ECE 257B: Principles of Wireless Networks

Lecture 12: Wireless Sensing Part 2

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Slides Courtesy of Mingmin Zhao and Fadel Adib

Interest in Sensing the Human Body

Heart Rate

Breathing

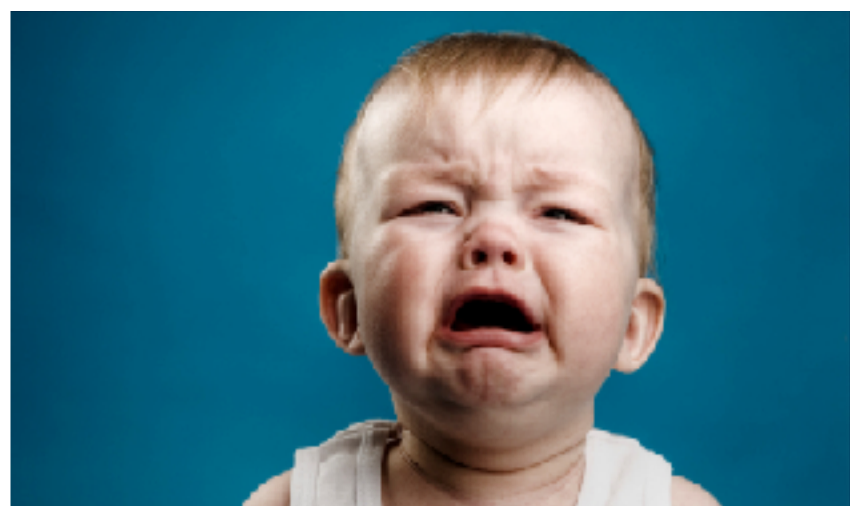
Locations

Gestures

Heart Rate Breathing Locations Gestures

On-body sensors can be cumbersome

Not suitable for elderly & babies



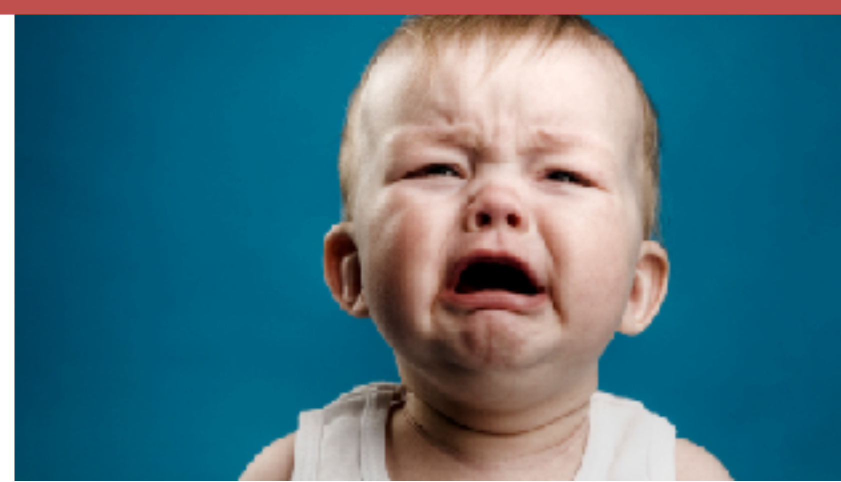
Heart Rate

Breathing

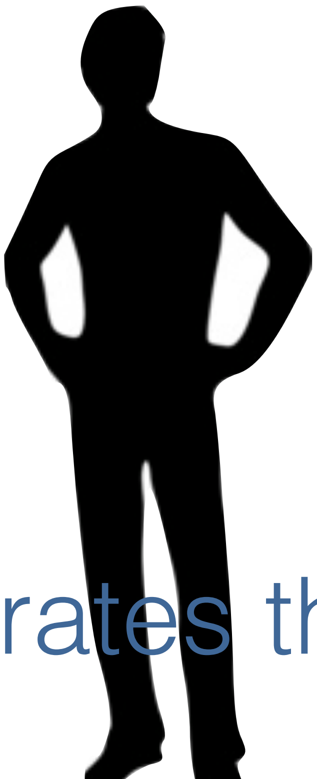
Locations

Gestures

Imagine enabling these applications without sensors on the human body

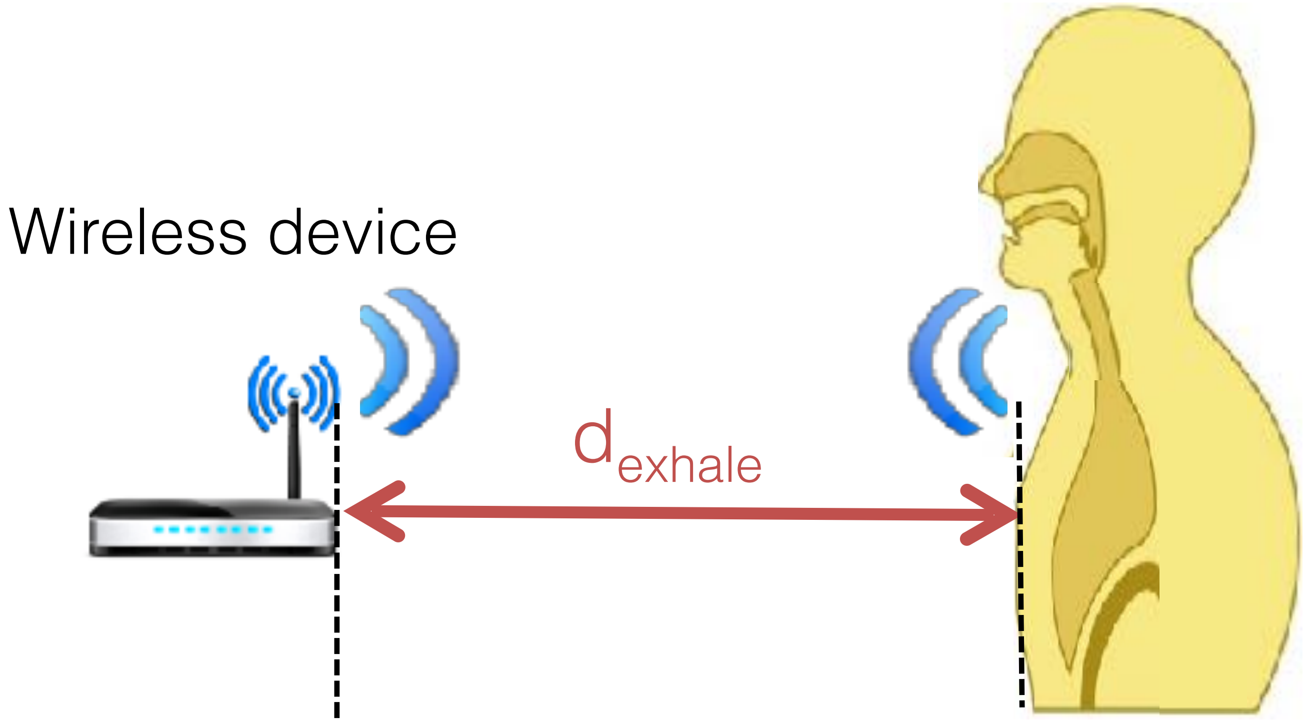


- Location
- Vital Signs
- Imaging

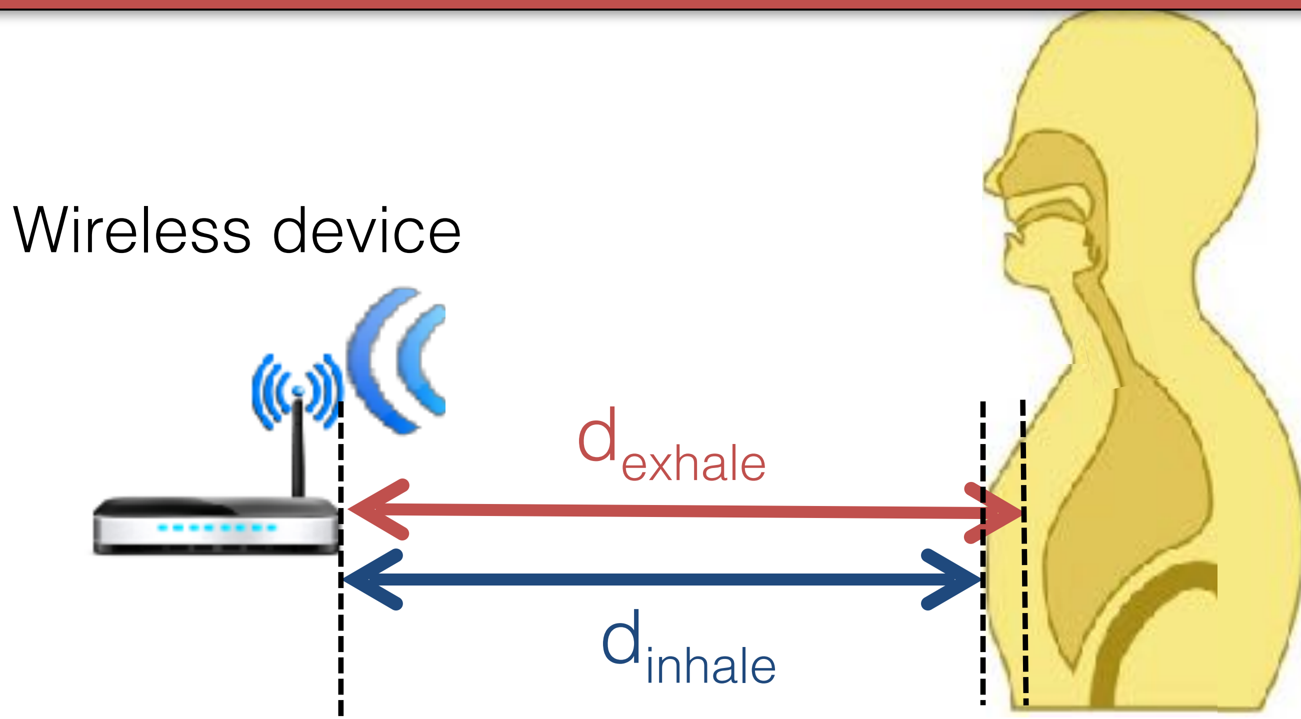


Operates through occlusions

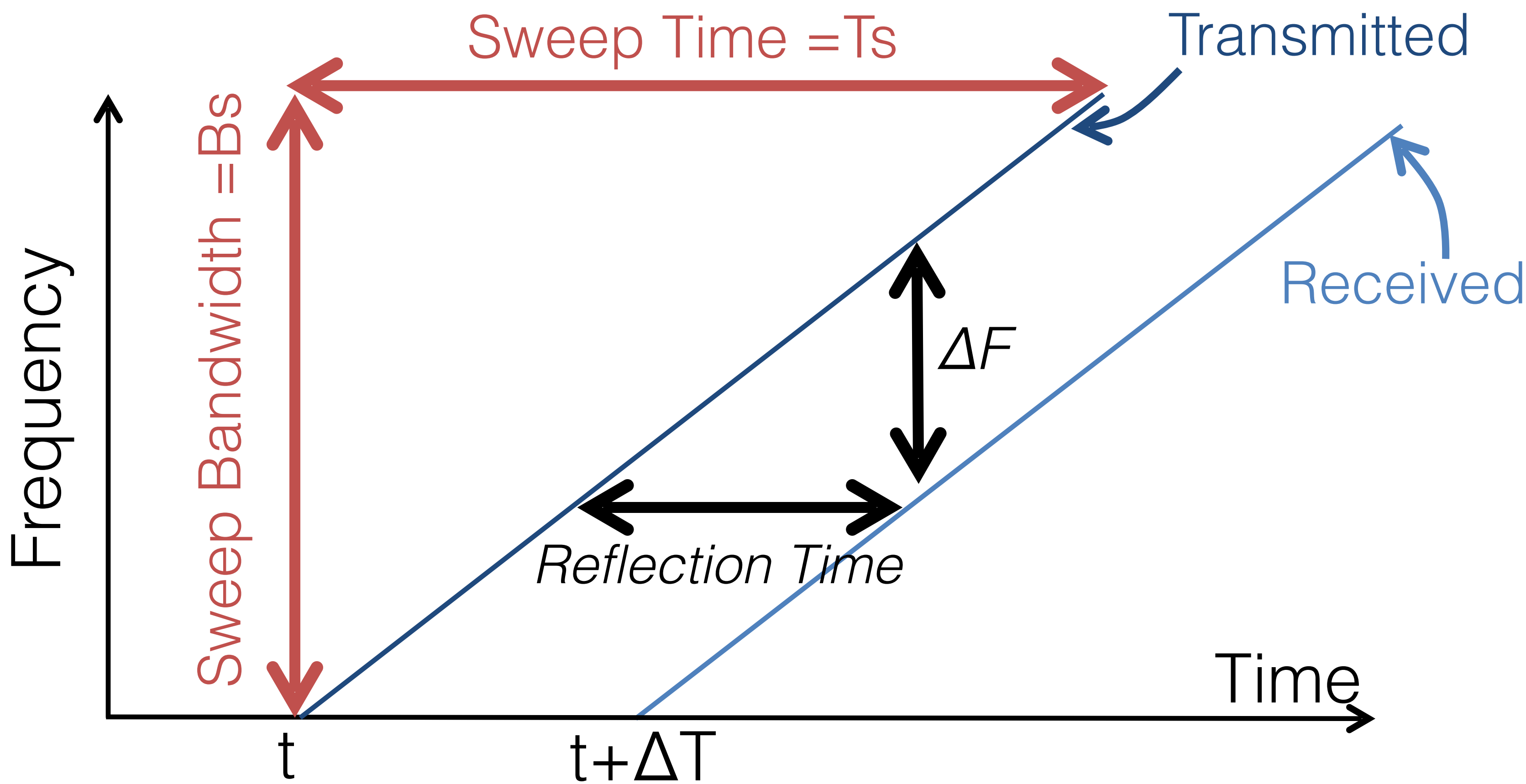
<u>Vital Radio:</u> Use wireless reflections off the human body to monitor breathing and heart rate


Wireless device
d_{exhale}

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



FMCW: Measure time by measuring frequency



Slope = k = Bs/Ts

Reflection Time =ΔF/k

FMCW

- FMCW Transmitted Signal:

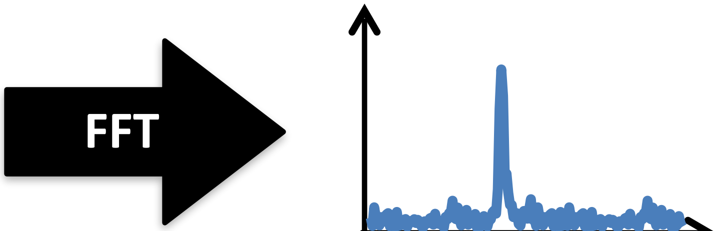
$$x(t) = e^{j2\pi(\frac{k}{2}(t^2+f_0 t))}$$

- FMCW Received Signal:

$$y(t) = \sum_i A_i e^{j2\pi(\frac{k}{2}((t-\tau_i)^2+f_0(t-\tau_i)))}$$

- FMCW after downconversion:

$$y_b(t) = \sum_i A_i e^{j2\pi(k\tau_i t+f_0\tau_i)}$$



$\Delta F = k\ \tau_i$

- Sampling Rate = B

$\Delta F < B \longrightarrow \tau_{max} = B/k = BxTs/Bs \longrightarrow d_{max} = cxBxTs/Bs$

FMCW

- FMCW Transmitted Signal:

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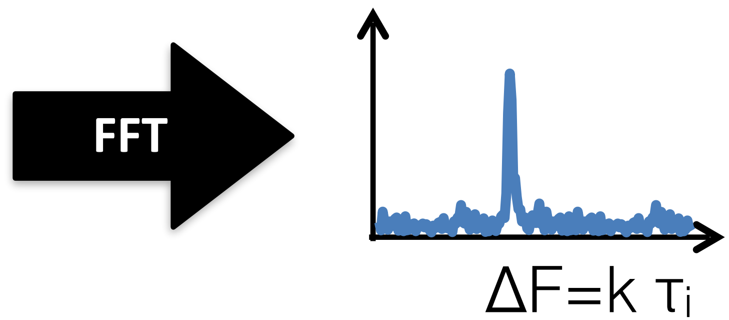

- Sampling Rate = B

$\Delta F < B \longrightarrow \tau_{max} = B/k = BxTs/Bs \longrightarrow d_{max} = cxBxTs/2Bs$

FMCW

- FMCW Transmitted Signal:

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- FMCW Received Signal:

$$y(t) = \sum_i A_i e^{j2\pi(\frac{k}{2}((t-\tau_i)^2+f_0(t-\tau_i)))}$$

- FMCW after downconversion:

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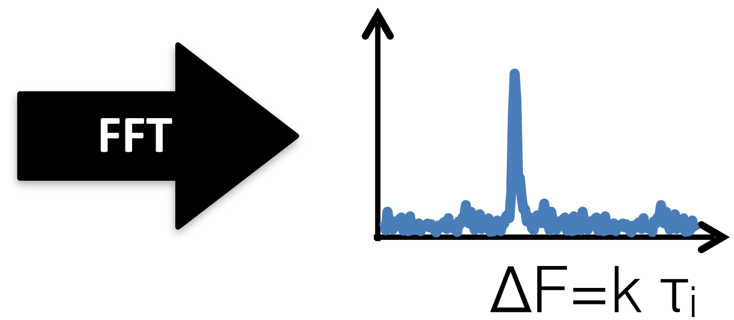

- Sampling Rate = B

$\Delta F < B \longrightarrow \tau_{max} = B/k = BxTs/Bs \longrightarrow d_{max} = cxBxTs/2Bs$

- Sampling Window = Ts

$dF > 1/Ts \longrightarrow \tau_{min} = 1/(kxTs) = 1/Bs \longrightarrow d_{min} = c/2Bs$

FMCW

- FMCW Transmitted Signal:

$$x(t) = e^{j2\pi(\frac{k}{2}(t^2+f_0 t))}$$

- FMCW Received Signal:

$$y(t) = \sum_i A_i e^{j2\pi(\frac{k}{2}((t-\tau_i)^2+f_0(t-\tau_i)))}$$

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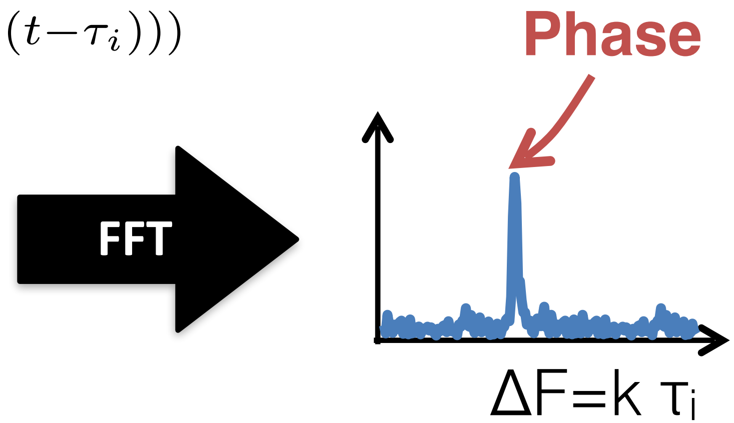


