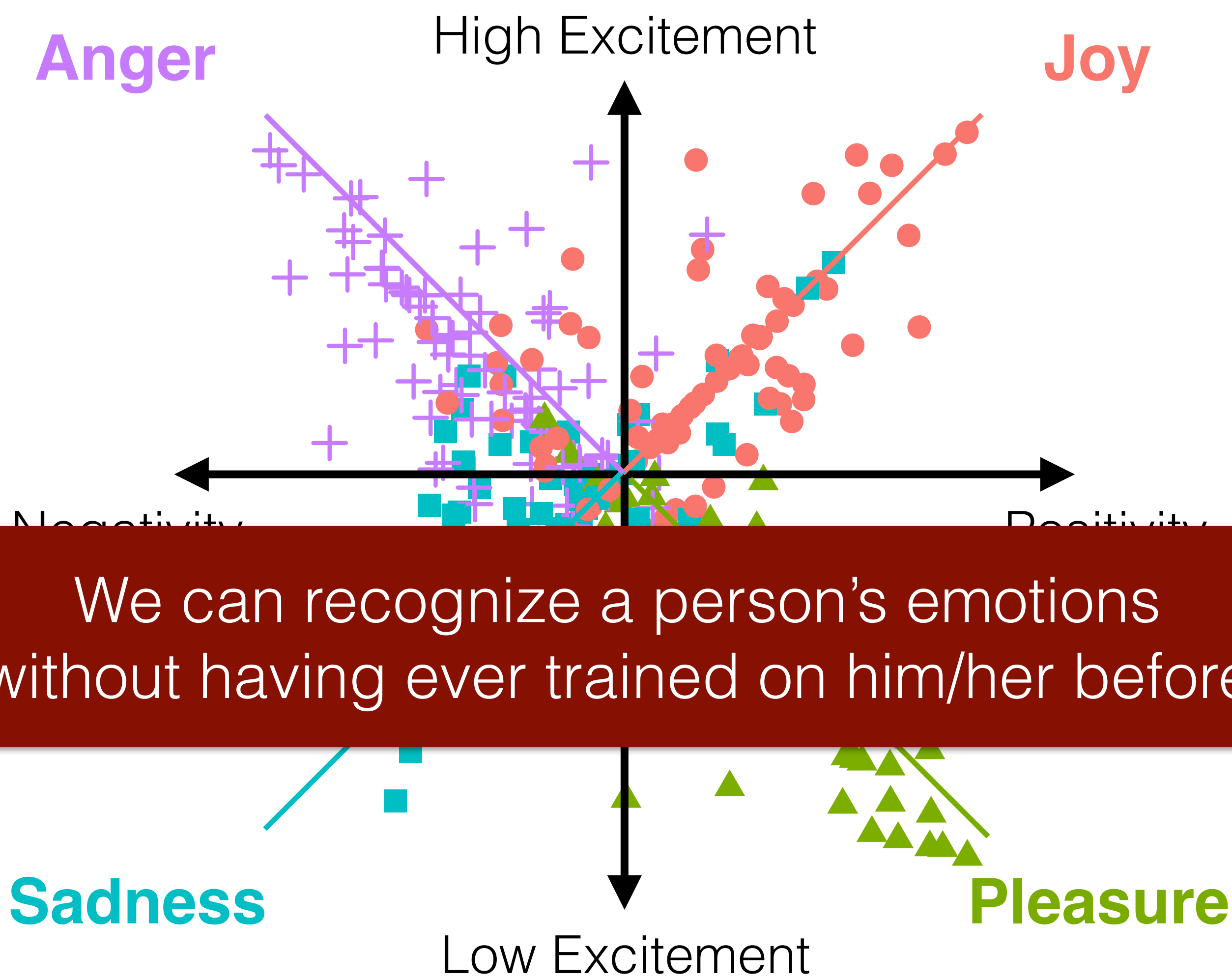


Person-independent Classification

- Train and test on the different person



We can recognize a person's emotions without having ever trained on him/her before

Comparison with ECG-based system