ECE 598HH: Special Topics in Wireless Networks and Mobile Systems

Lecture 15: Wireless Sensing Part 2

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CSL: COORDINATED SCIENCE LAB

Slides Courtesy of Mingmin Zhao and Fadel Adib

Interest in Sensing the Human Body

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Interest in Sensing the Human Body

Heart Rate

Breathing

Interest in Sensing the Human Body

Heart Rate

Breathing

Locations

Interest in Sensing the Human Body

Heart Rate

Breathing

Locations

Gestures

Heart Rate Breathing Locations Gestures

On-body sensors can be cumbersome

Heart Rate

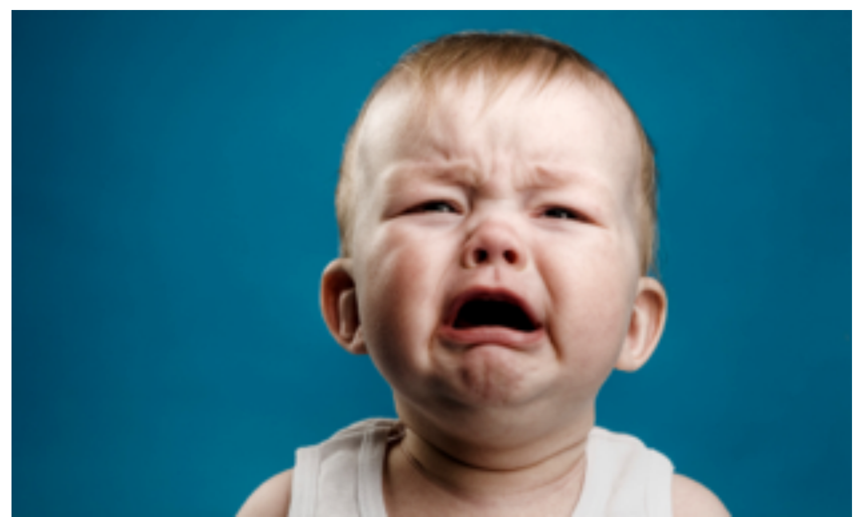
Breathing

Locations

Gestures

On-body sensors can be cumbersome

Not suitable for elderly & babies



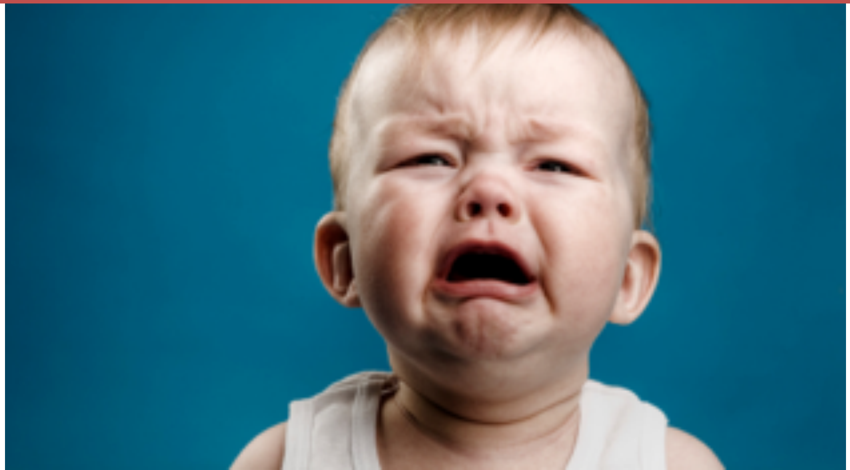
Heart Rate

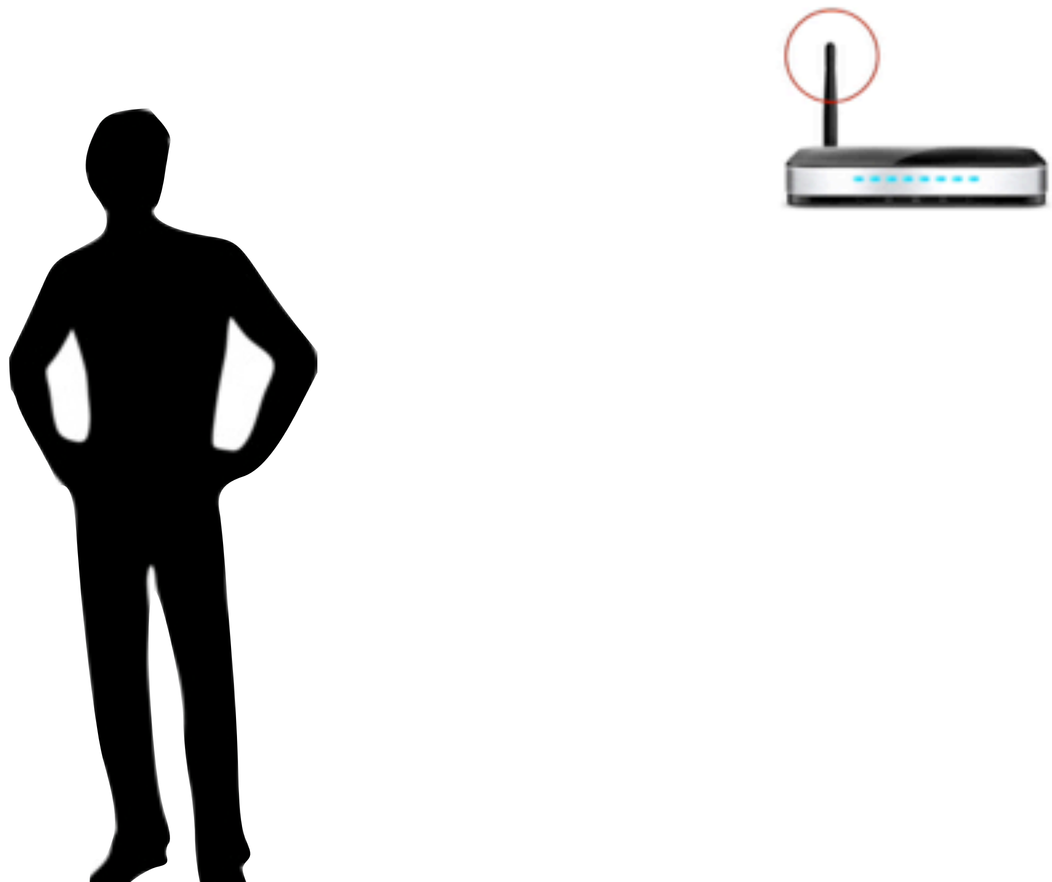
Breathing

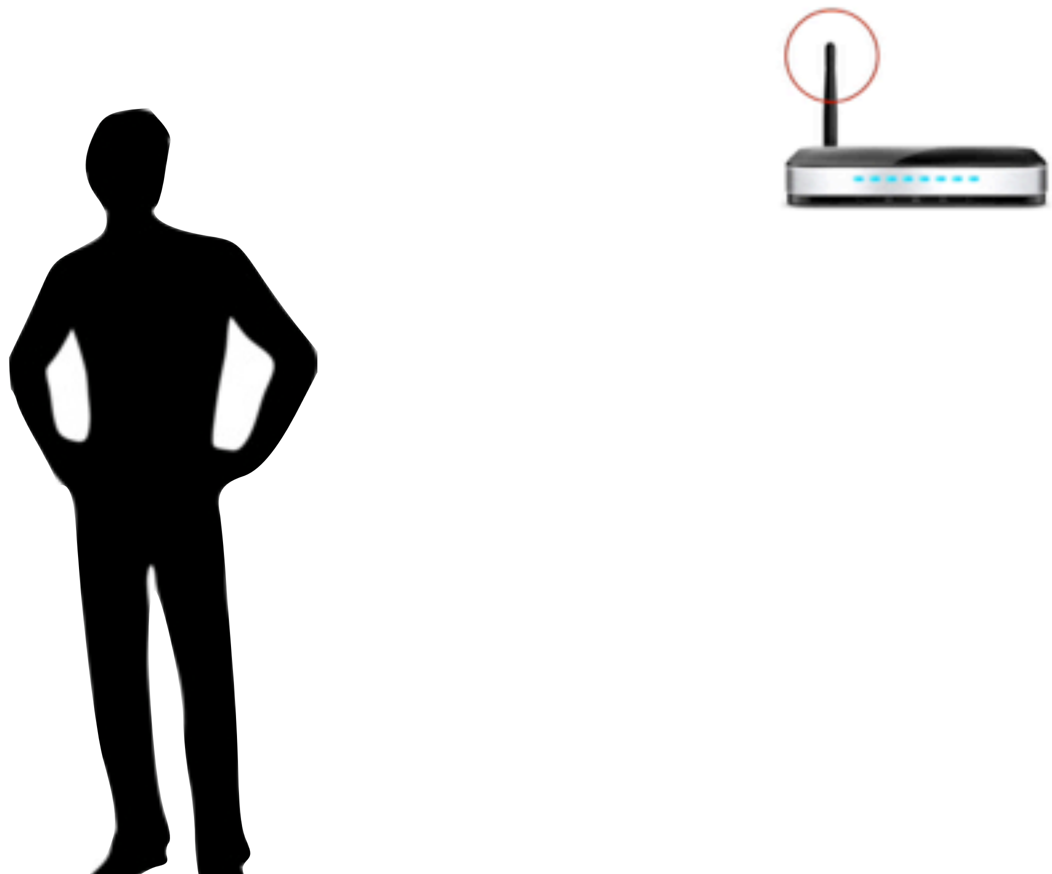
Locations

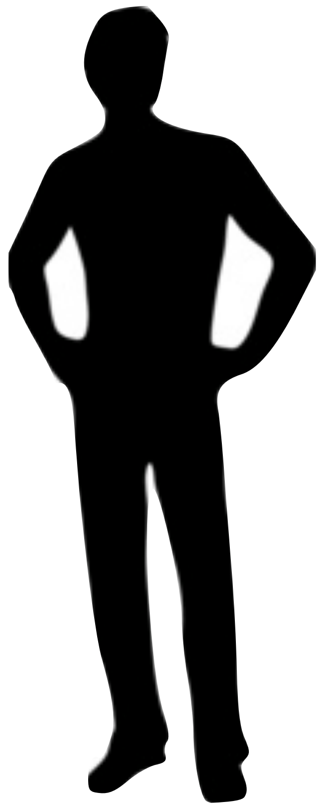
Gestures

Imagine enabling these applications without sensors on the human body

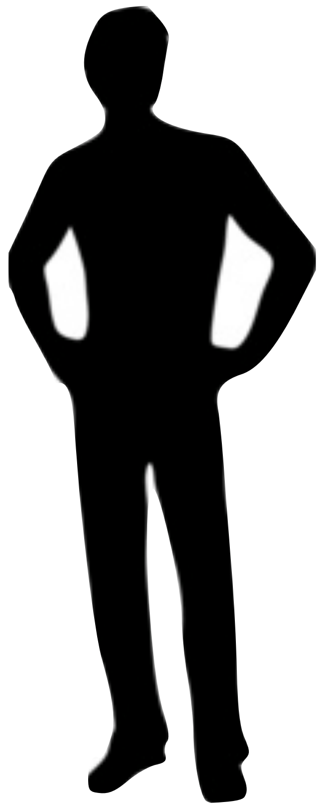








- Location