- Phase of peak = $f_0\tau_i$
  - Phase wraps around 2pi
  - Use peak position $\Delta F=k\,\tau_i$ for course estimate of τ_i
  - Use peak phase $f_0\tau_i$ for fine estimate of τ_i

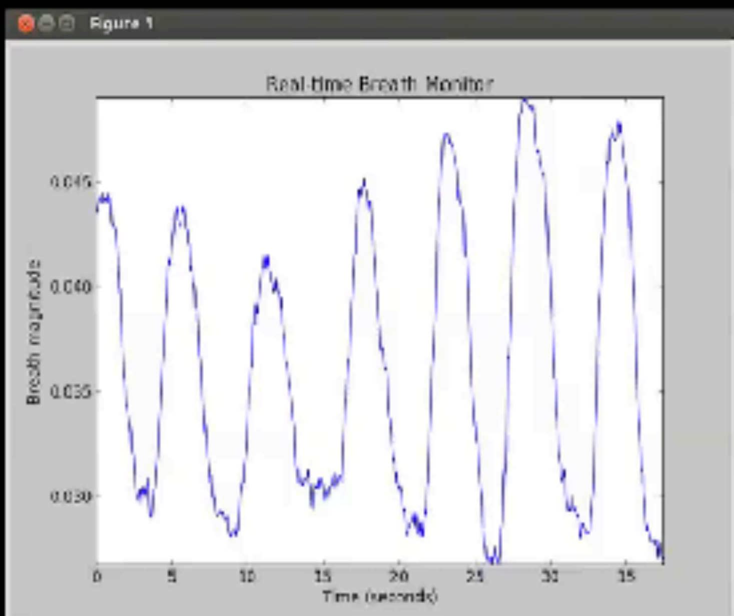
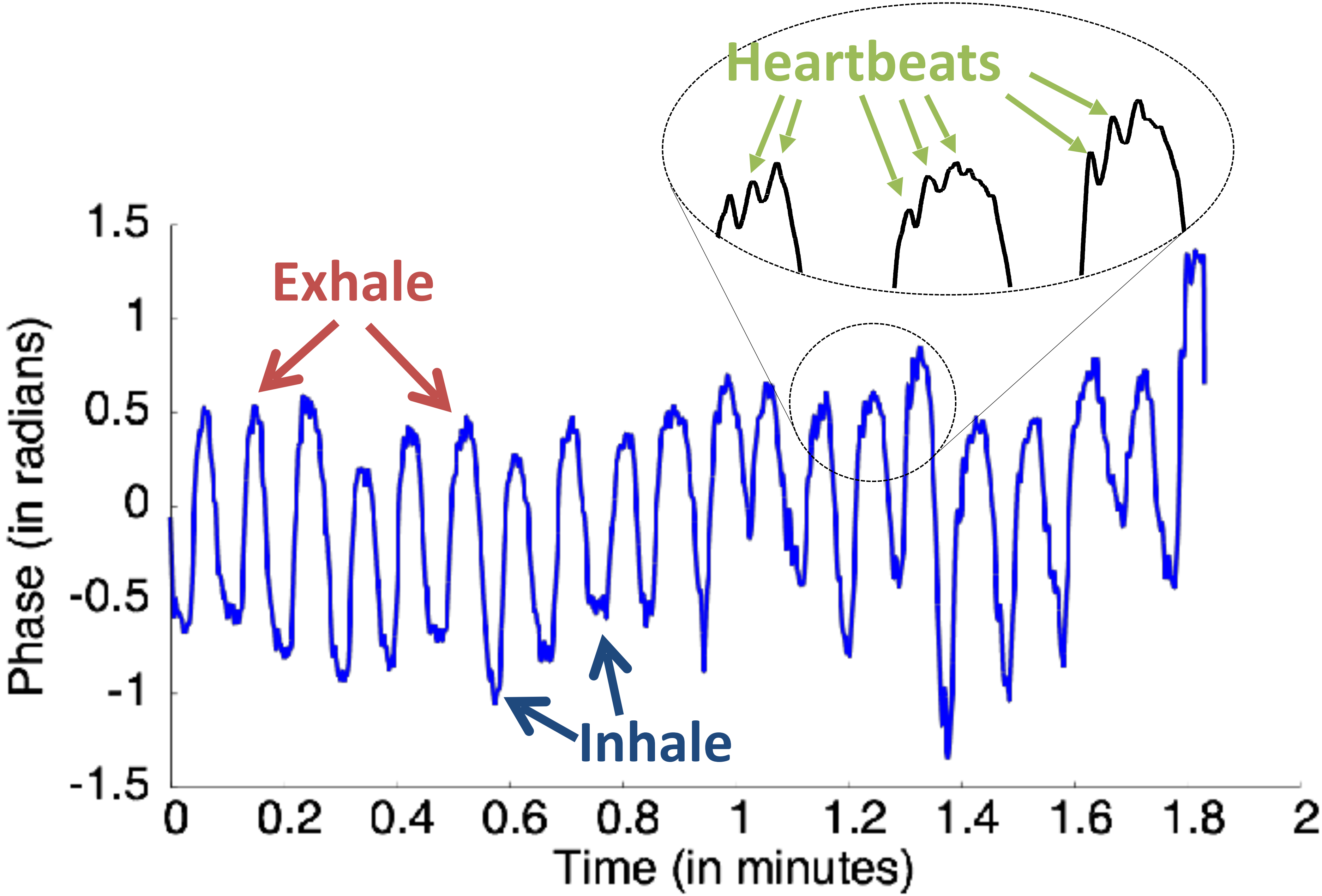


Figure 1
Real-time Breath Monitor
0.045
0.040
0.035
0.030
Breath magnitude
0
5
10
15
20
25
30
Time (seconds)

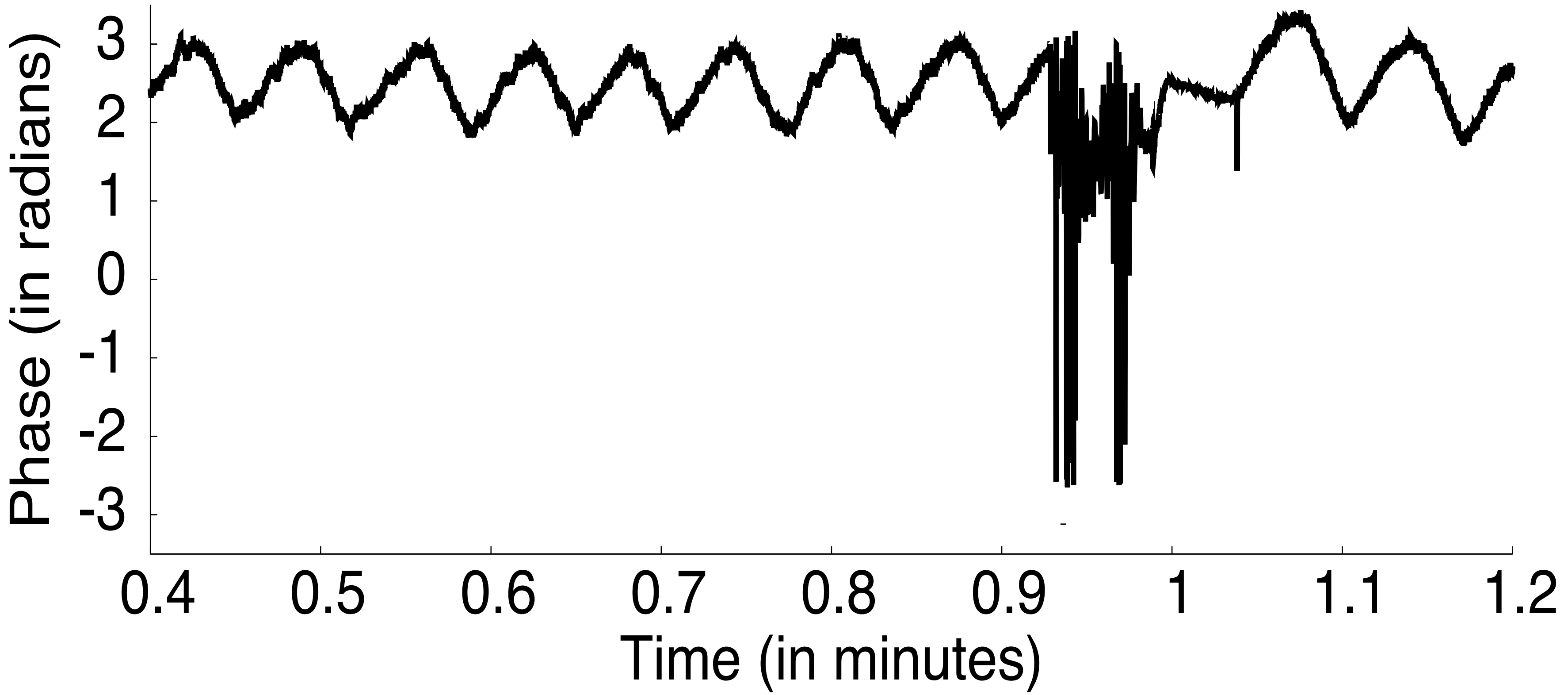
Let’s zoom in on these signals



Heartbeats
Exhale
Inhale
1.5
1
0.5
0
-0.5
-1
-1.5
Phase (in radians)
0
0.2
0.4
0.6
0.8
1
1.2
1.4
1.6
1.8
2
Time (in minutes)

What happens when a person moves his limb?

What happens when a person moves his limb?



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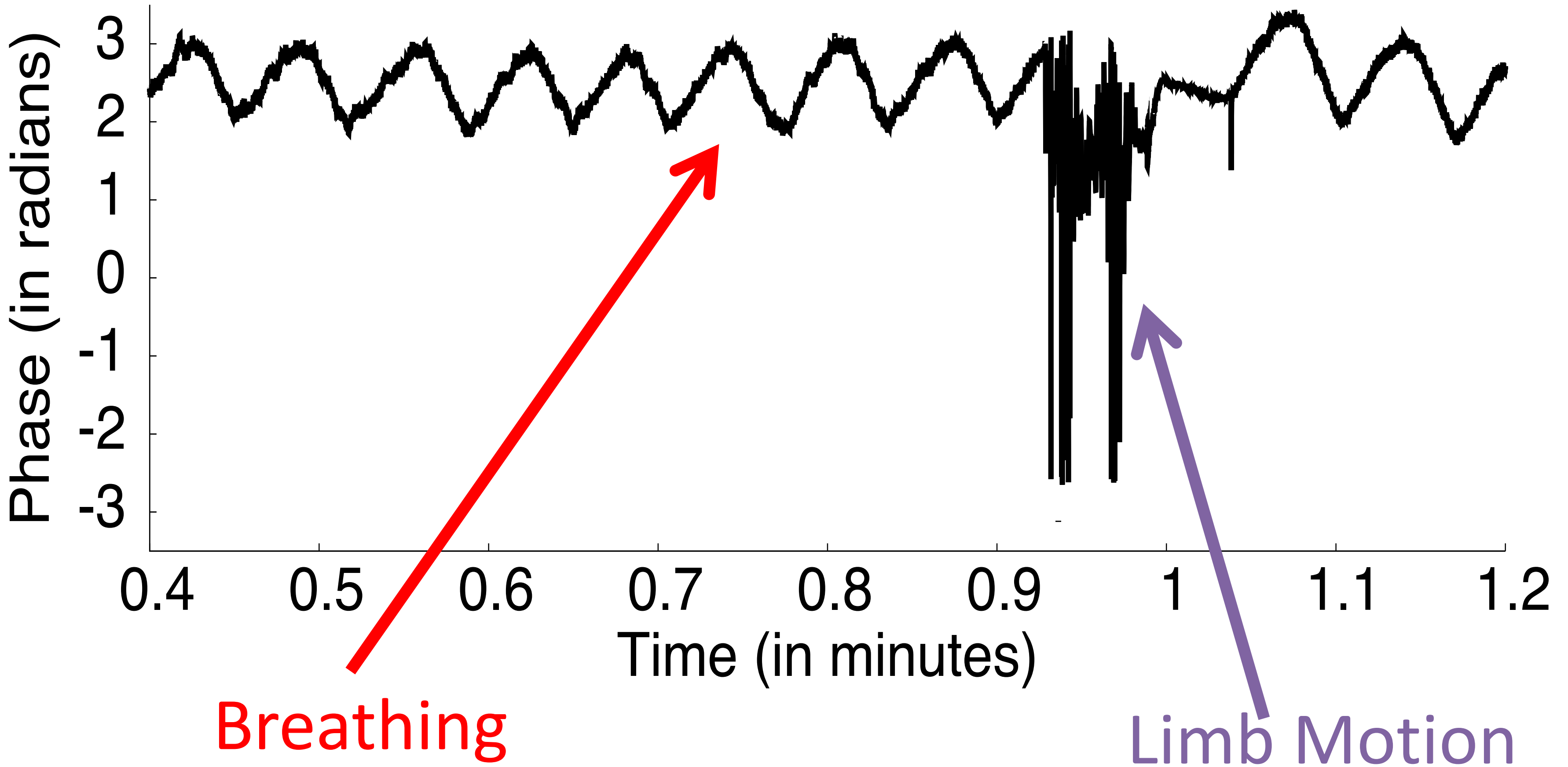
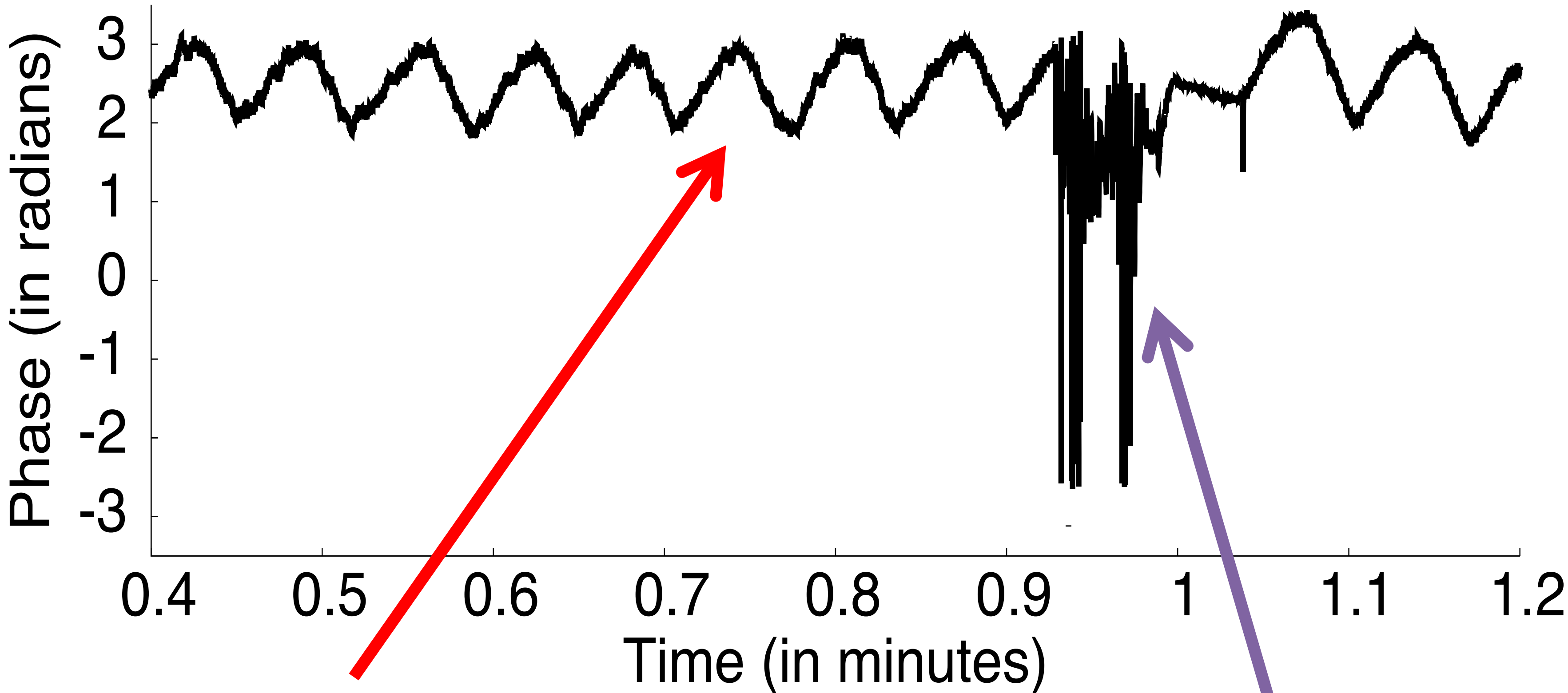


Periodic

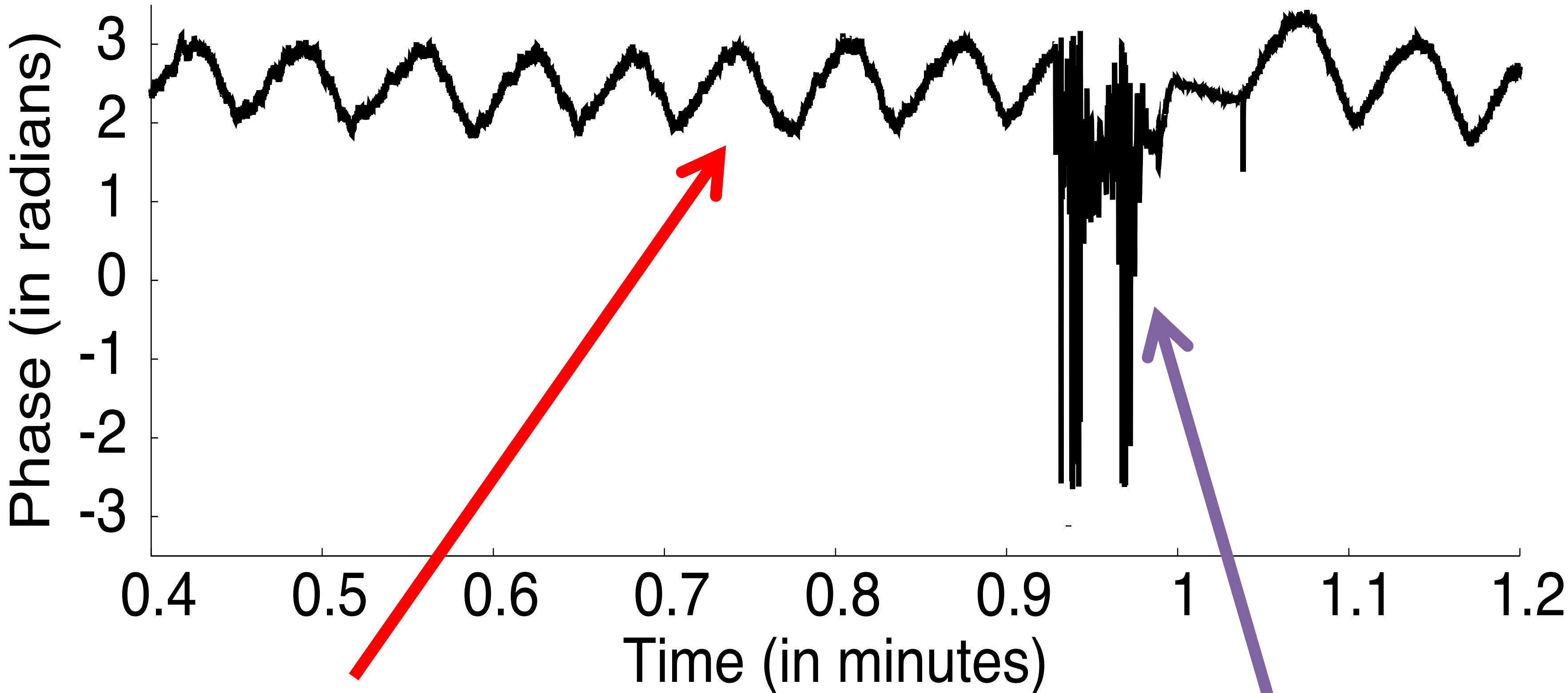
Not periodic

What happens when a person moves his limb?