- Vital Signs
- Imaging

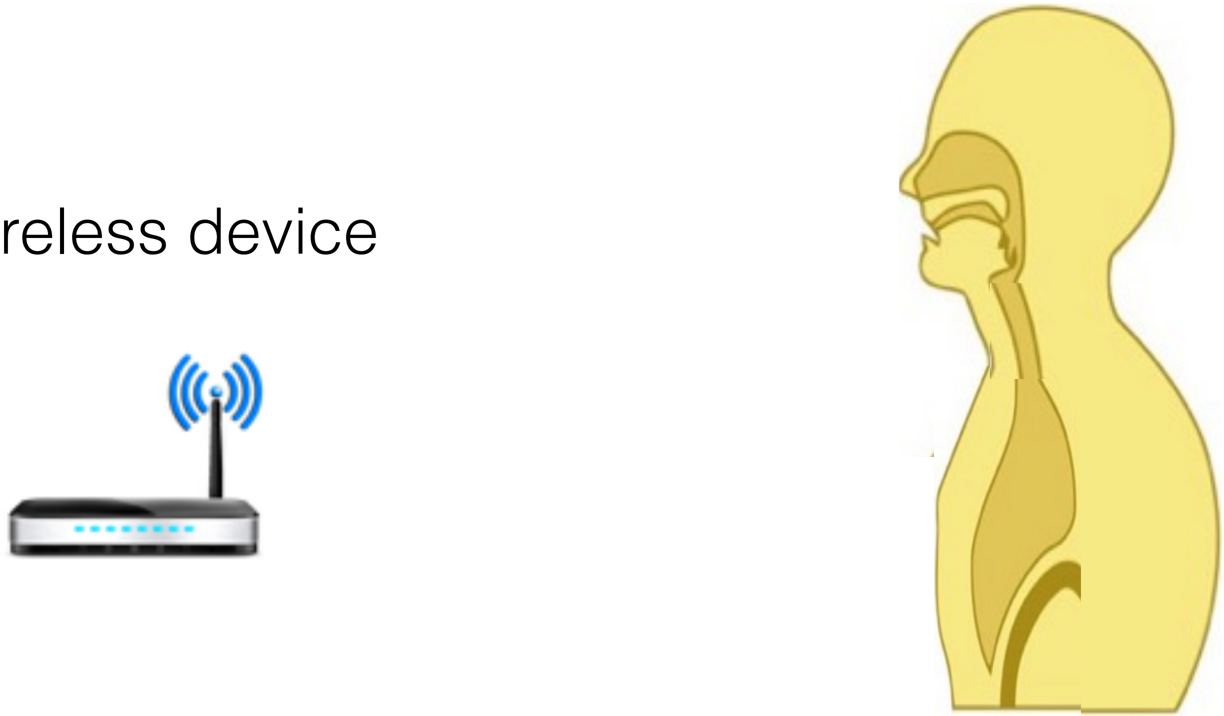


- Location
- Vital Signs
- Imaging

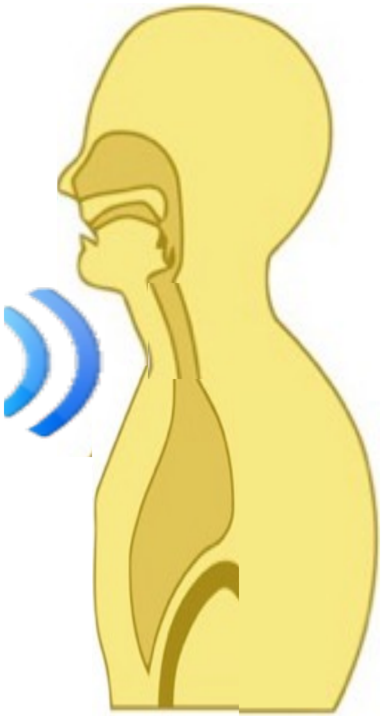
Operates through occlusions

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

Wireless device



Wireless device



Device analyzes the wireless reflections to compute distance to the body

Wireless device

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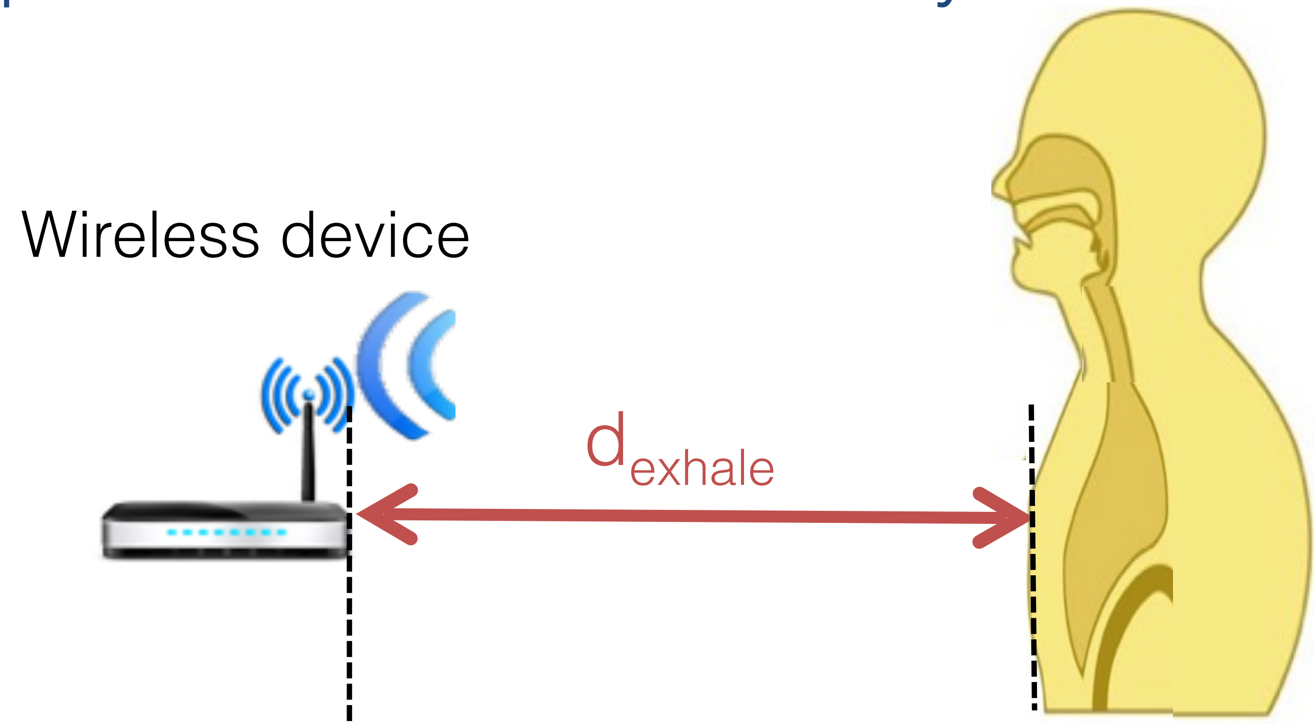

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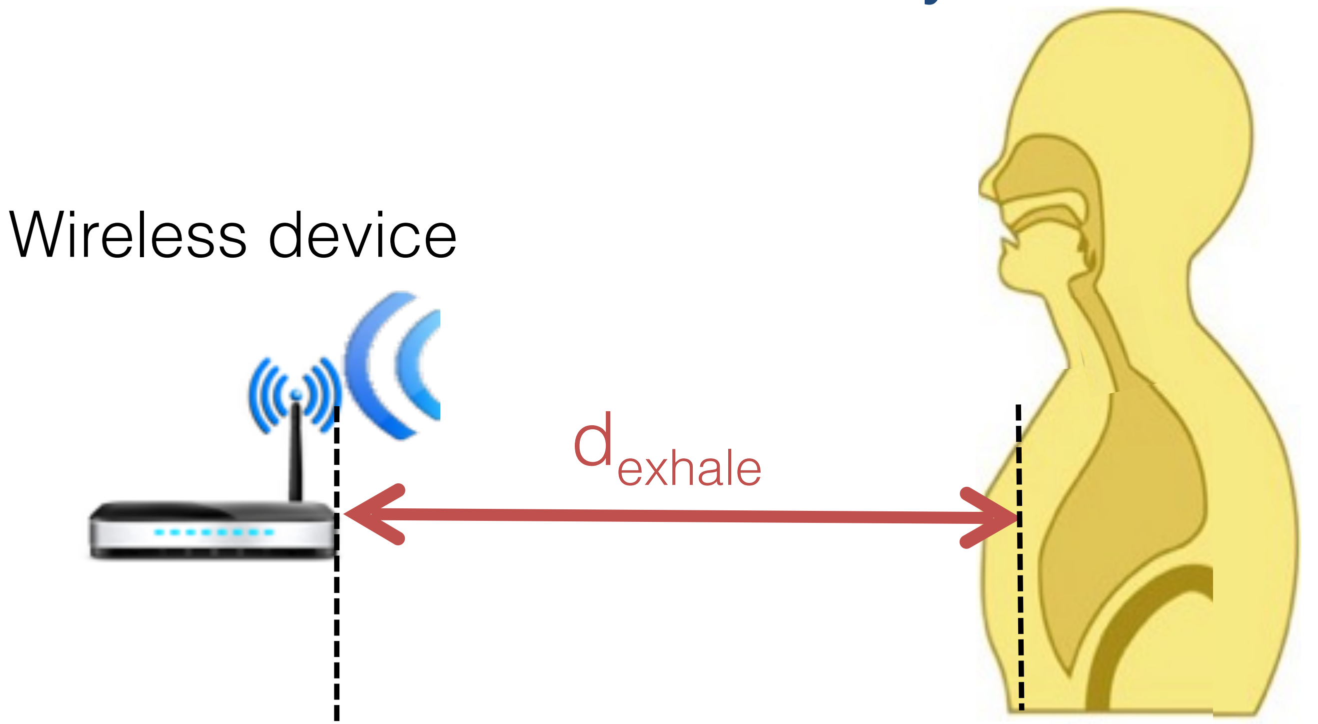

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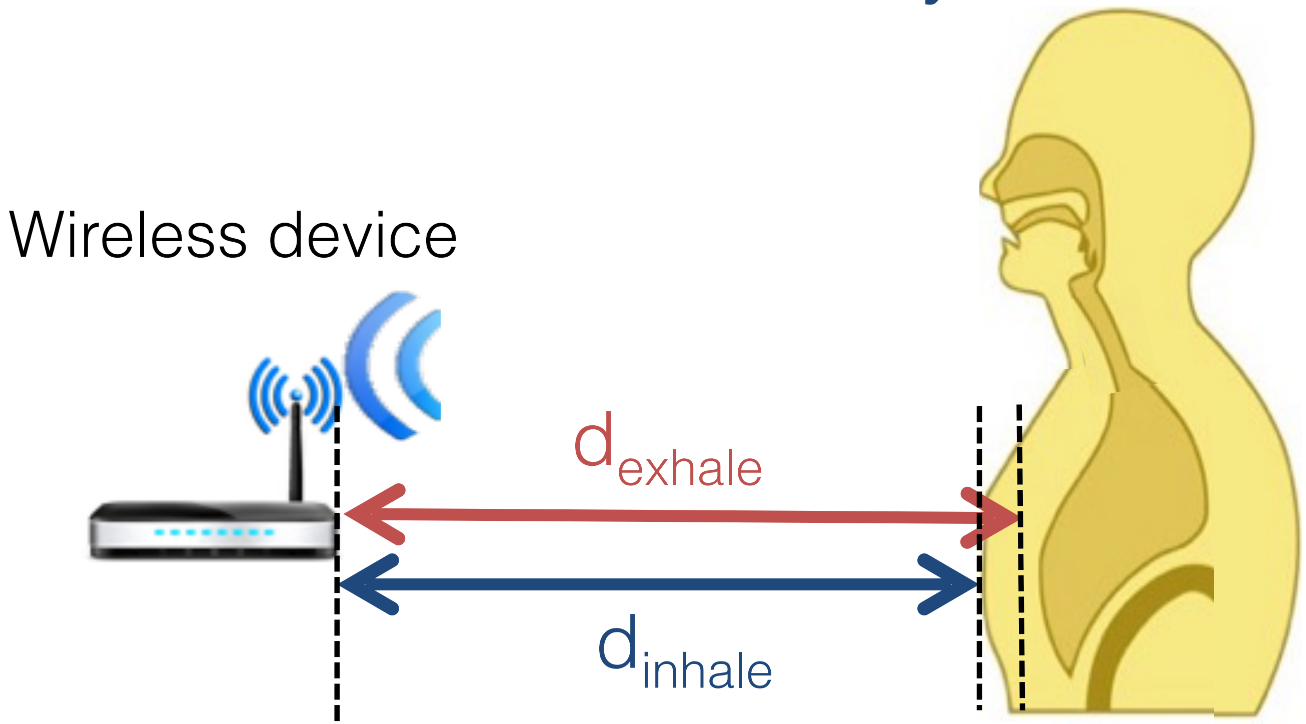
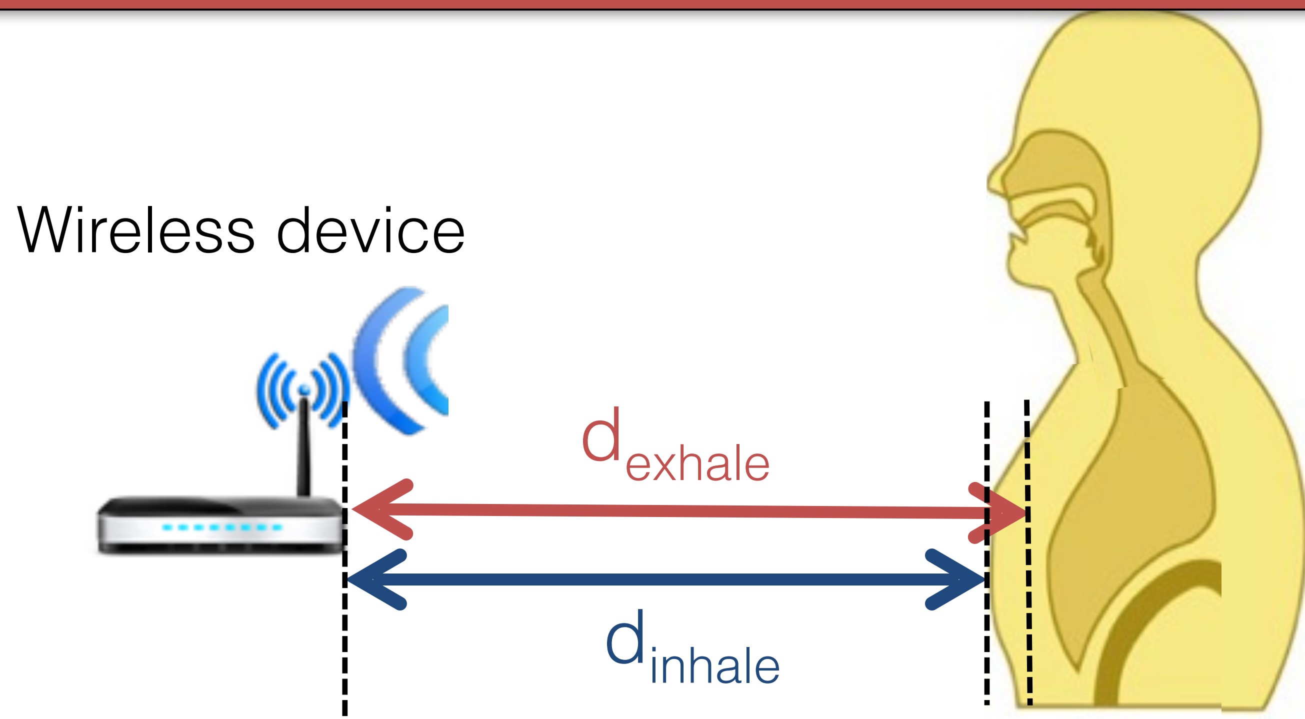


Problem: Localization accuracy is only 12cm and cannot capture vital signs



FMCW: Measure time by measuring frequency

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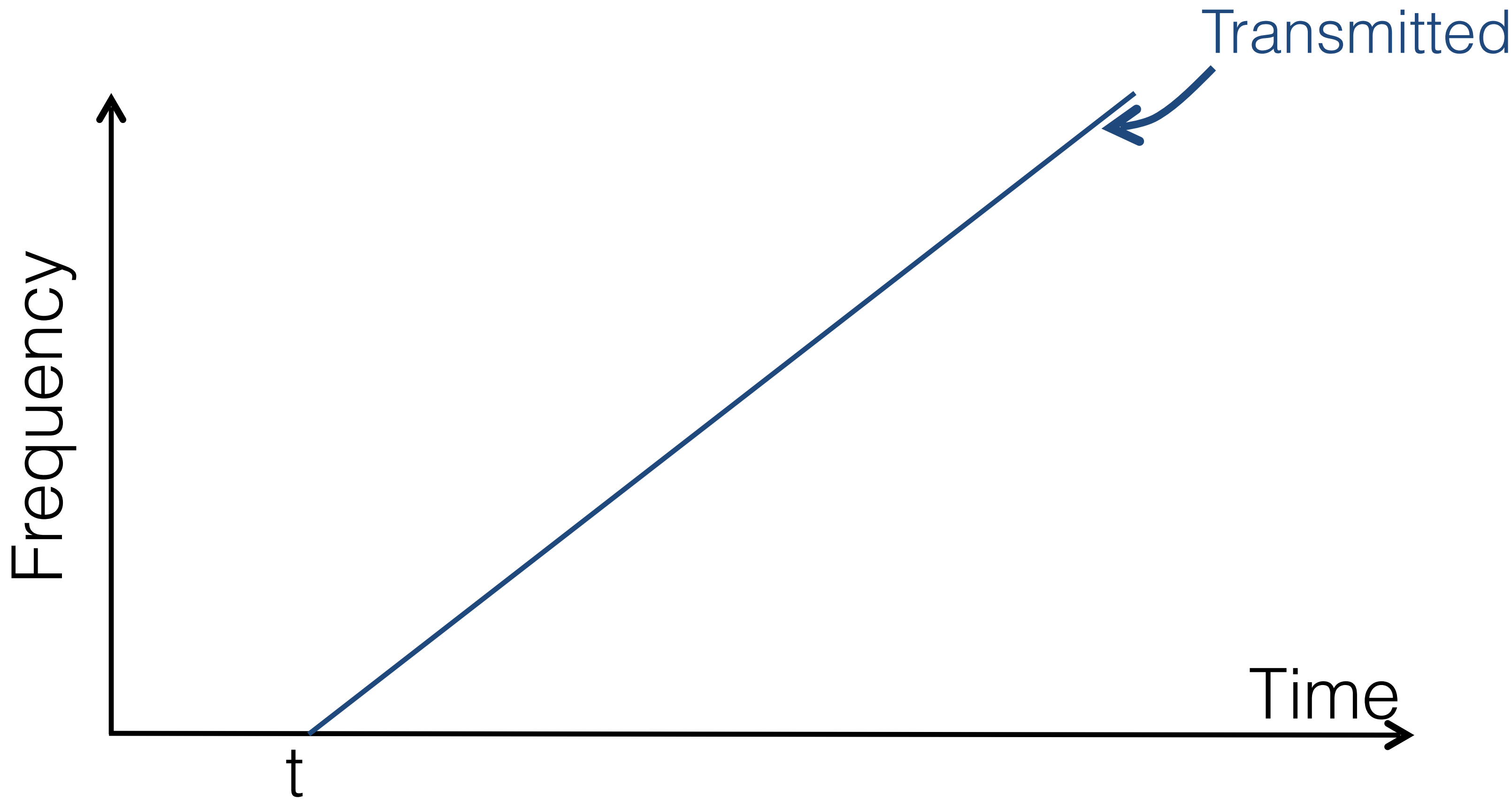