Use periodicity test to eliminate variations that are not due to breathing/heartbeats

What happens when a person moves his limb?

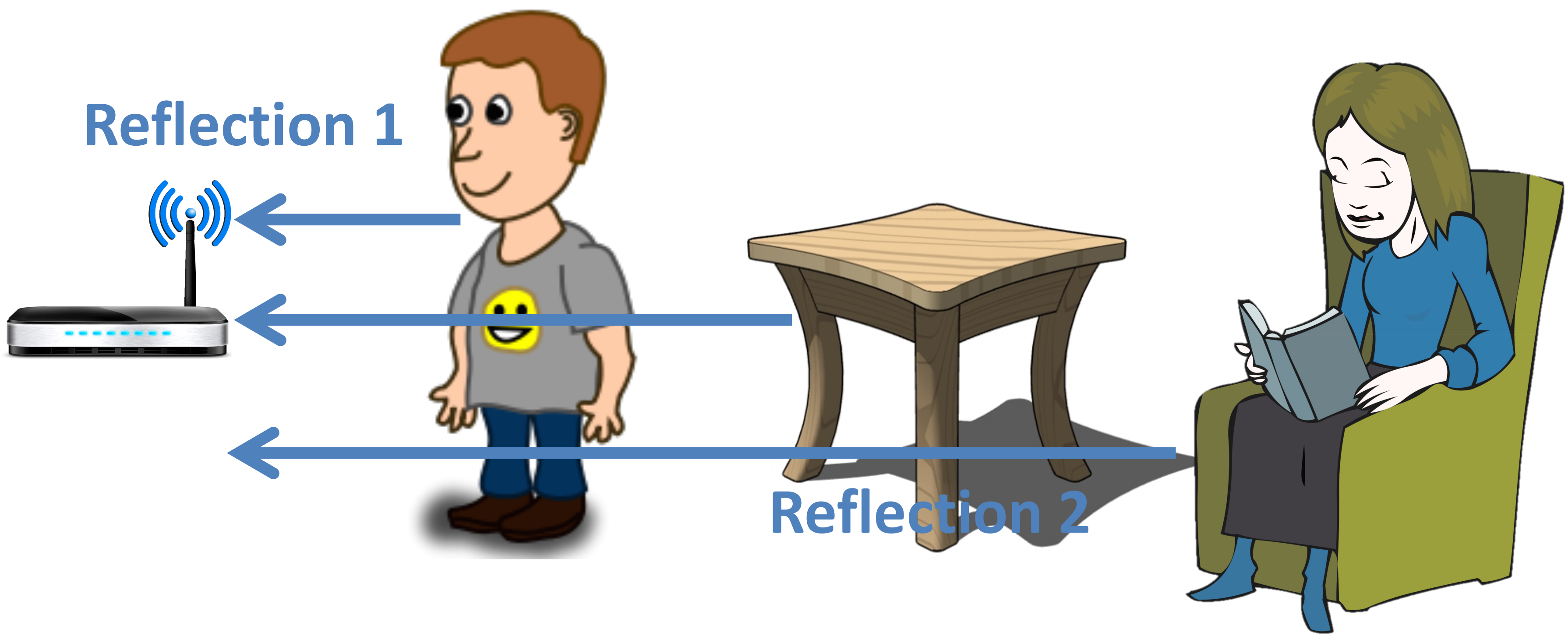


Band-pass filter the cleaned signals to extract breathing and heart rate

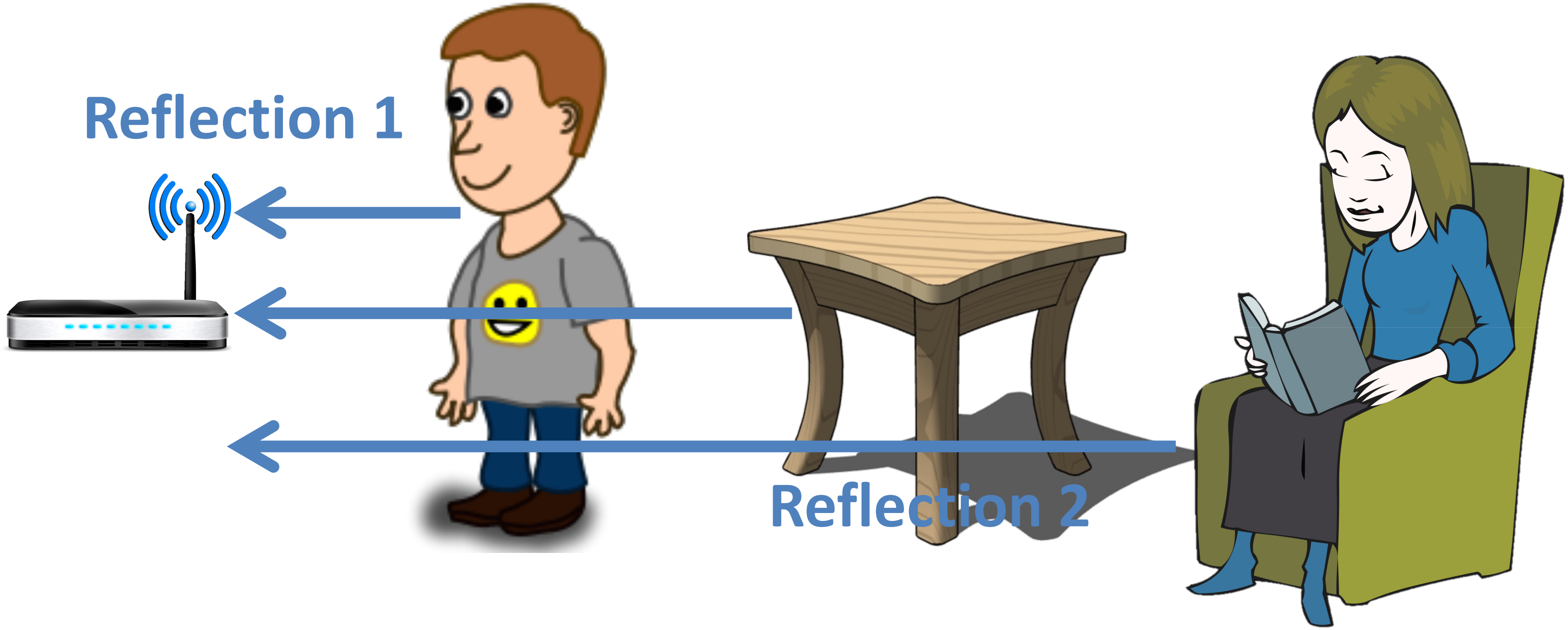
What happens with multiple users in the environment?

Reflections from different objects collide

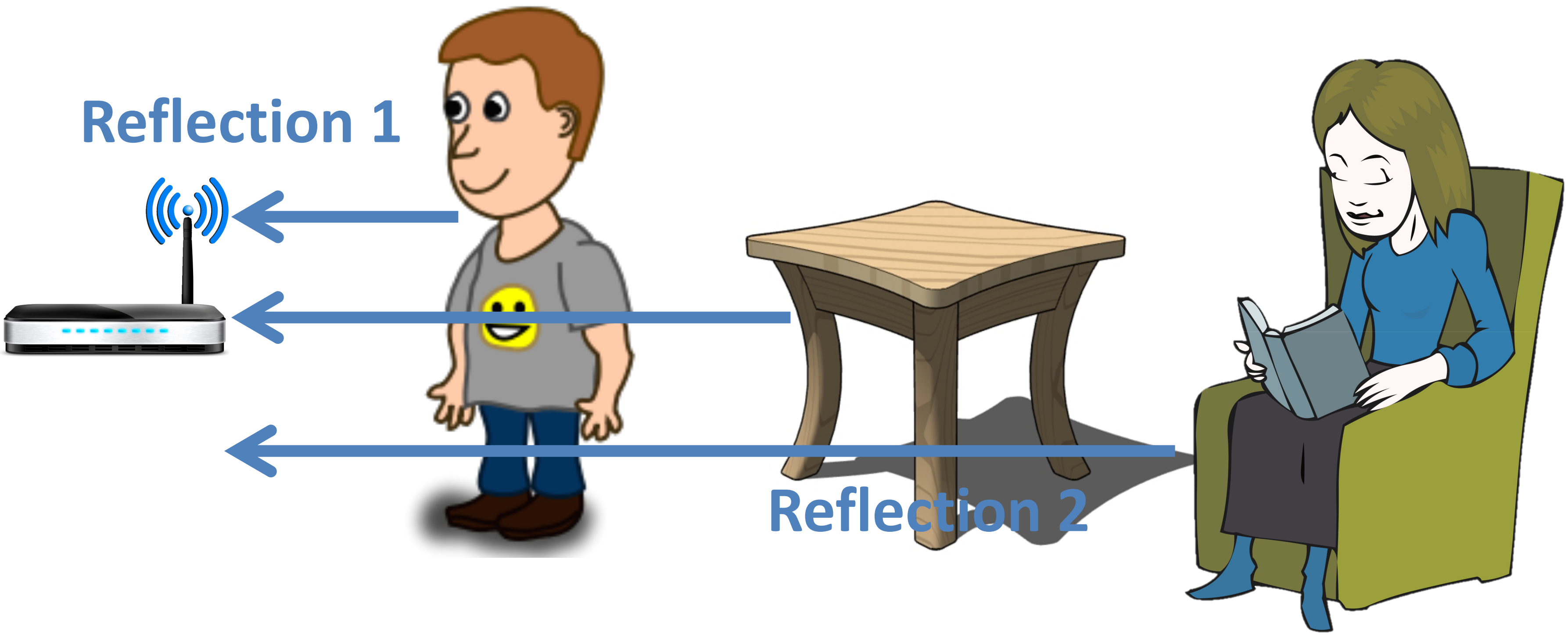
<u>Problem:</u> Phase becomes meaningless!



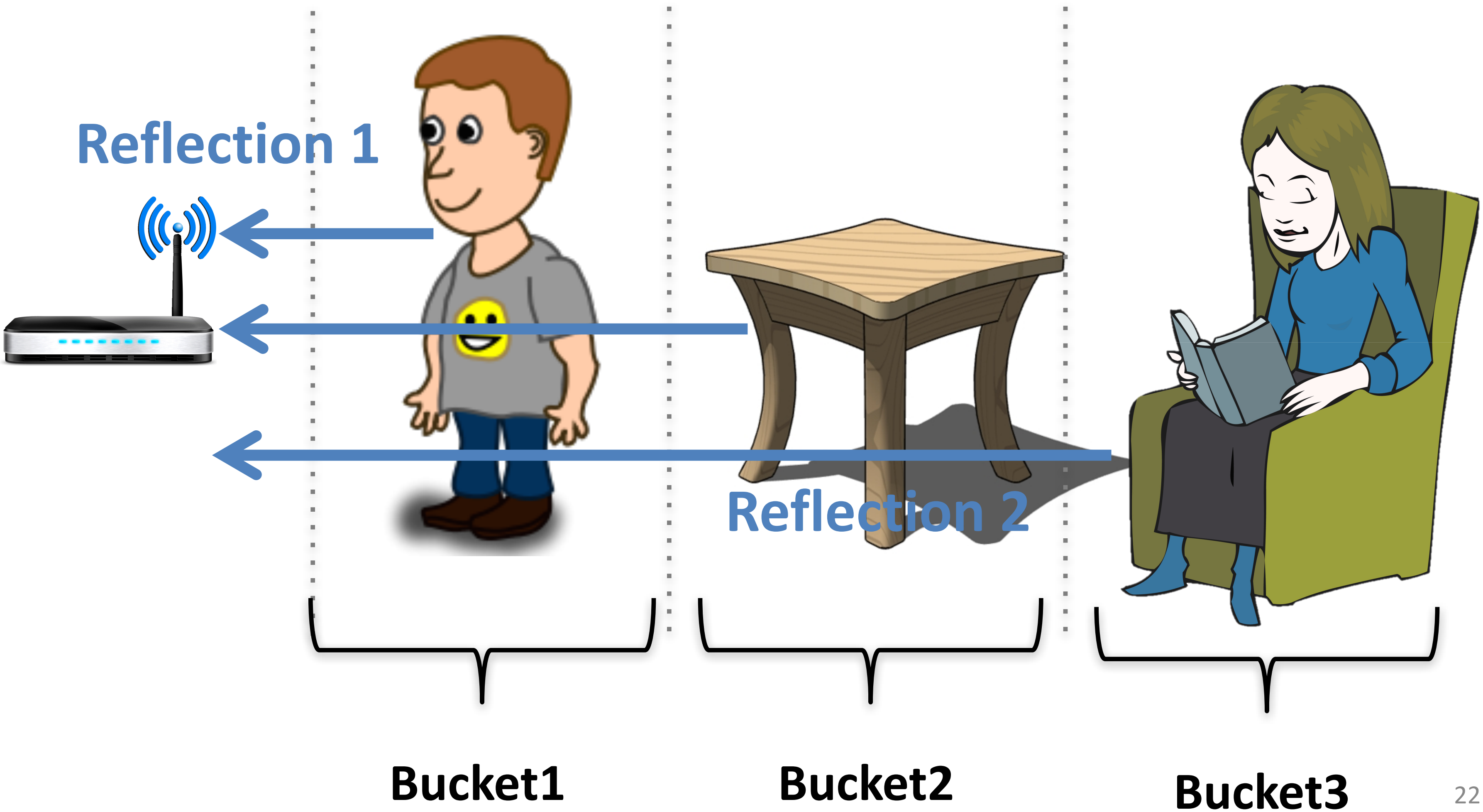
Idea: Wireless localization can be used to locate various devices



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



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



Baby Monitoring

Can you tell people's emotions even if they don't show up on their faces?

Smart Homes that adapt to our mood

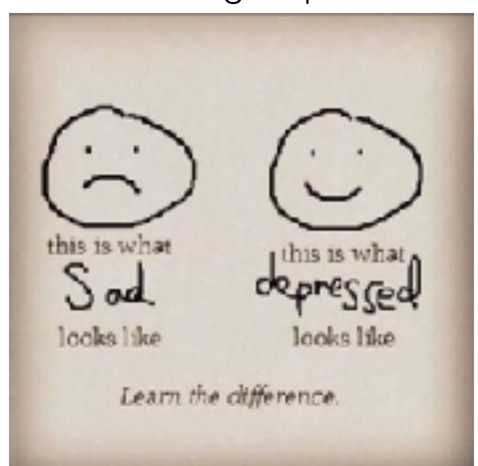
Did I get the Job? …. No

Does my advisor like my work?

Graduate student

Advisor

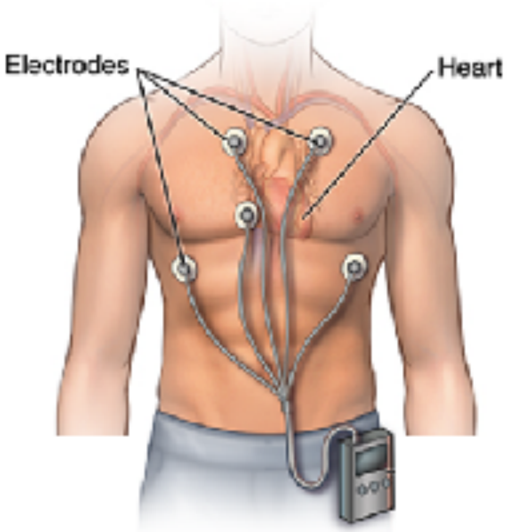
Combating Depression



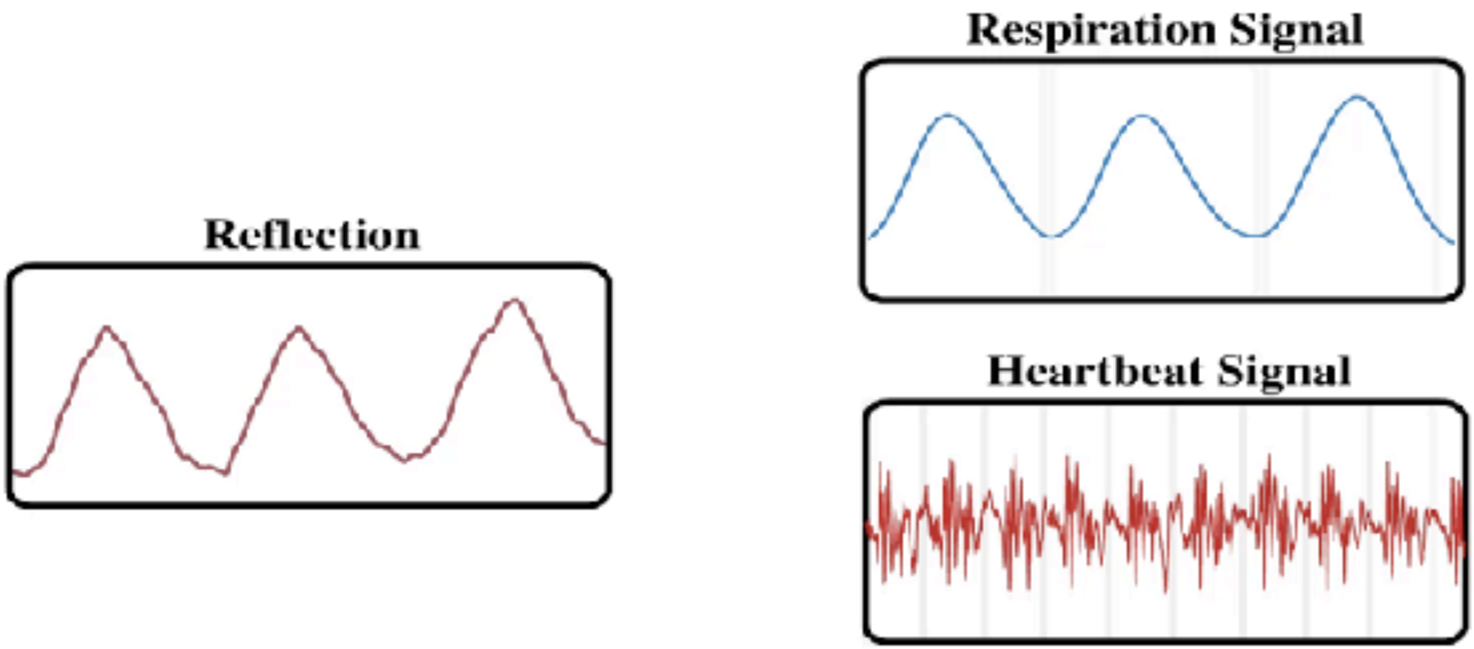
Is the date going well!

Existing approaches measure vital signs

- Use ECG to get very accurate heartbeats

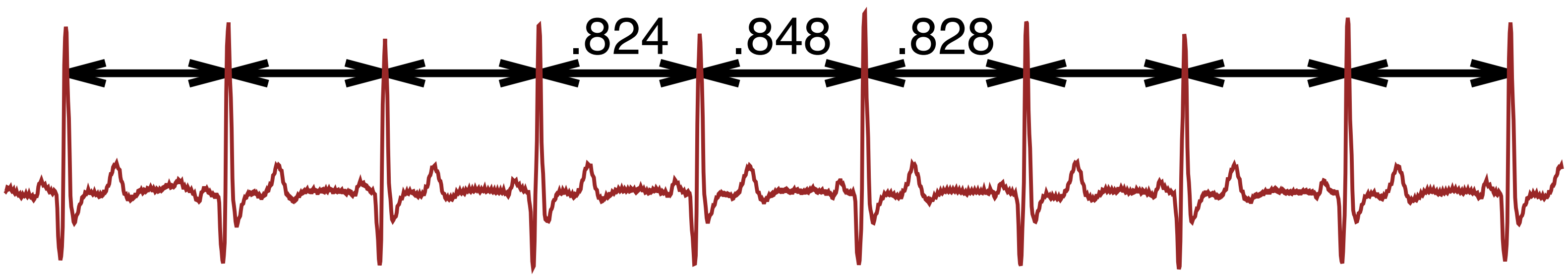


Emotion recognition using wireless signals



Key challenge: Inter-Beat Interval (IBI)

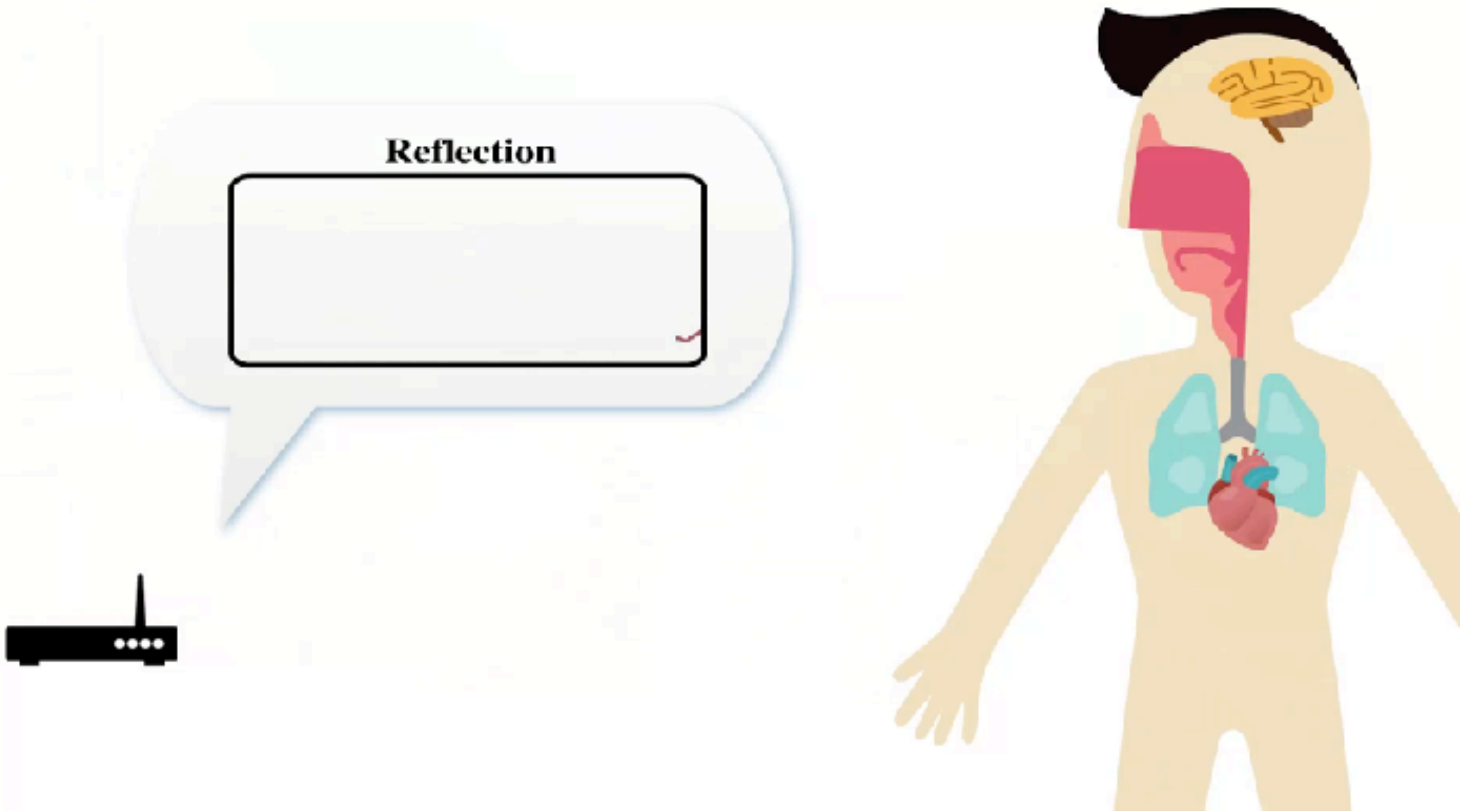
- Emotion recognition needs accurate measurements of the length of every single heartbeat



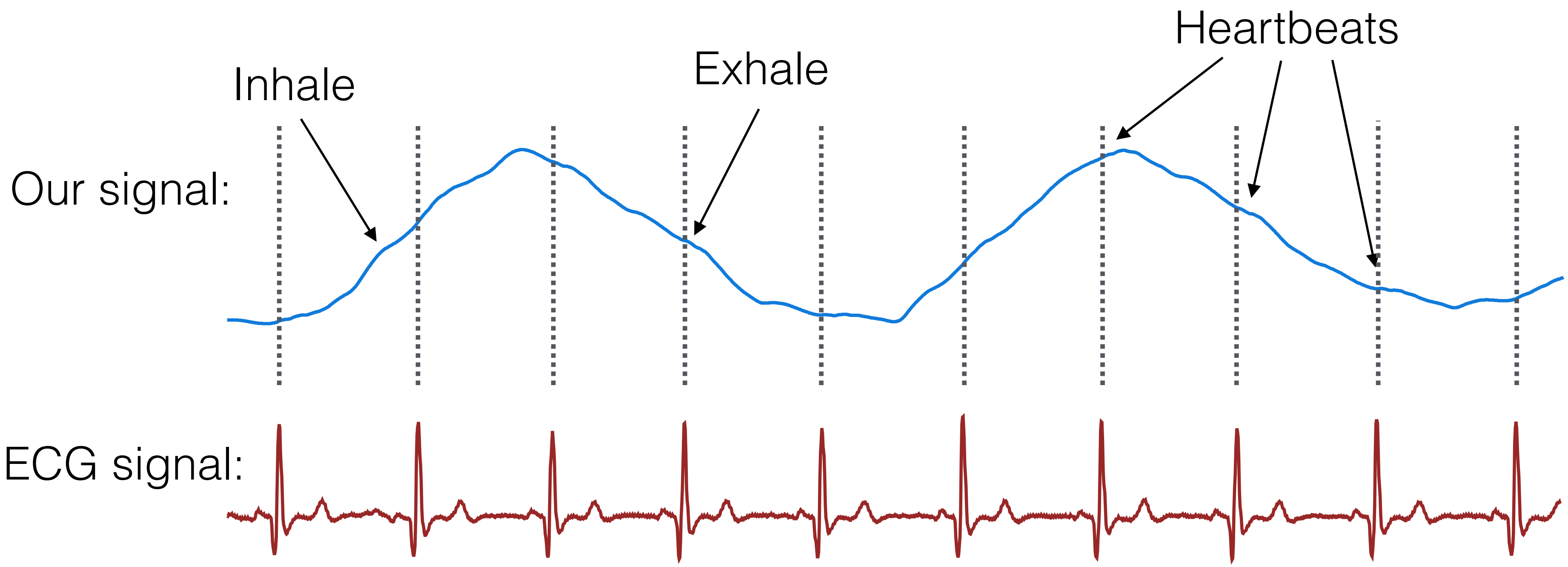
We need to extract IBI with accuracy over 99%

Input signal

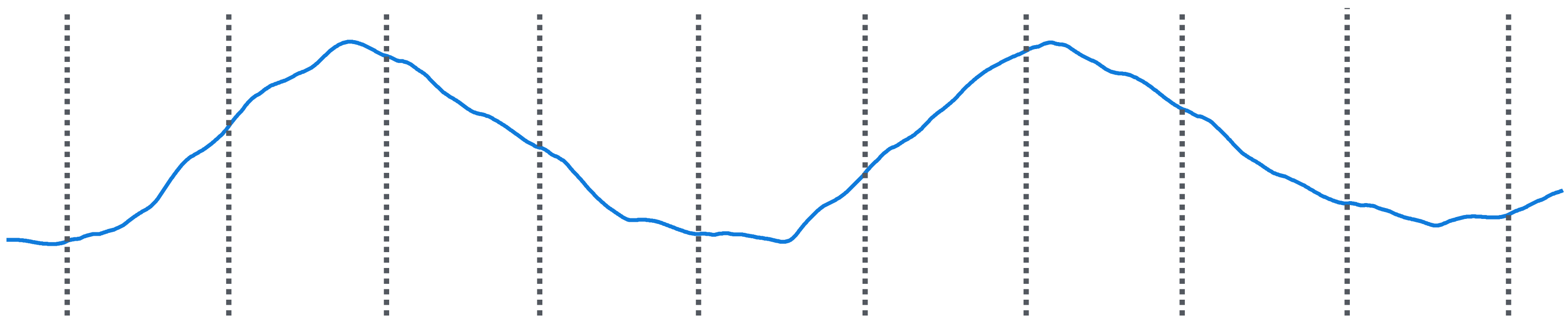
Wireless reflection of the human body



Input signal



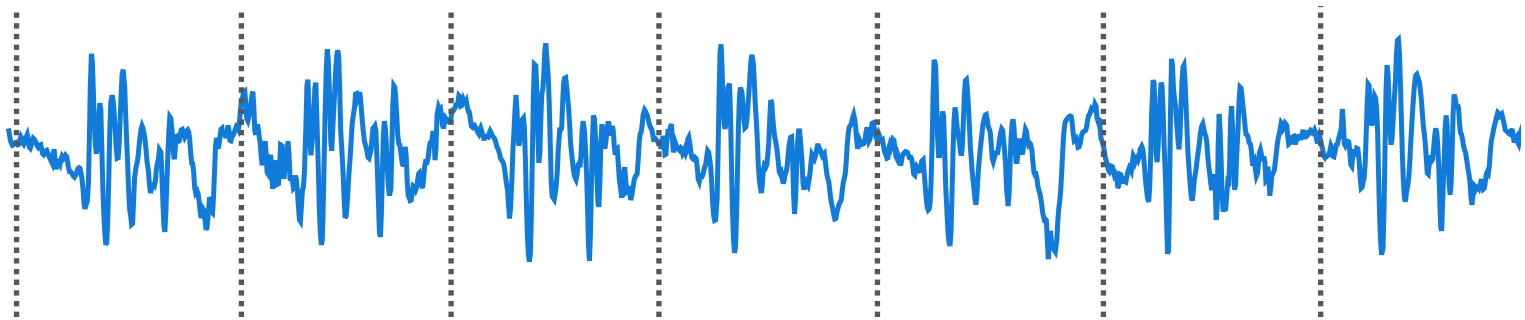
Step 1: Remove breathing signal



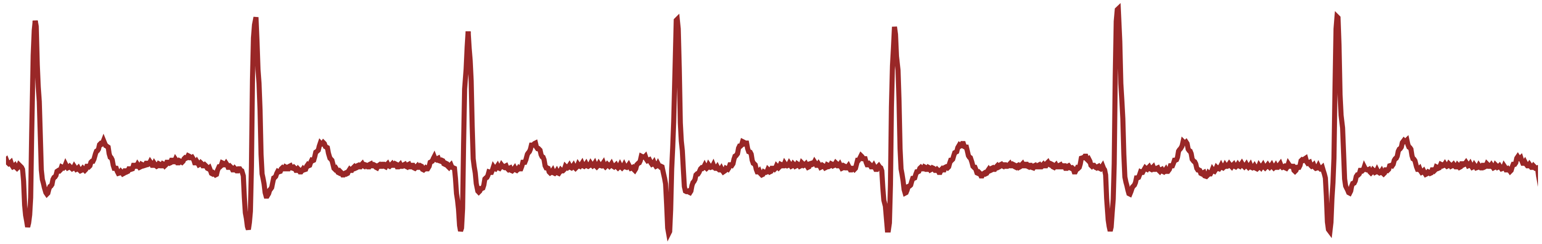
- Breathing masks heartbeats
- We use acceleration filter
  - Heartbeat involves rapid contraction of muscle
  - Breathing is slow and steady

Heartbeat signal

- Output of acceleration filter

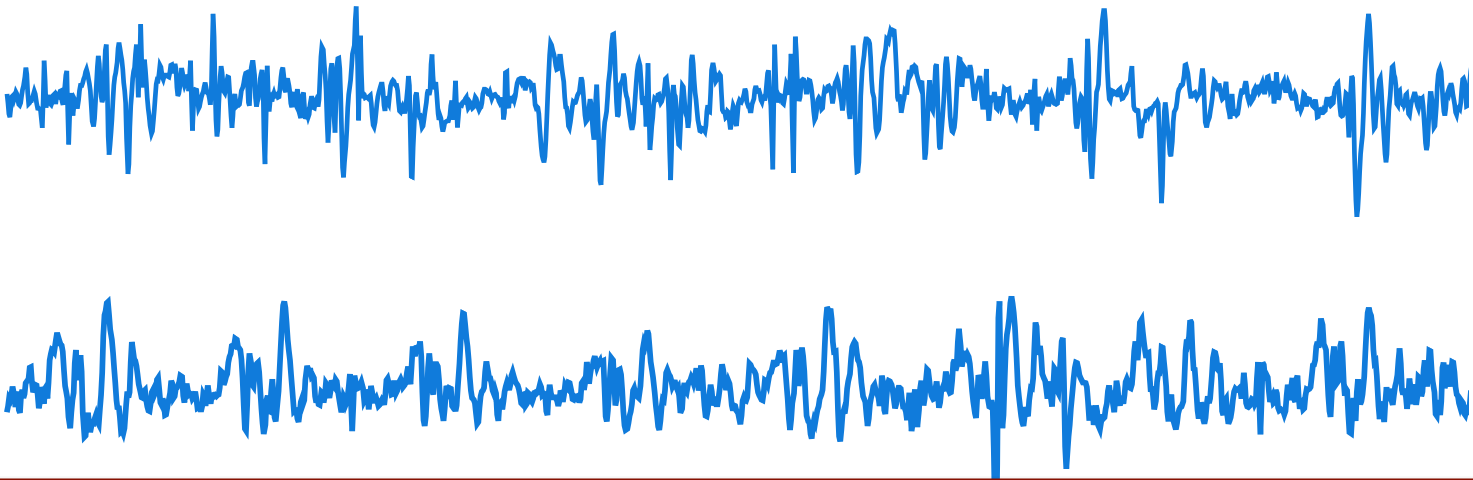


- ECG signal

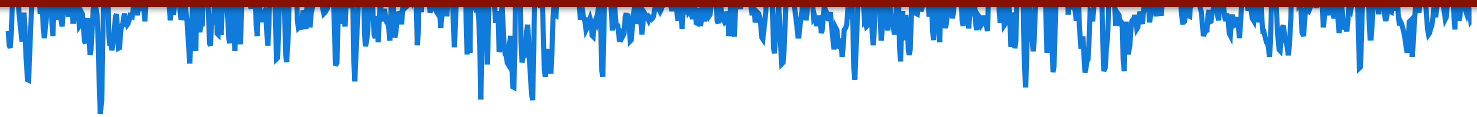


Heartbeat signal

- Other typical examples:



How to segment the signal into individual heartbeats?