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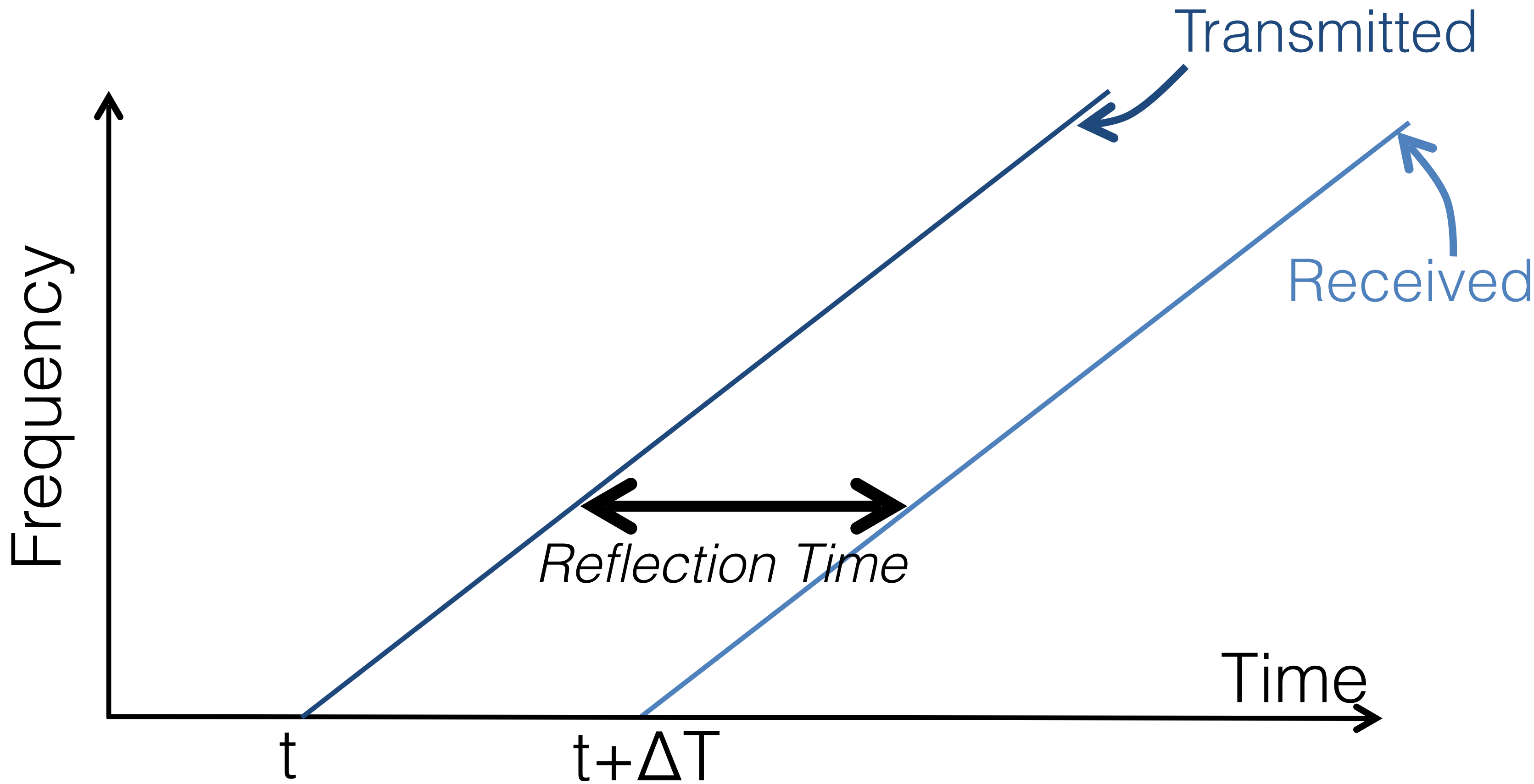

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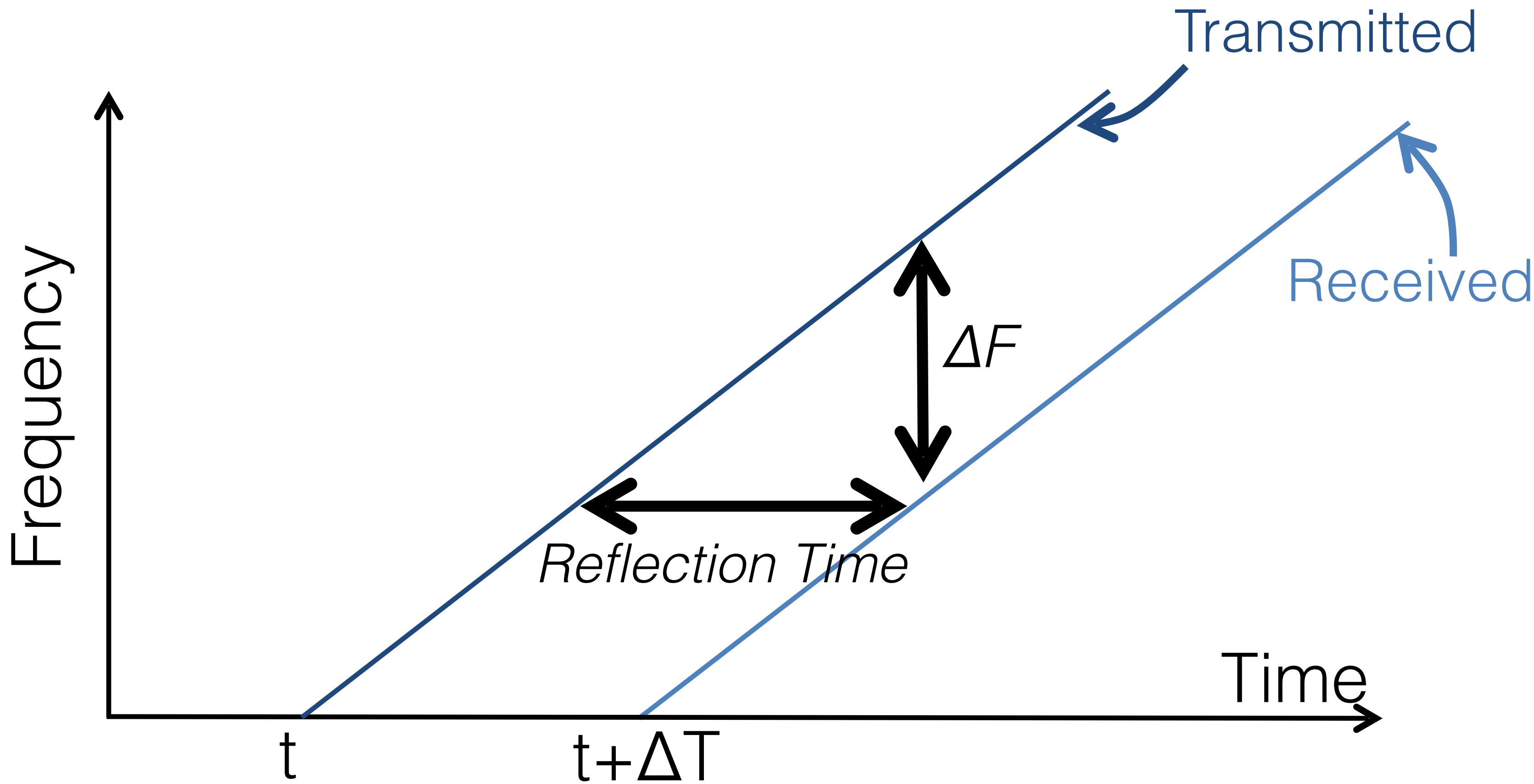