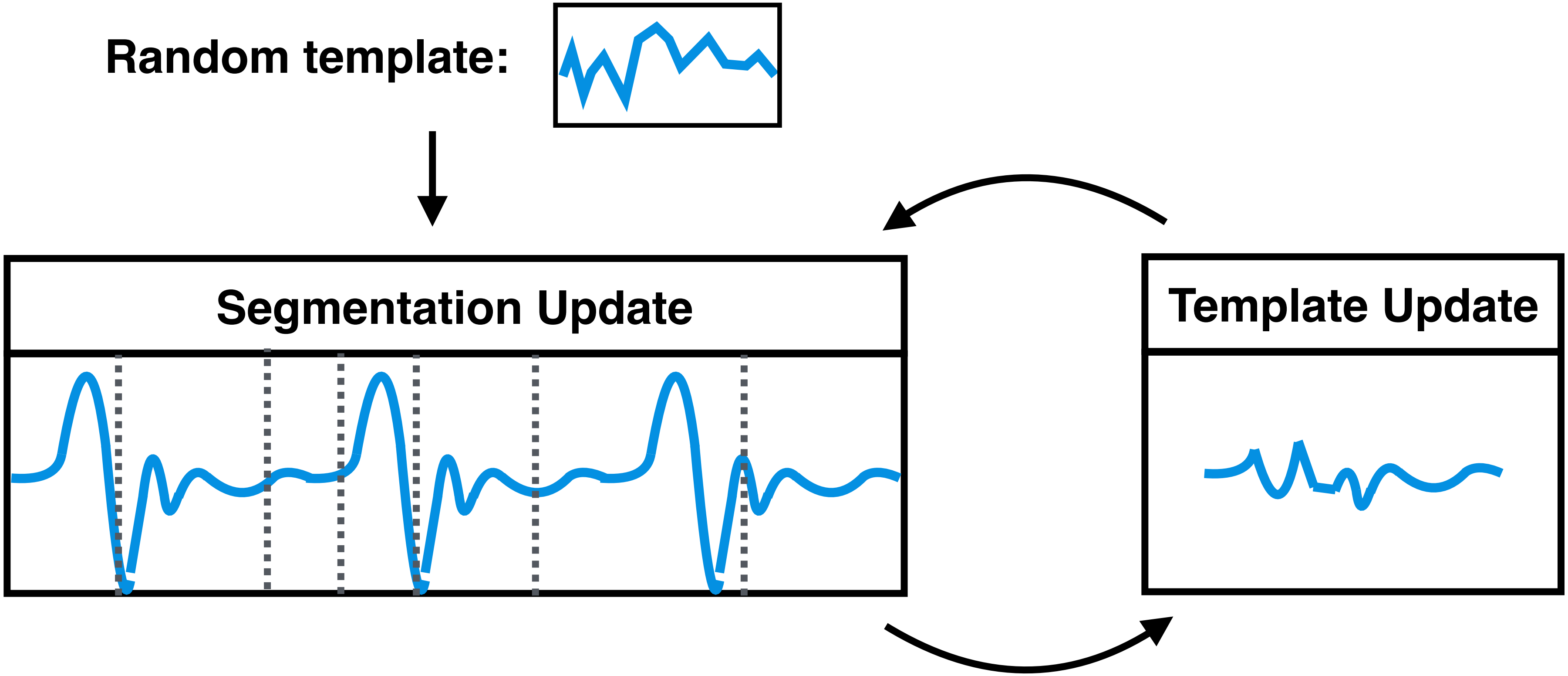


Step 2: Heartbeat segmentation

- **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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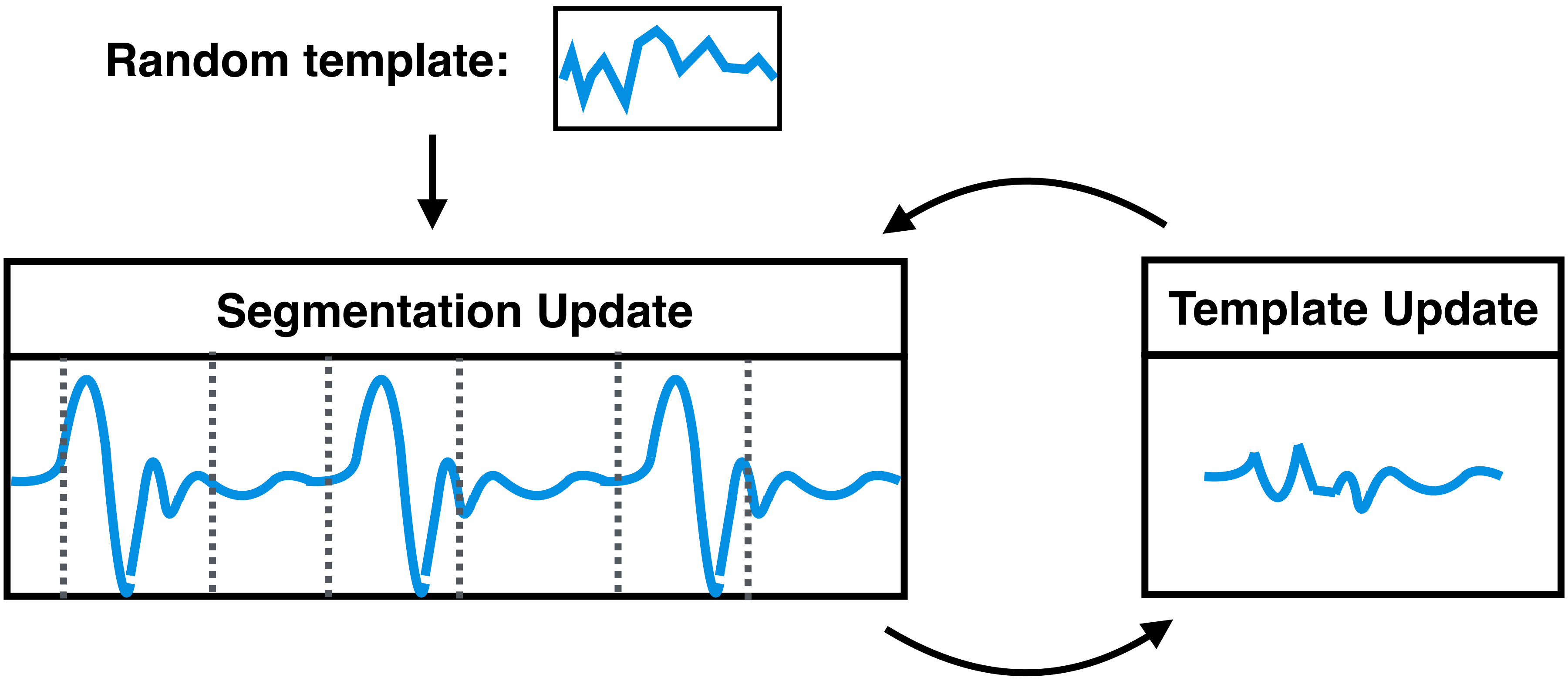

Step 2: Heartbeat segmentation

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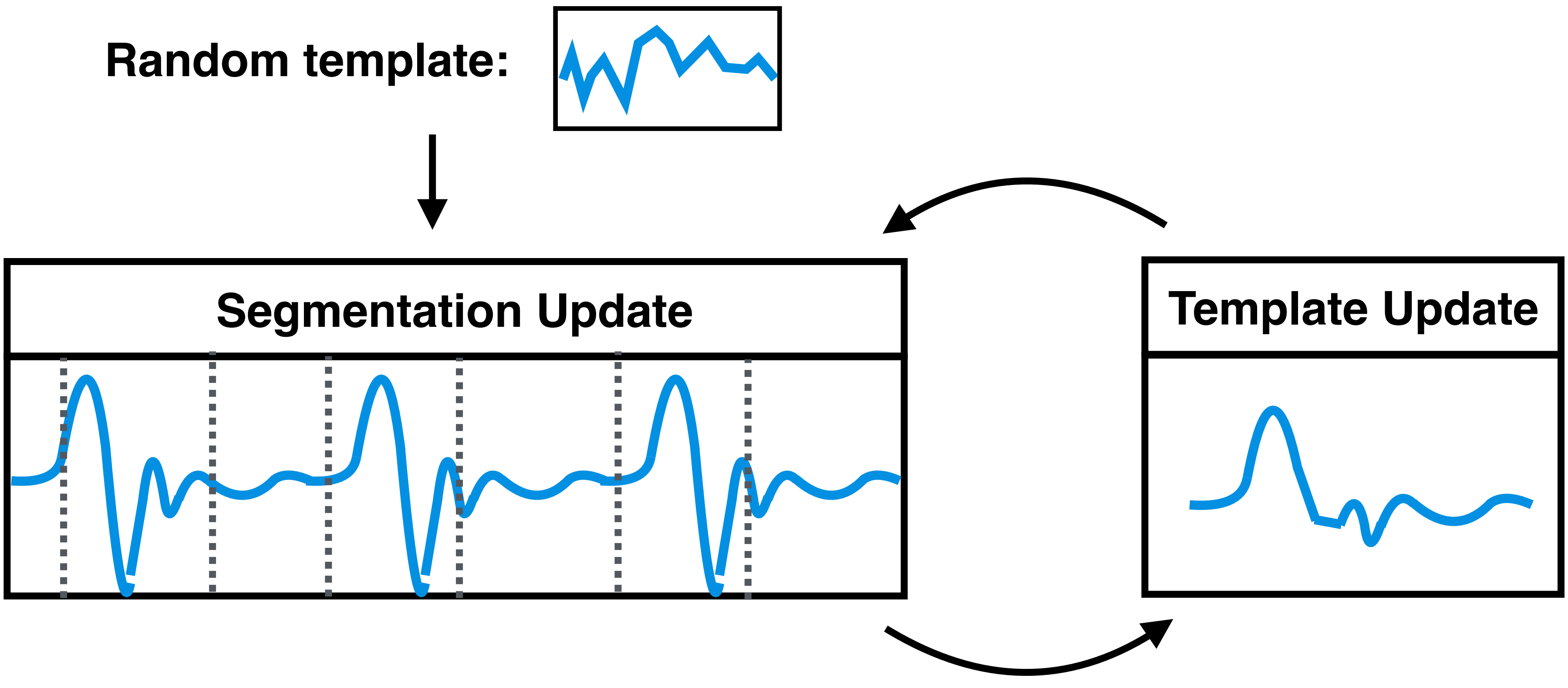

Step 2: Heartbeat segmentation

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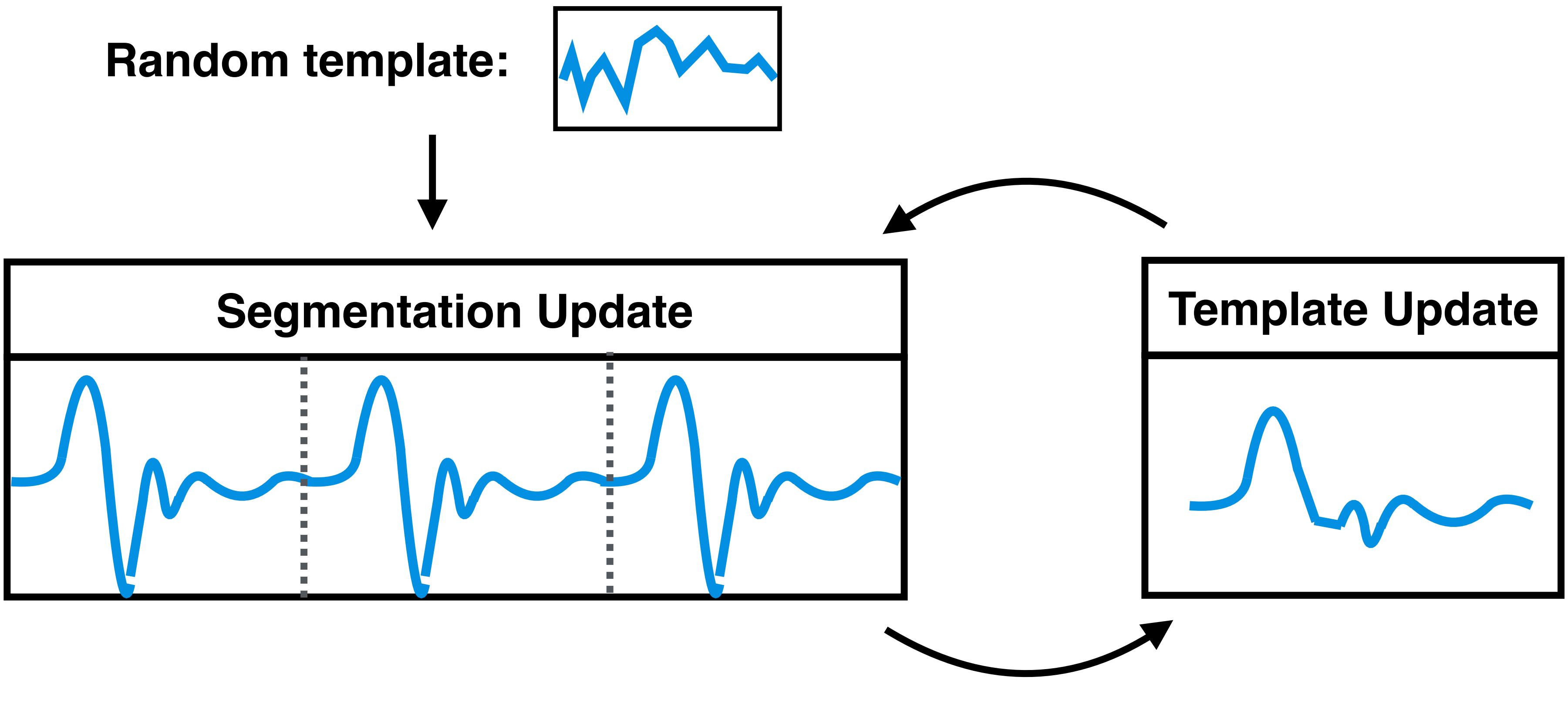

Step 2: Heartbeat segmentation

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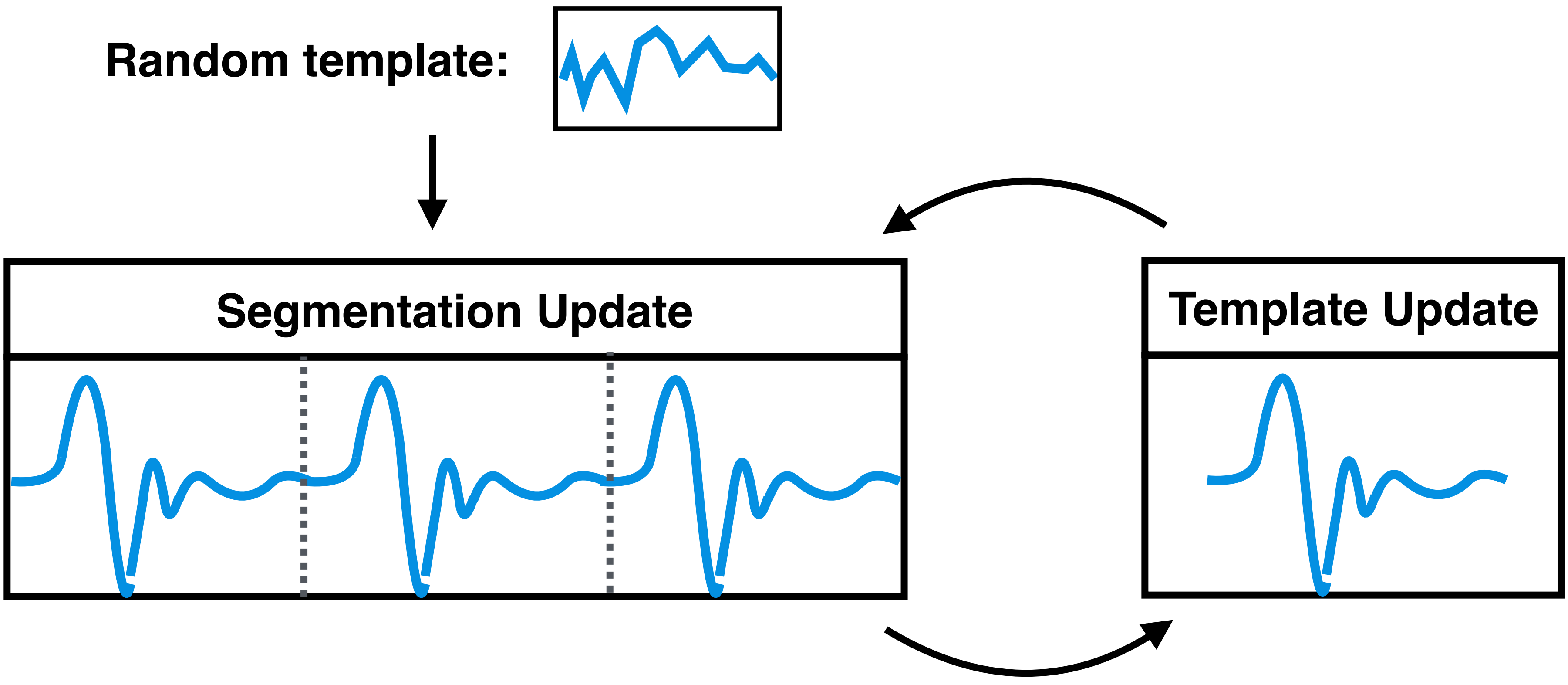
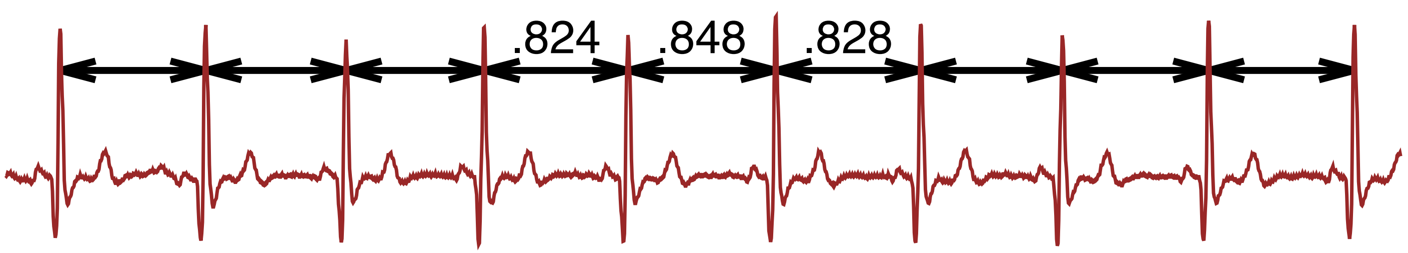


Caveat: Shrinking & Expanding

- 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 template warping

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

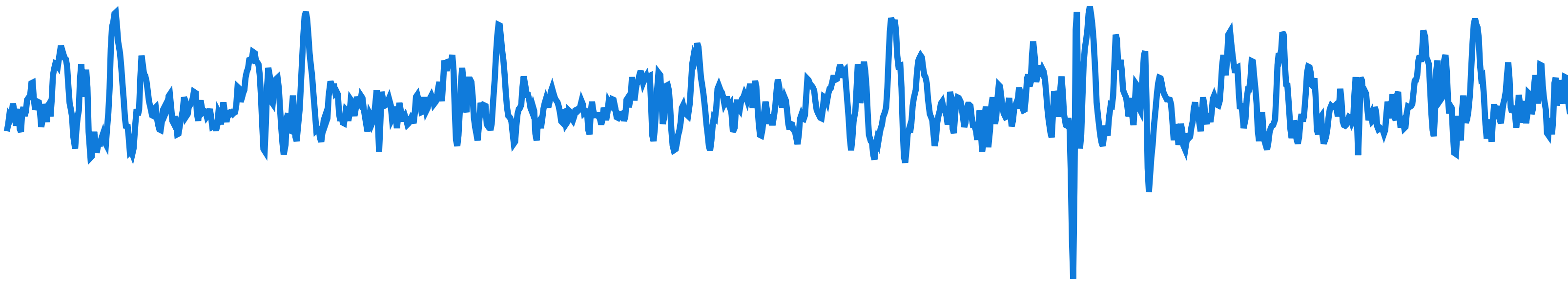
Need to recover both segmentation and template

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

segmentation template warping

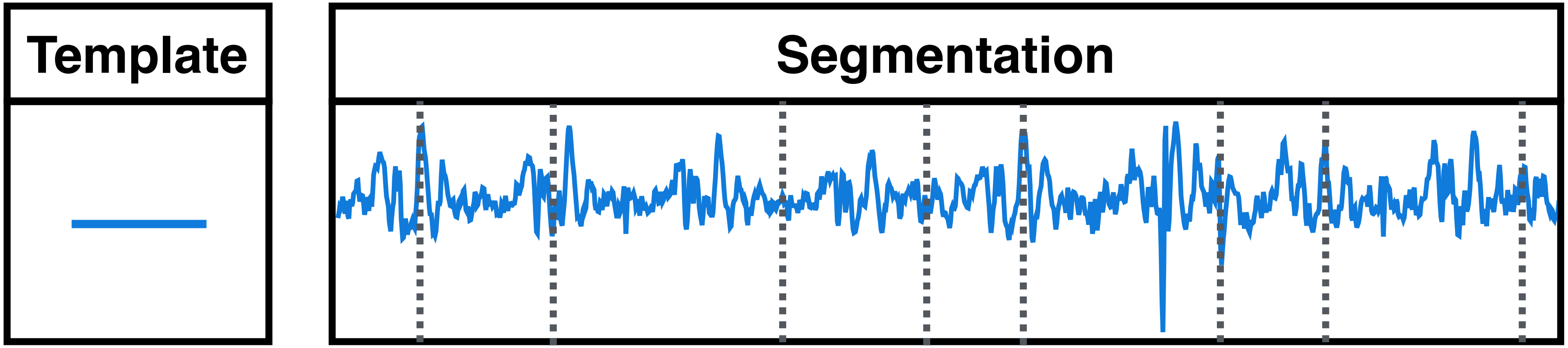
Segmentation Update	Template Update
$\mathcal{S}^{l+1} = \arg\min_{\mathcal{S}} \sum_{s_i \in \mathcal{S}} \|s_i - \omega(\boldsymbol{\mu}^l, \|s_i\|)\|^2$	$\boldsymbol{\mu}^{l+1} = \arg\min_{\boldsymbol{\mu}} \sum_{s_i \in \mathcal{S}^{l+1}} \|s_i - \omega(\boldsymbol{\mu}, \|s_i\|)\|^2$
(dynamic programming)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

Example run



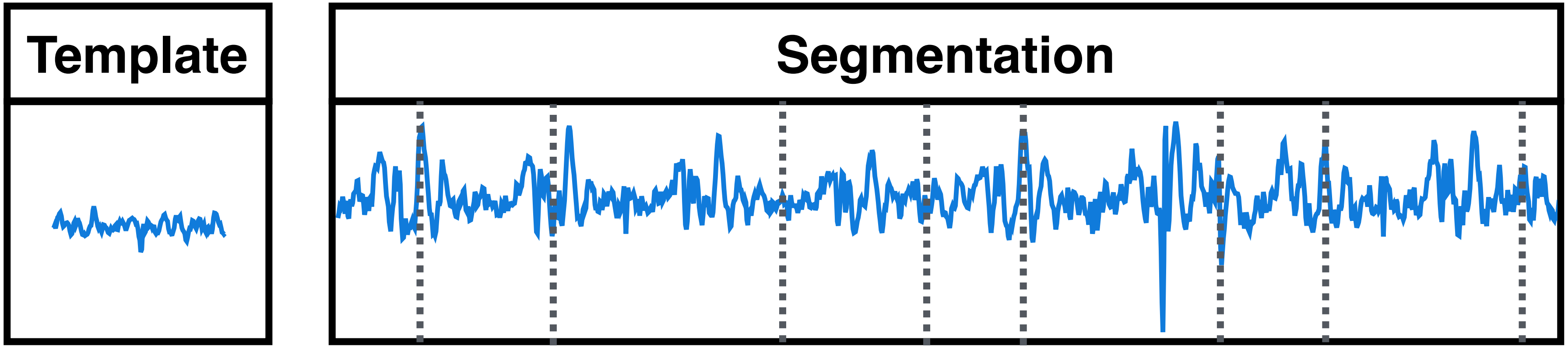
Example run

Iteration 1:



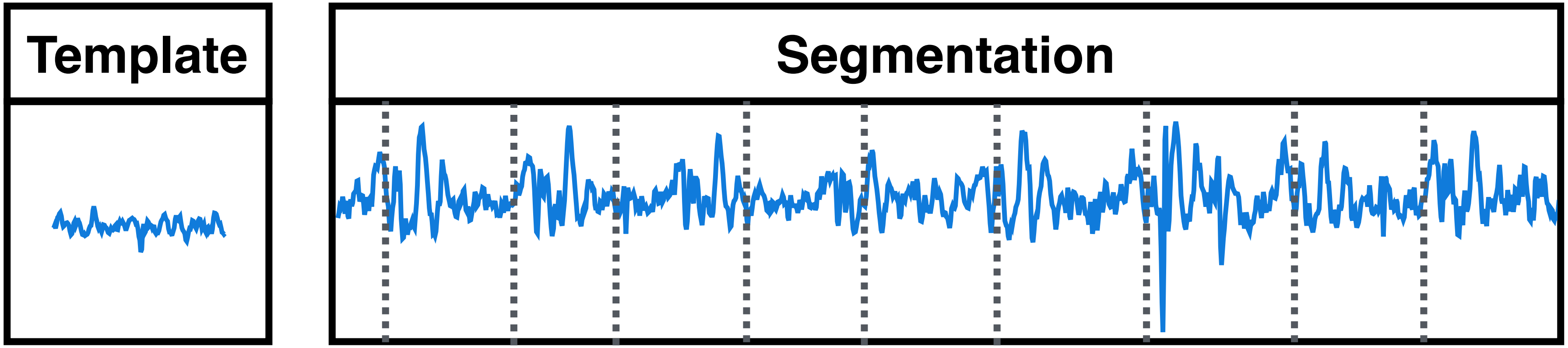
Example run

Iteration 2:



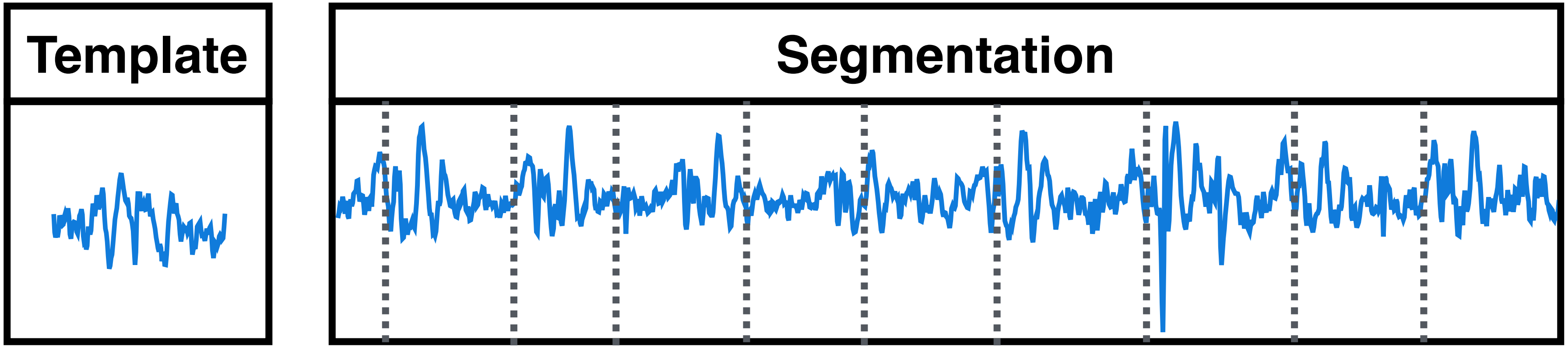
Example run

Iteration 2:



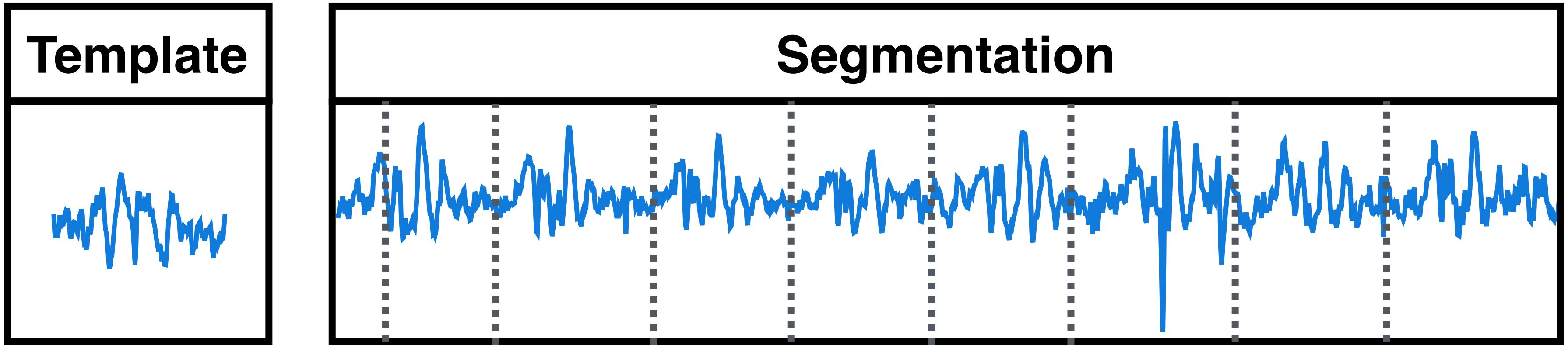
Example run

Iteration 3:



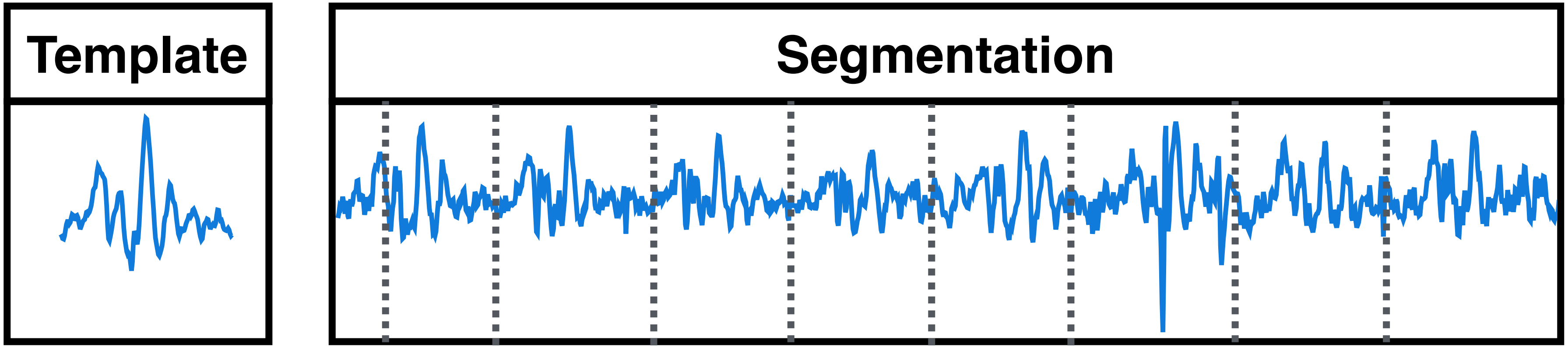
Example run

Iteration 3:



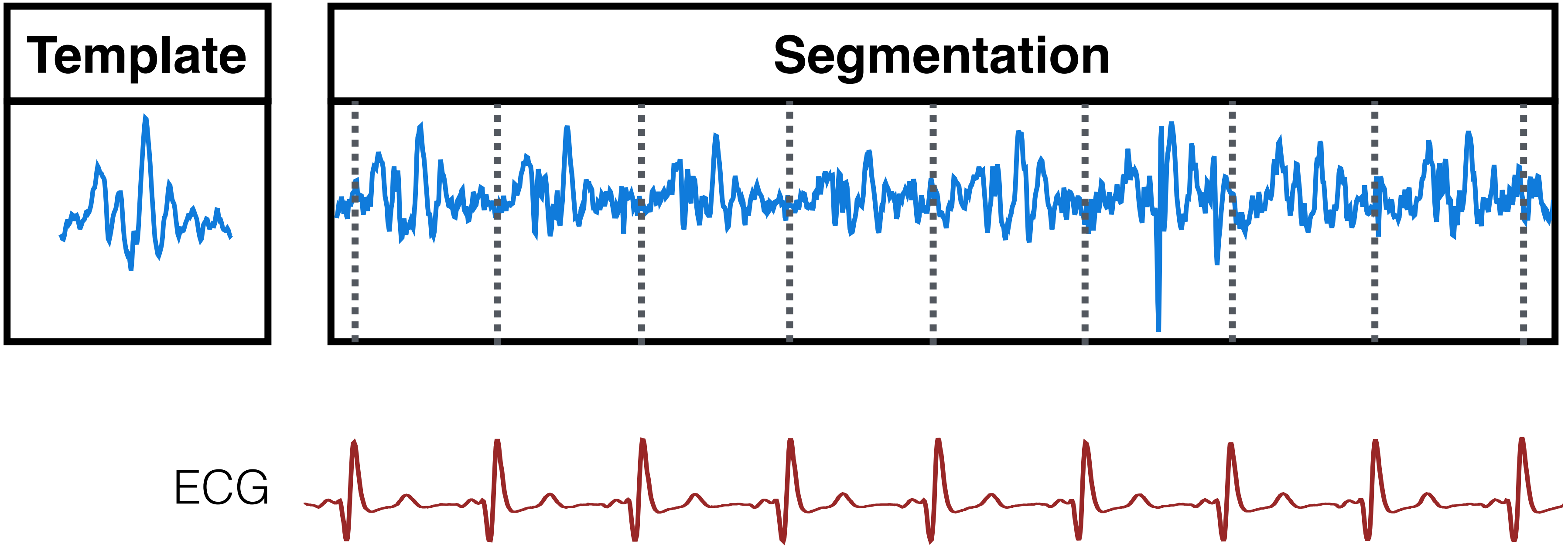
Example run

Iteration 7:



Example run

Iteration 7:



From vital signs to emotions

Physiological Features for Emotion Recognition

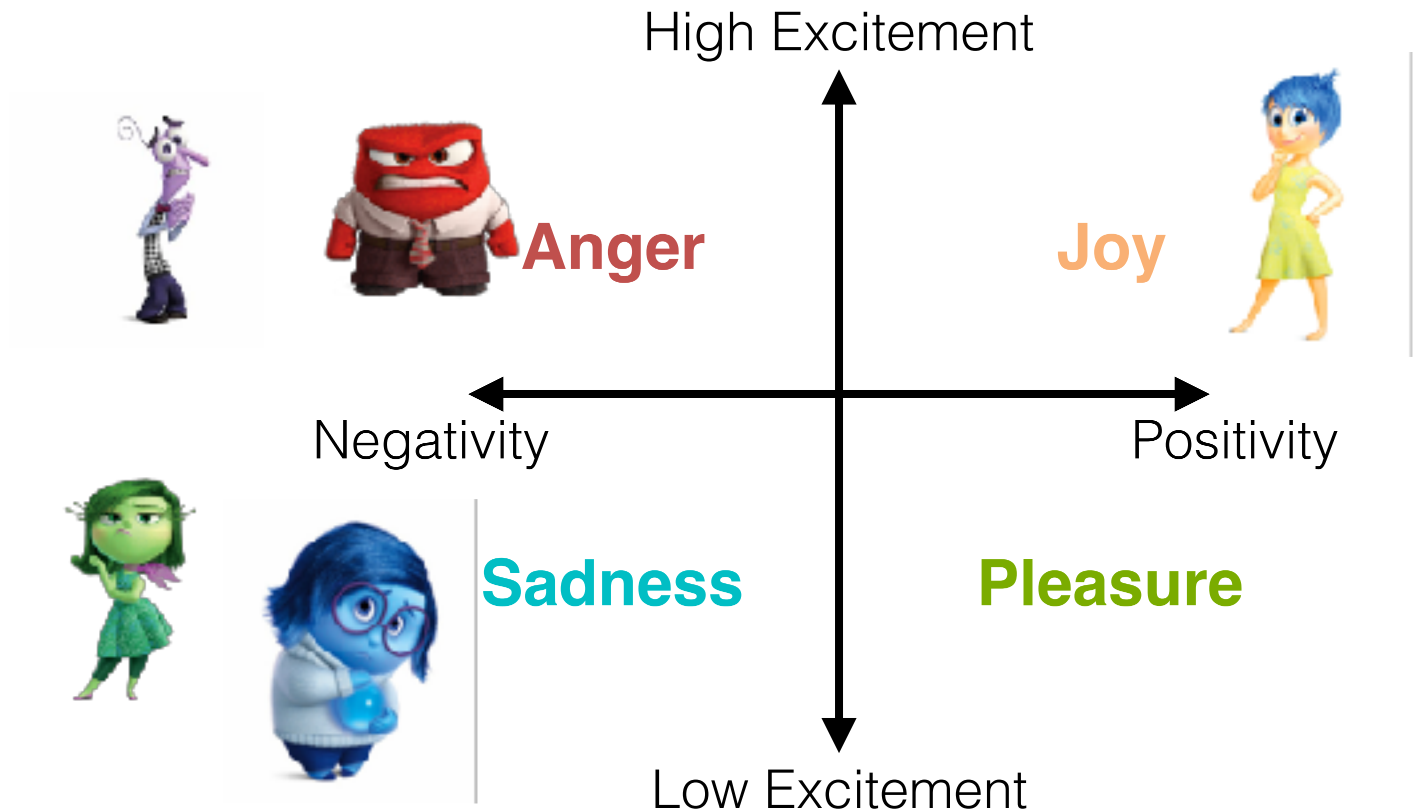
- 37 Features similar to ECG-based methods
  - Variability of IBI
  - Irregularity of breathing