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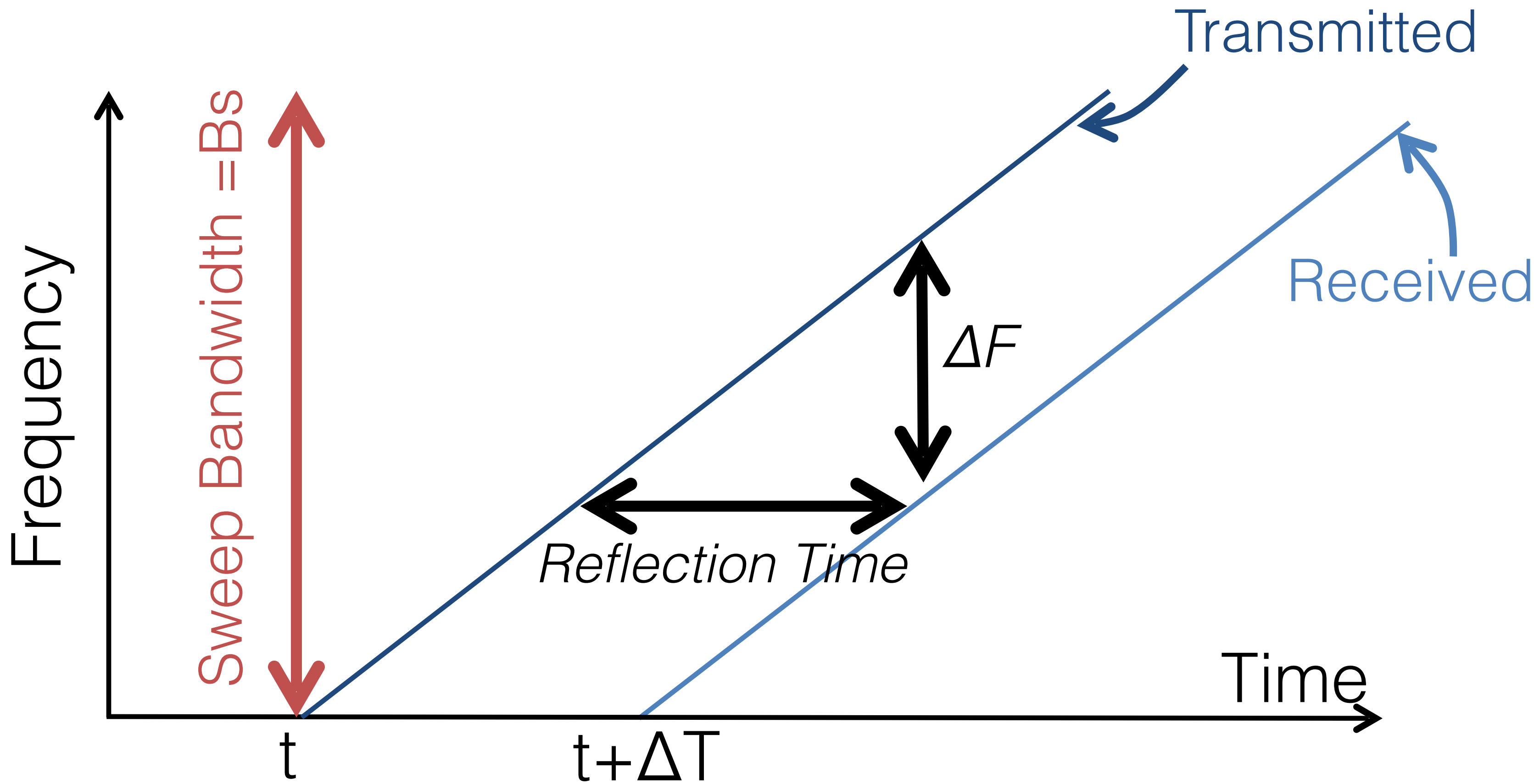

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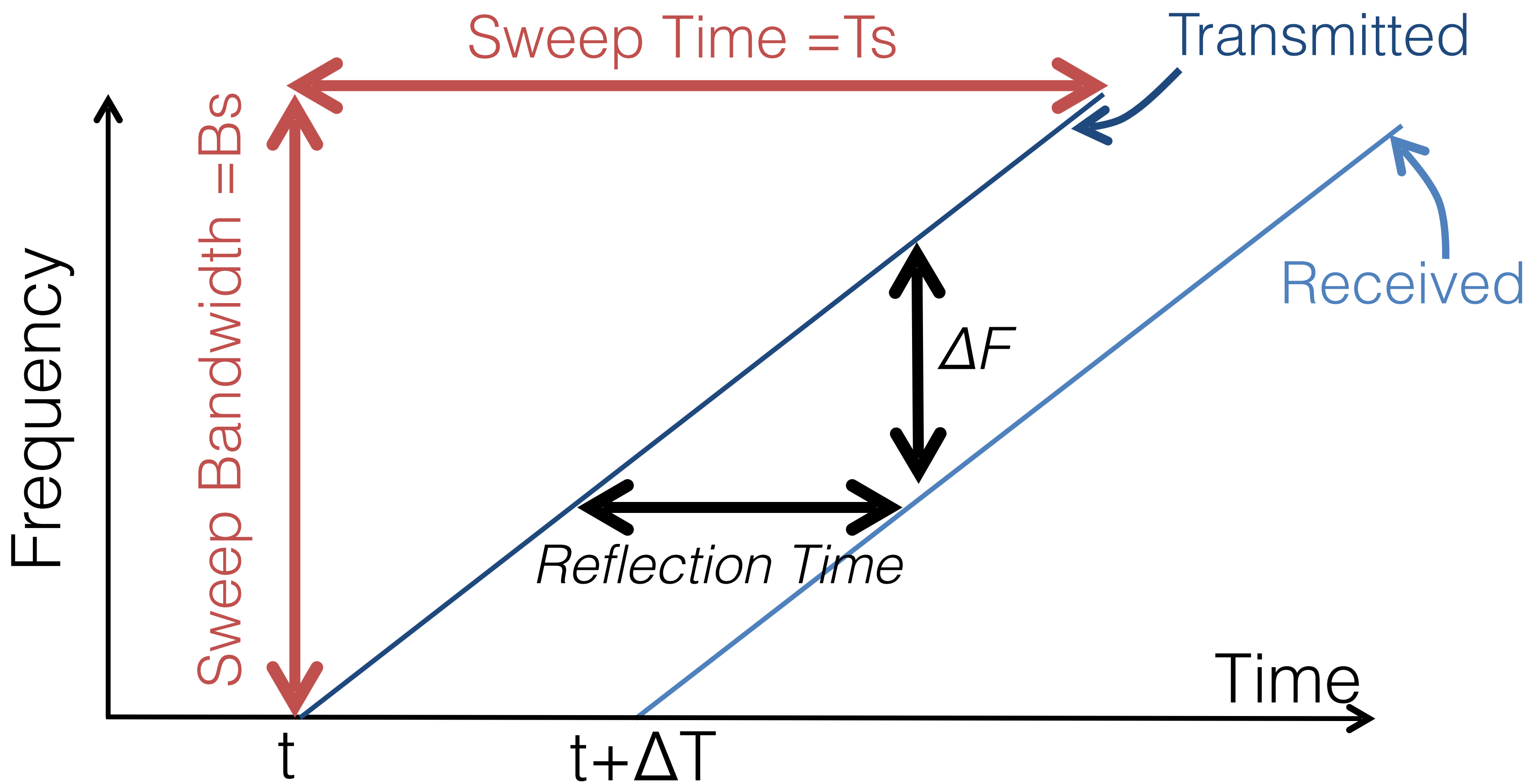