Emotion Classification

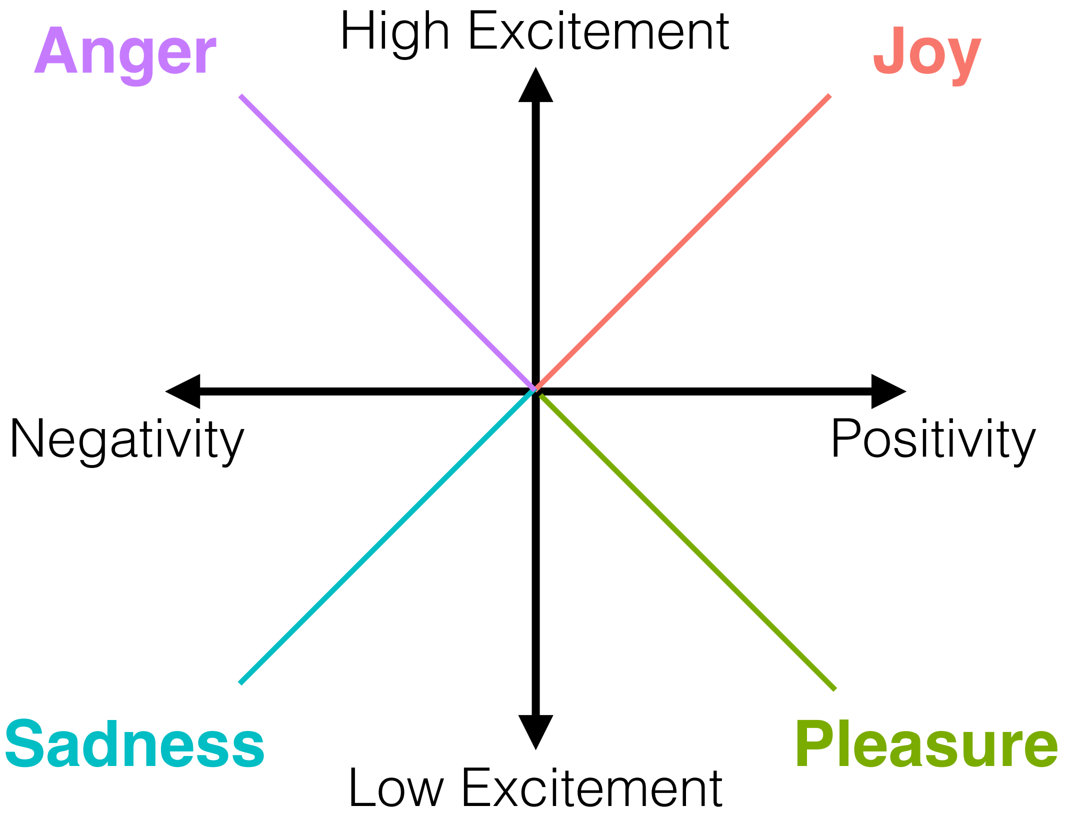
- Recognize emotion using physiological features
- Used L1-SVM classifier
    - select features and train classifier at the same time

Emotion Model

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

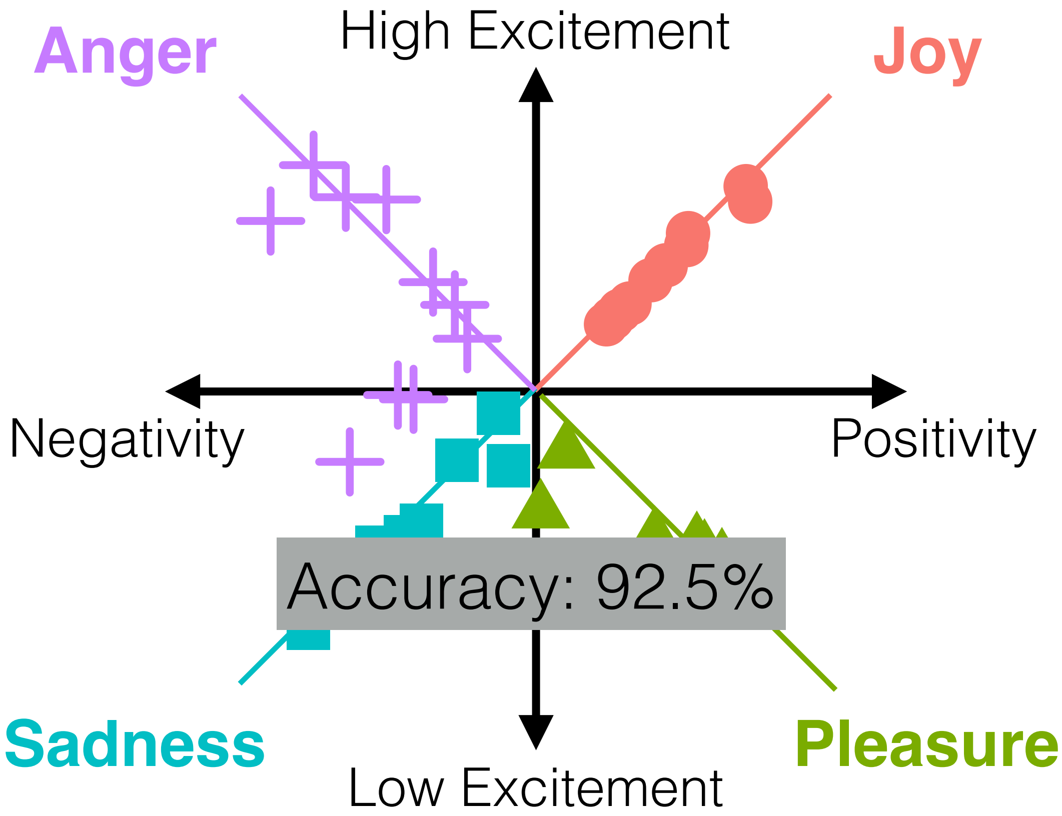


Does it detect emotion accurately?



Person-dependent Classification

- Train and test on the same person



Person-independent Classification

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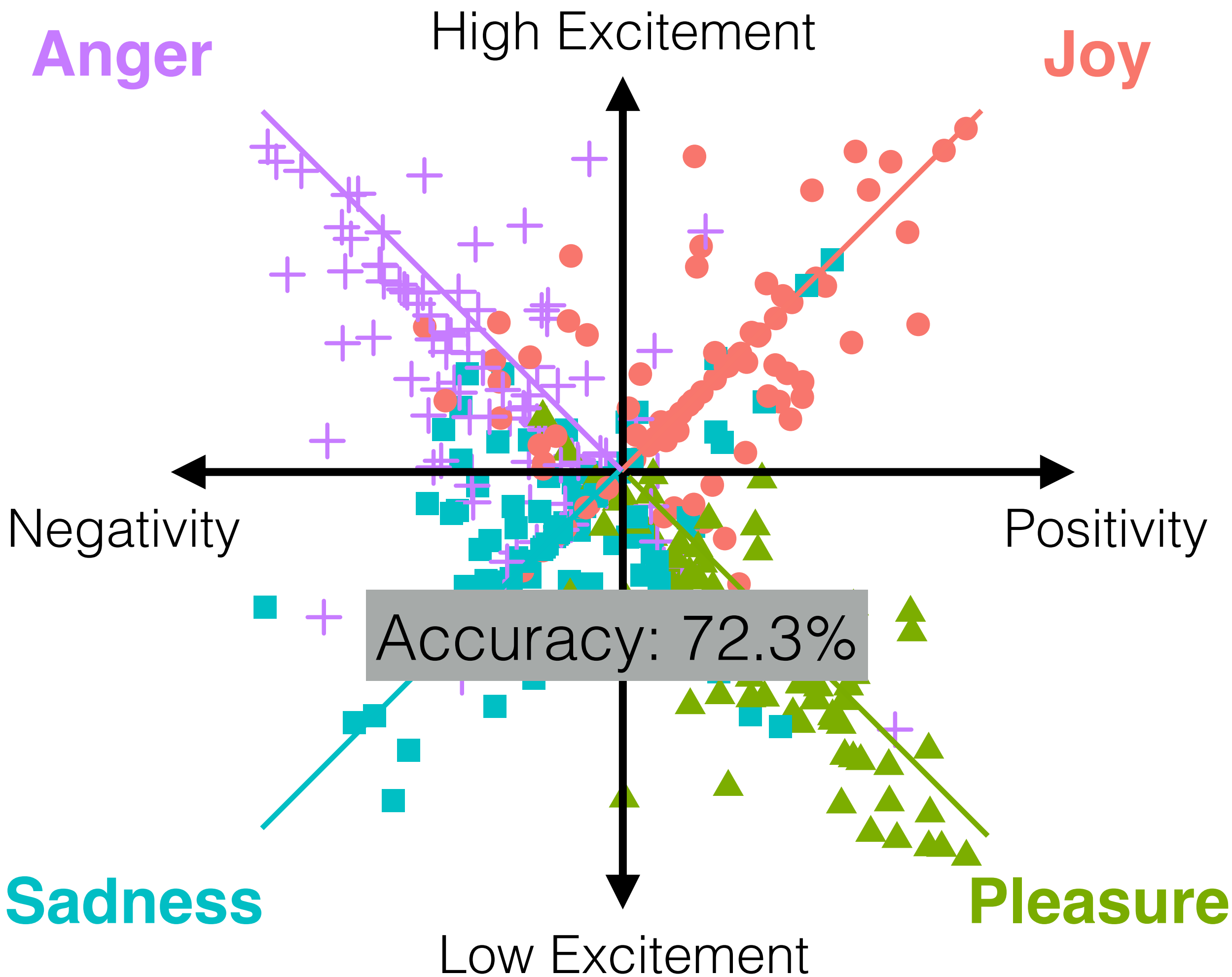
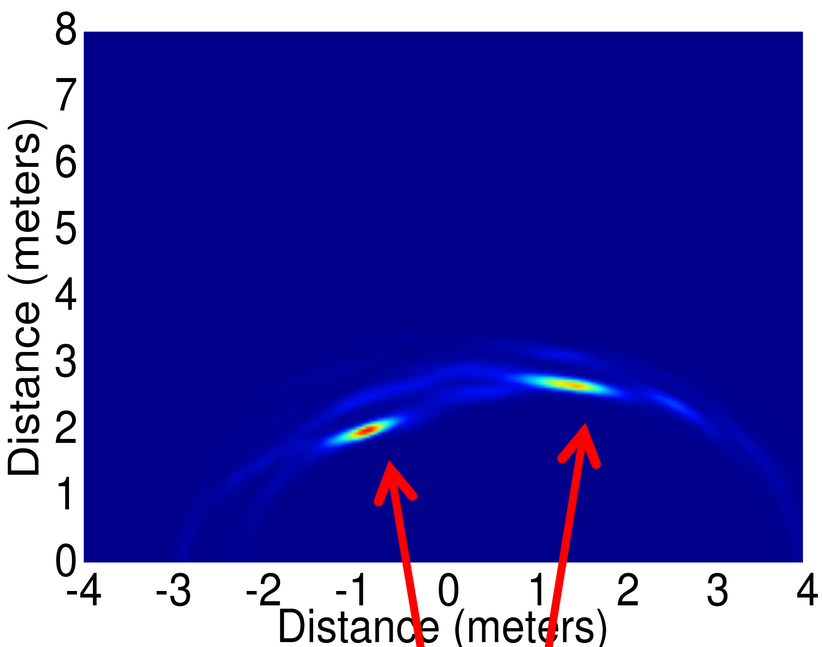


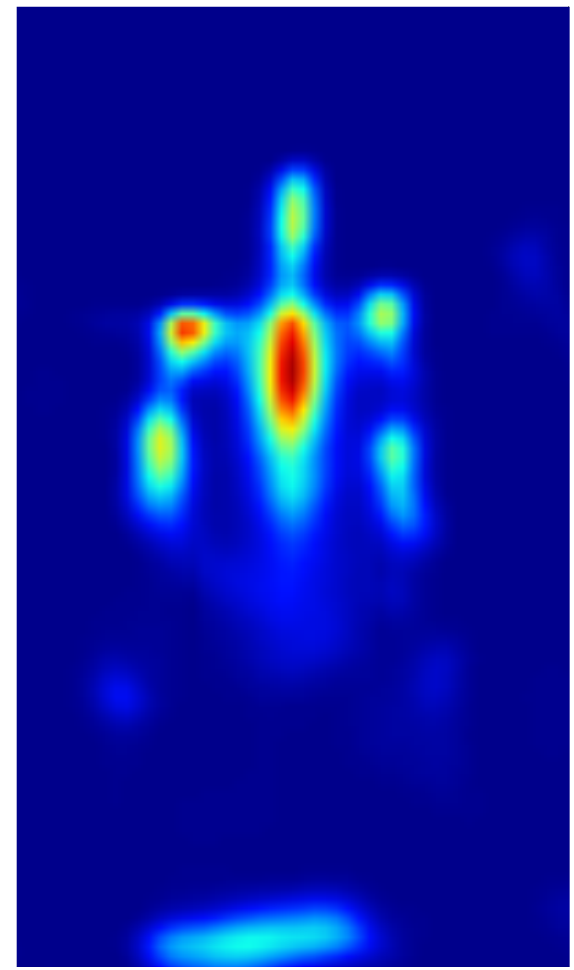
RF Imaging

People are points

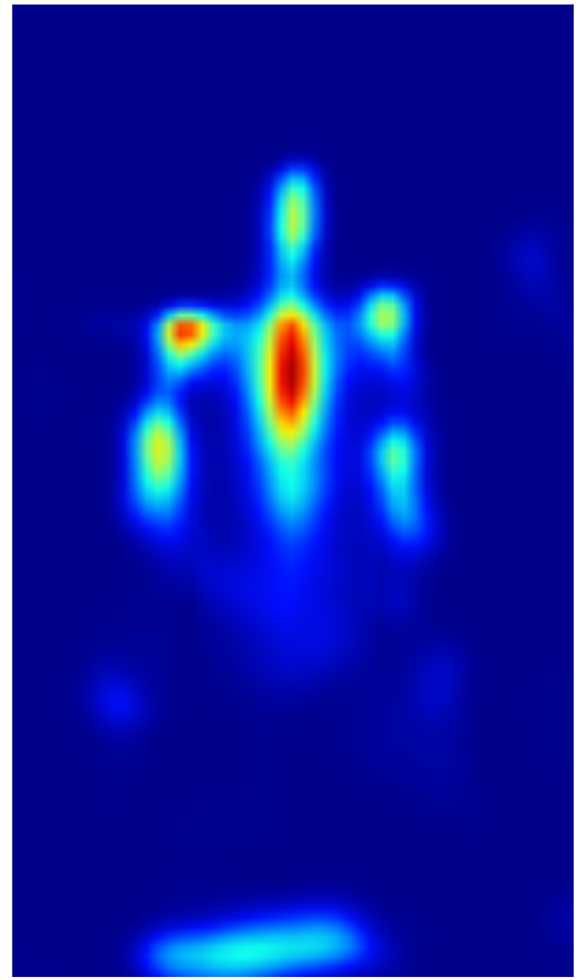


Localize the two users

Want a silhouette



Capturing a Coarse Human Silhouette



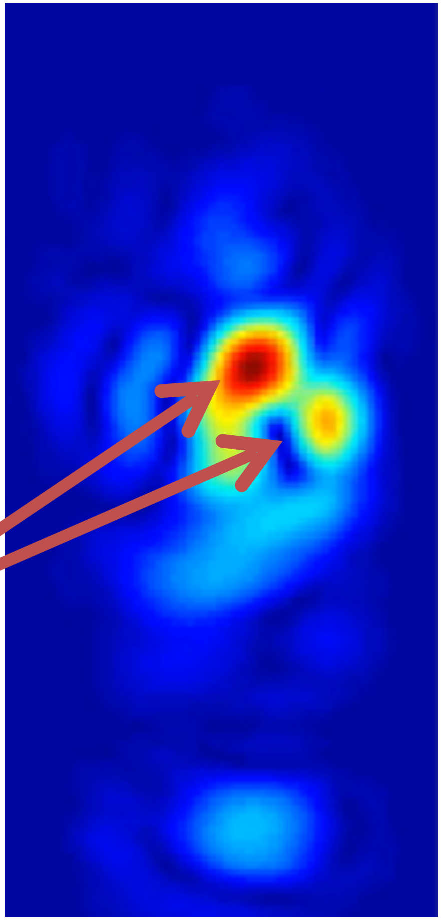
Traditional Imaging		RF Imaging
Cannot image through occlusions like walls	+	Walls are transparent and can image through them
Form 2D images using lenses	−	No lenses at these frequencies
Get a reflection from all points: can image all the body	−	No reflections from most points: all reflections are specular

RF Imaging

- Walls are transparent and can image through them
- No lenses at these frequencies → Our Solution: A component that scans 3D space with RF and outputs reflection snapshots at every point in time
- No reflections from most points: all reflections are specular → ?

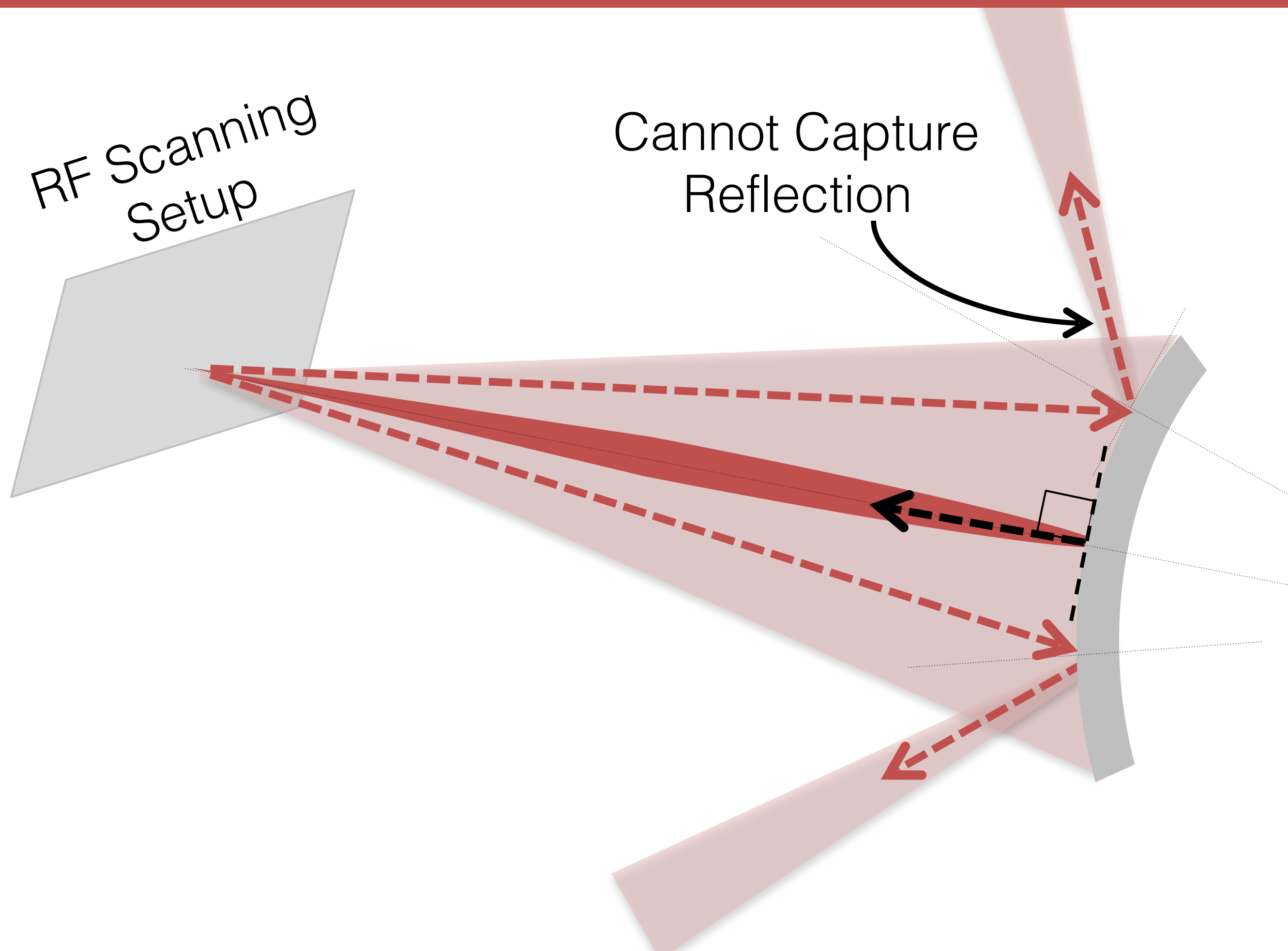
Challenge: We only obtain blobs in space

Output of 3D RF Scan

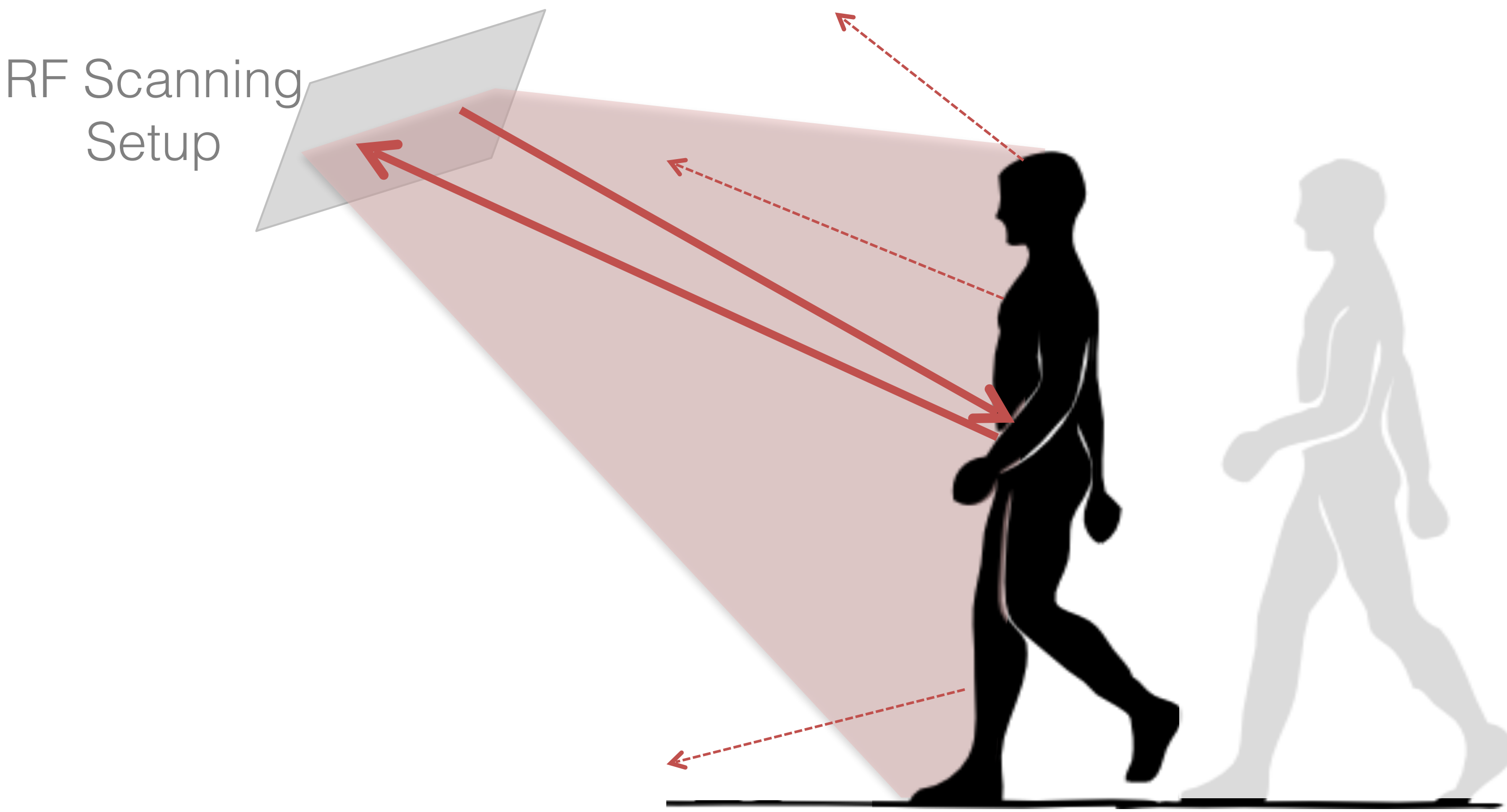


Blobs of reflection power

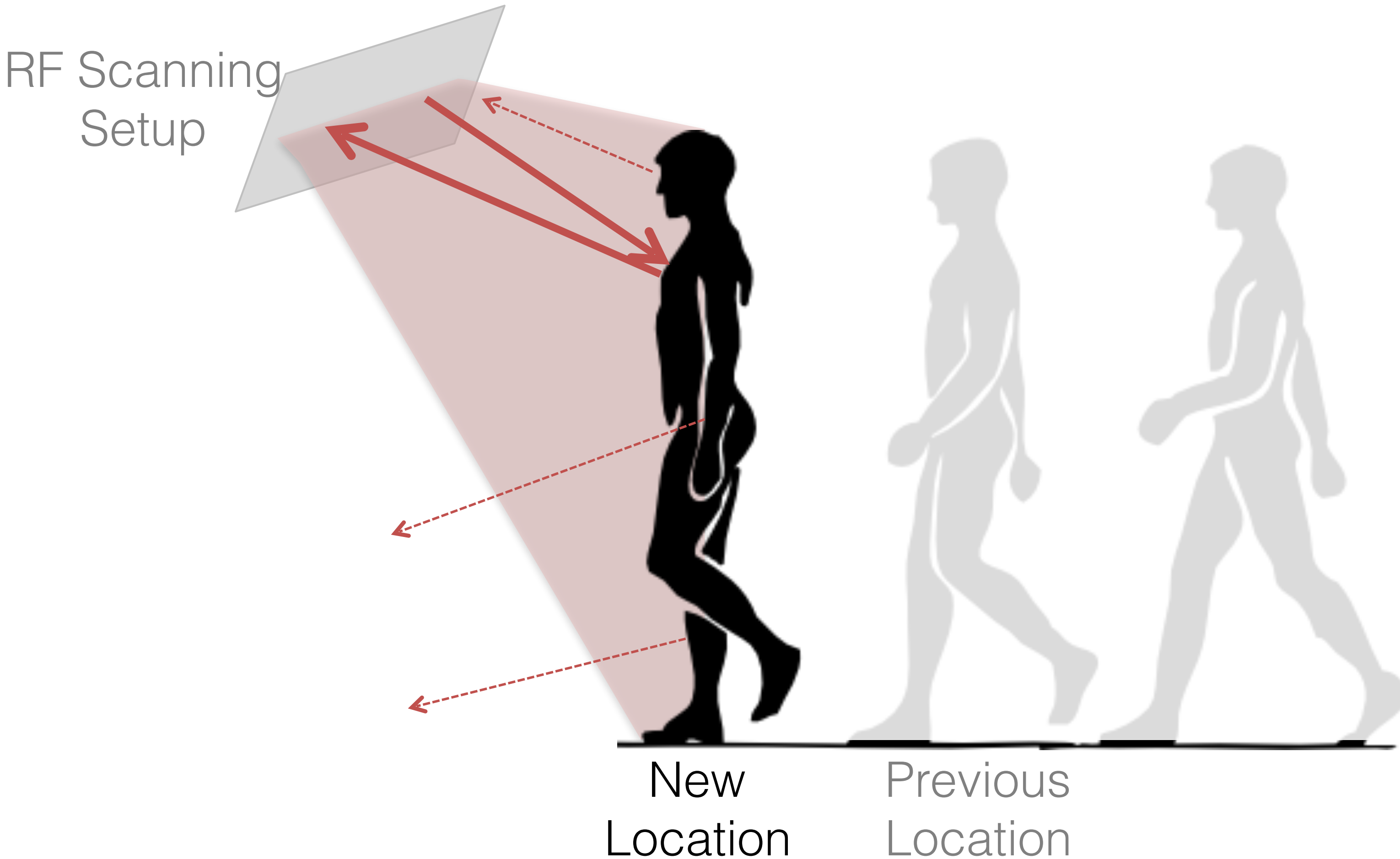
At every point in time, we get reflections from only a subset of body parts.



Solution Idea: Exploit Human Motion and Aggregate over Time

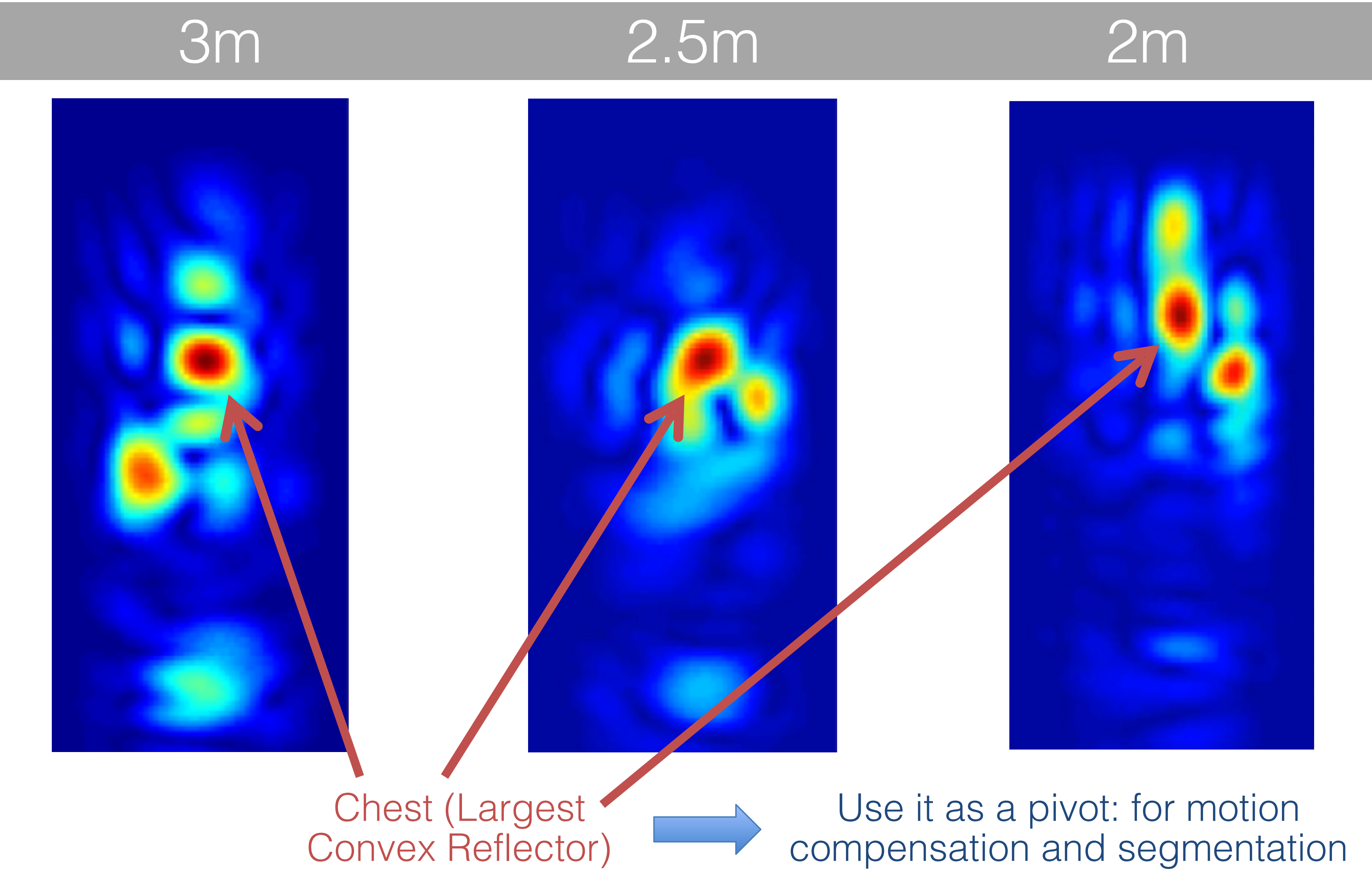


Solution Idea: Exploit Human Motion and Aggregate over Time

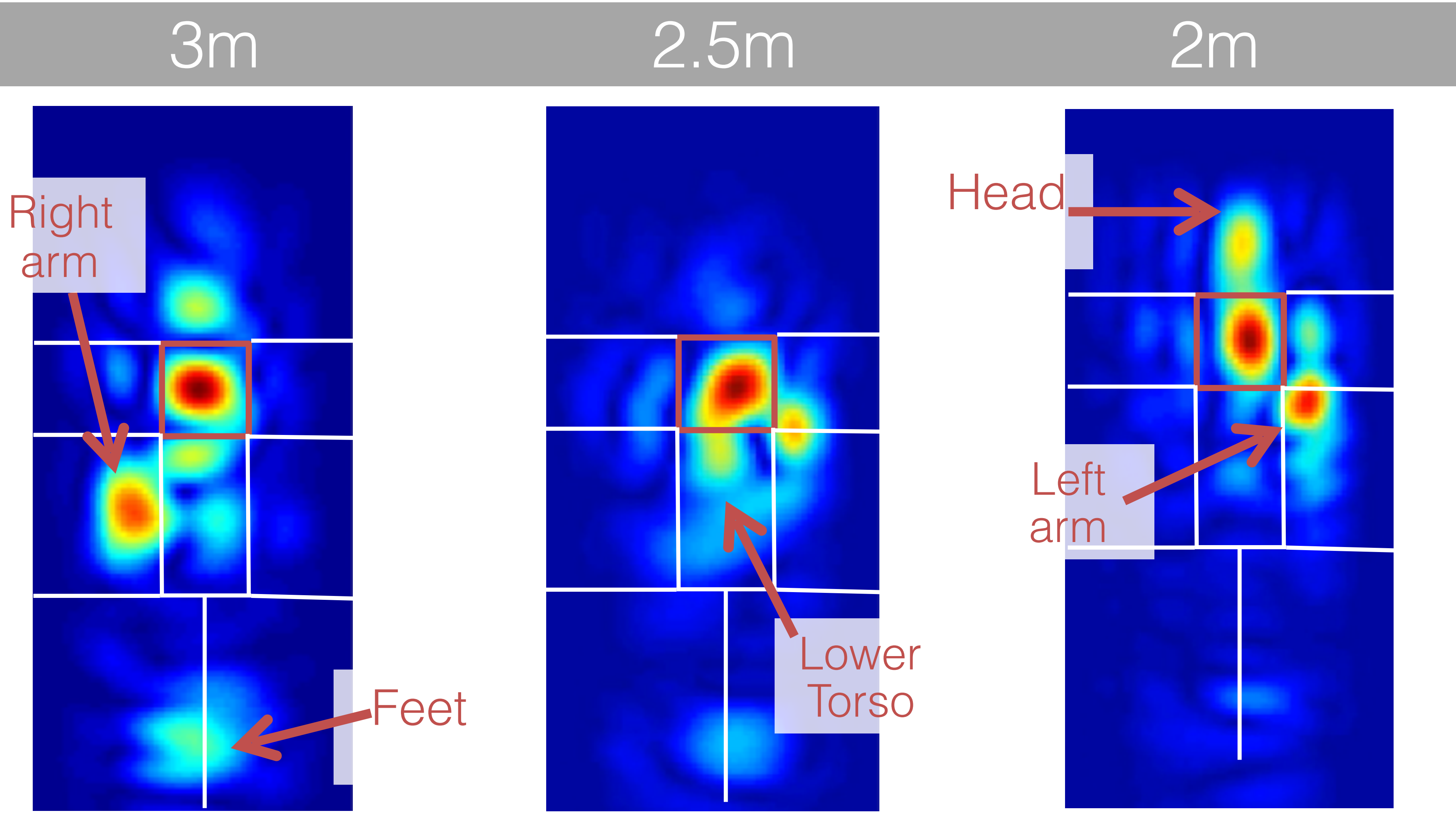


Combine the various snapshots

Human Walks toward Sensor



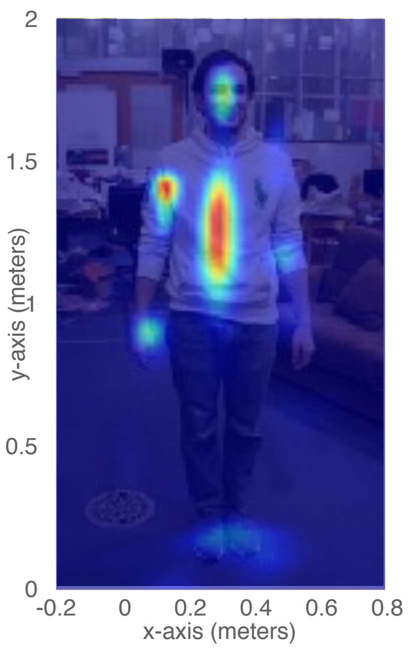
Human Walks toward Sensor

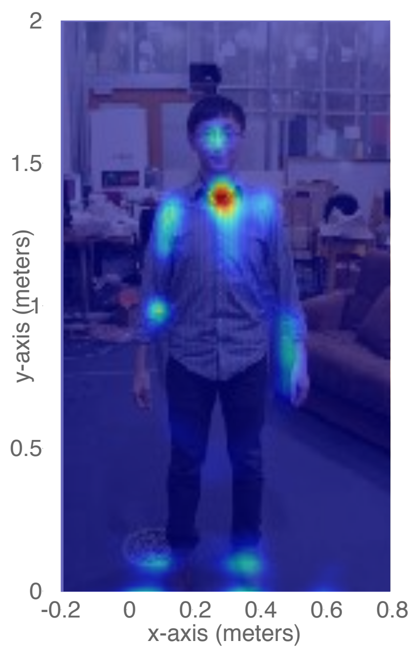


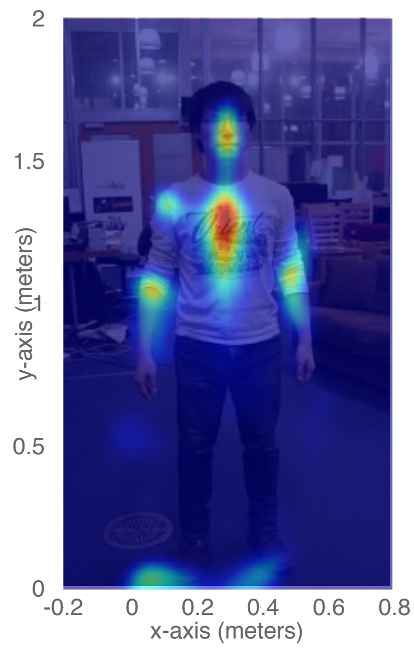
Combine the various snapshots

Human Walks toward Sensor

Sample Captured Figures through Walls







Through-wall classification accuracy of 90% among 13 users