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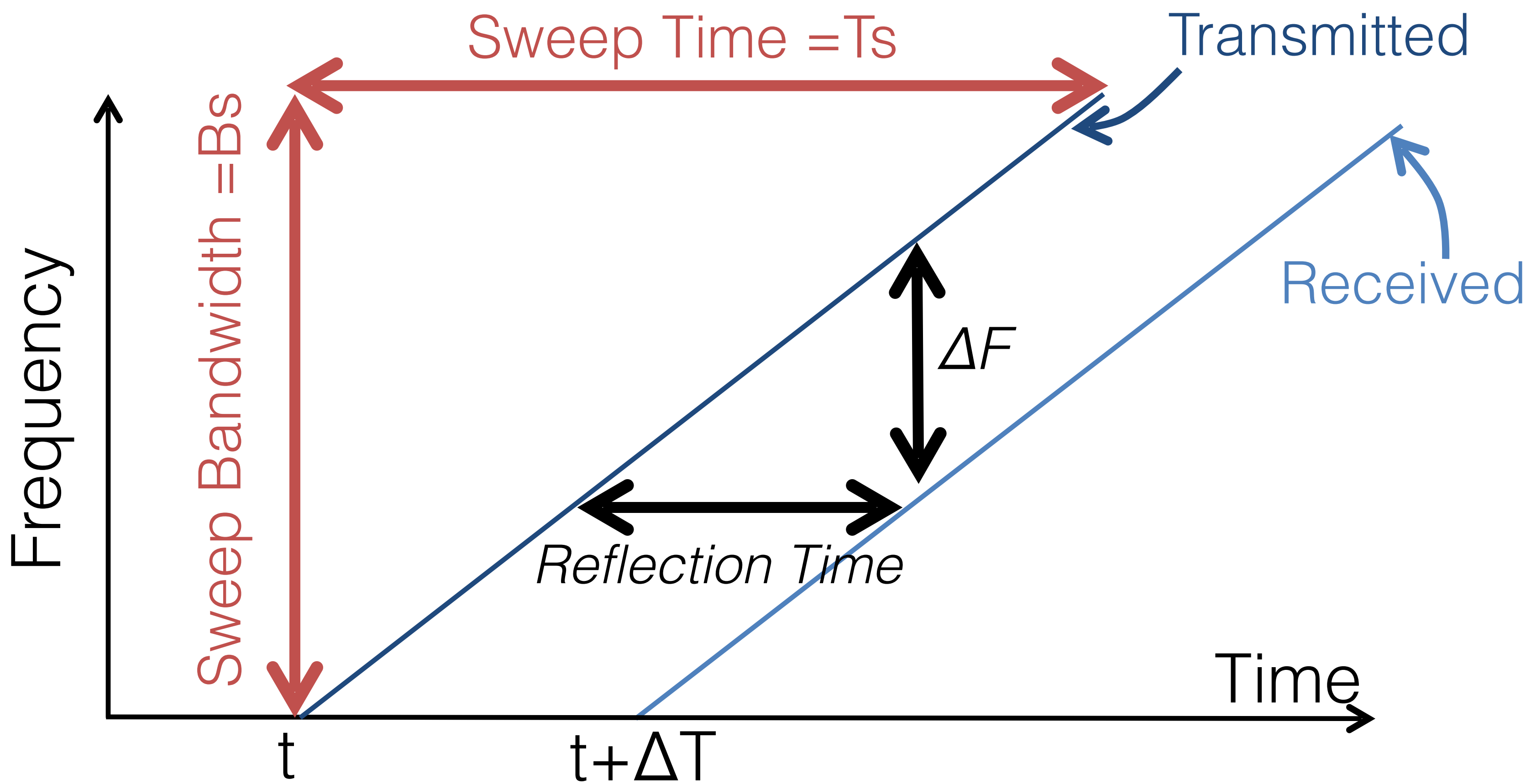
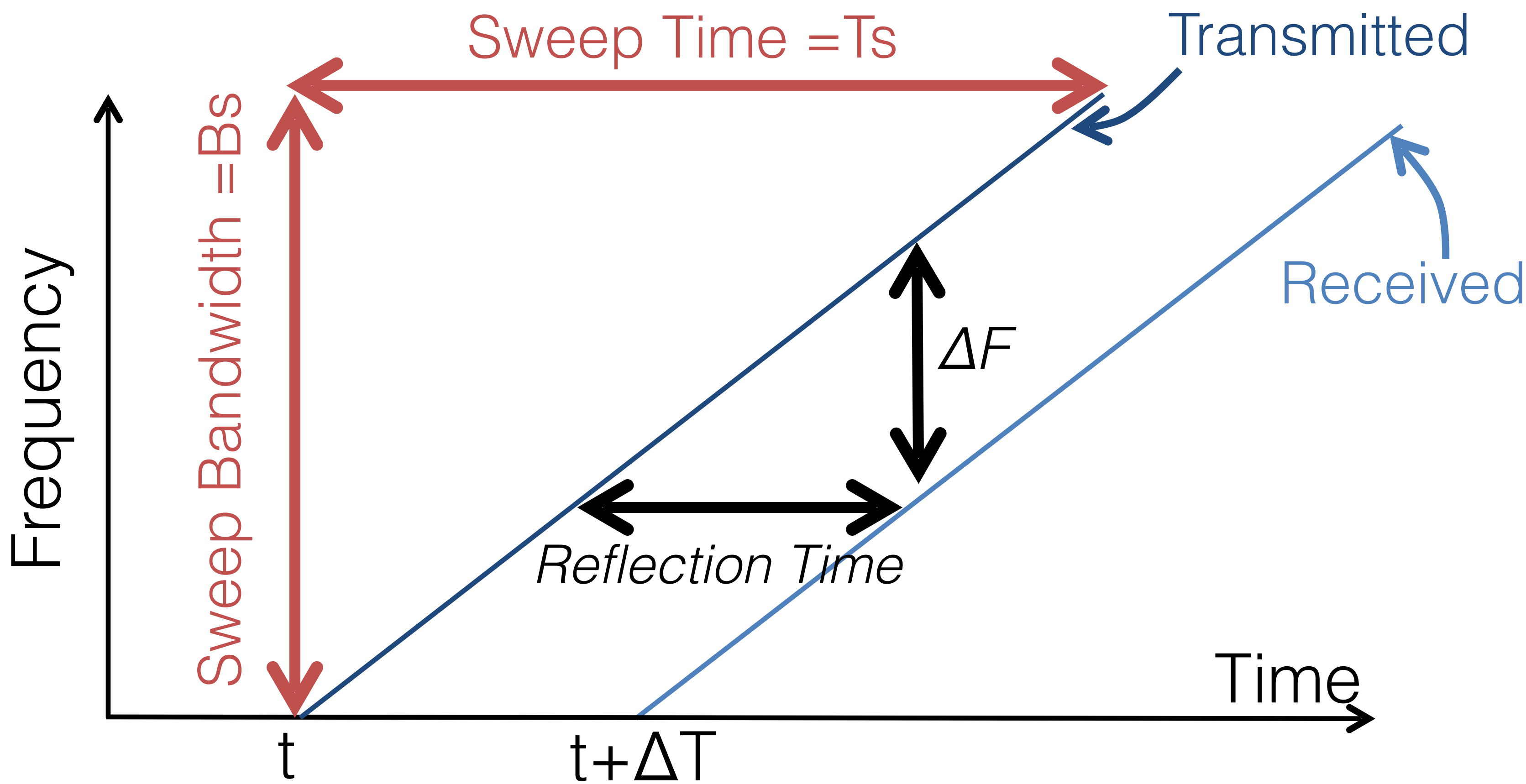


Slope = k = Bs/Ts

FMCW: Measure time by measuring frequency



Slope = k = Bs/Ts

Reflection Time =ΔF/k

FMCW

FMCW

- FMCW Transmitted Signal:

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

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

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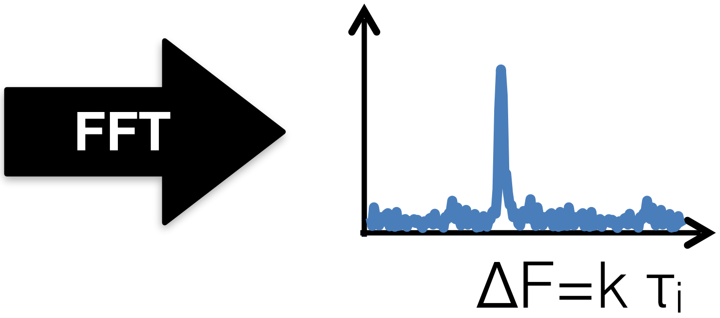

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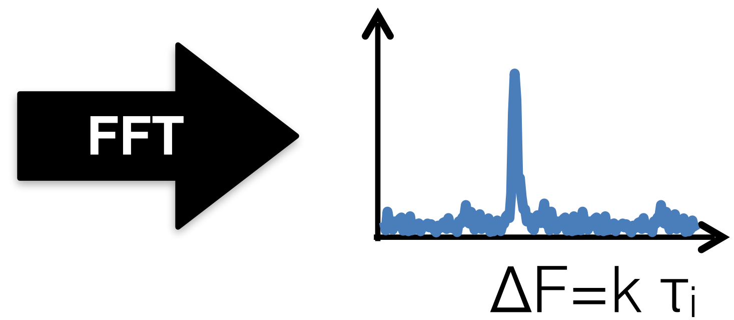

- Sampling Rate = B

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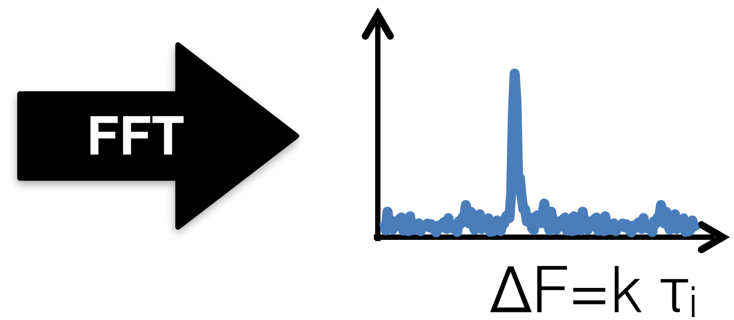

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  ΔF < B

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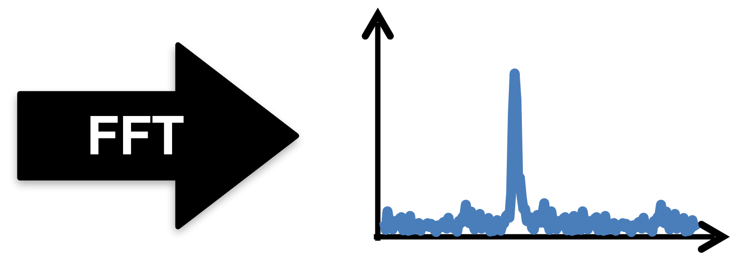

$\Delta F = k\ \tau_i$

- Sampling Rate = B

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

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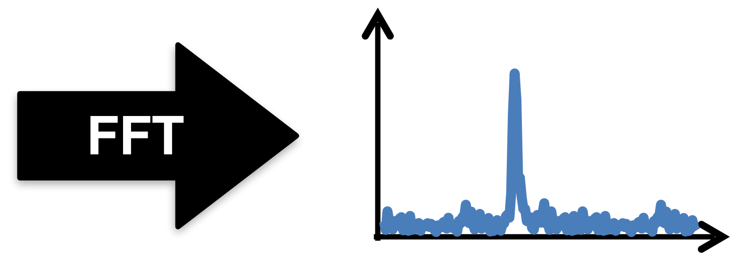

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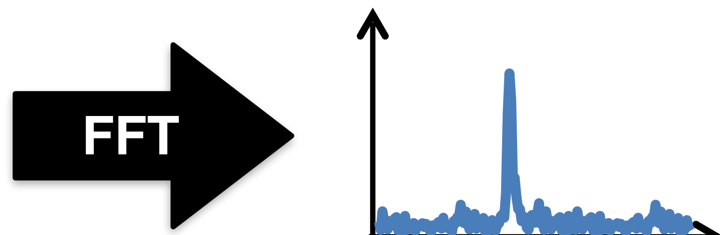

$\Delta F = k\ \tau_i$

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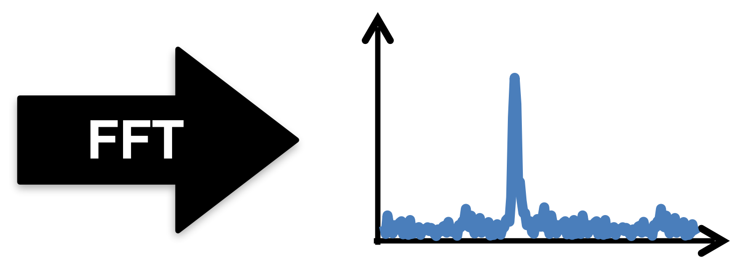

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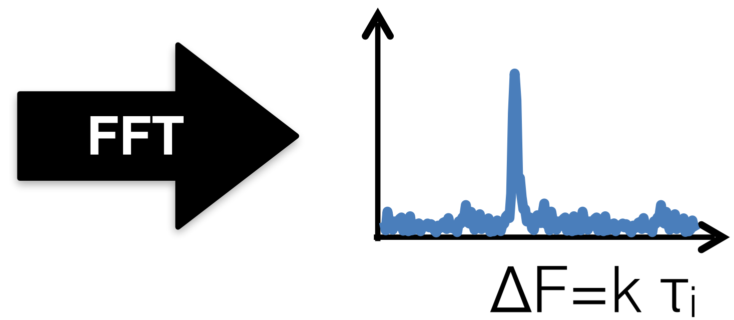

- Sampling Rate = B

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

- Sampling Window = Ts

dF > 1/Ts

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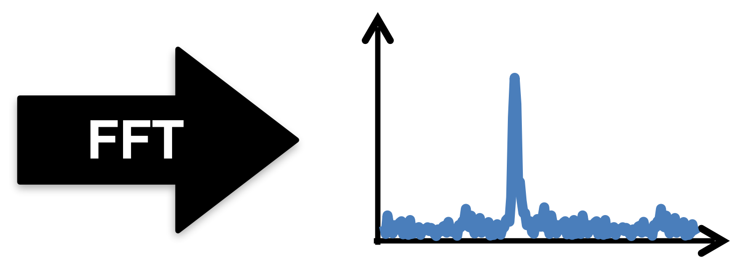

$\Delta F = k\,\tau_i$

- Sampling Rate = B

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

- Sampling Window = Ts

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

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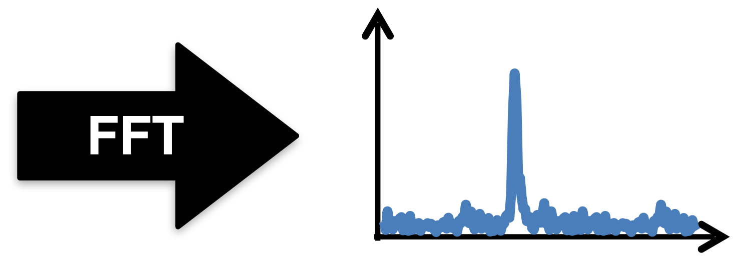

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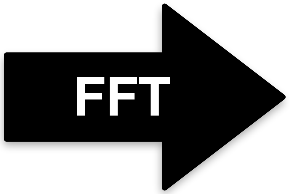

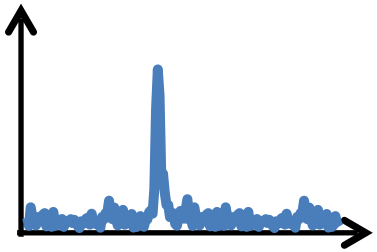

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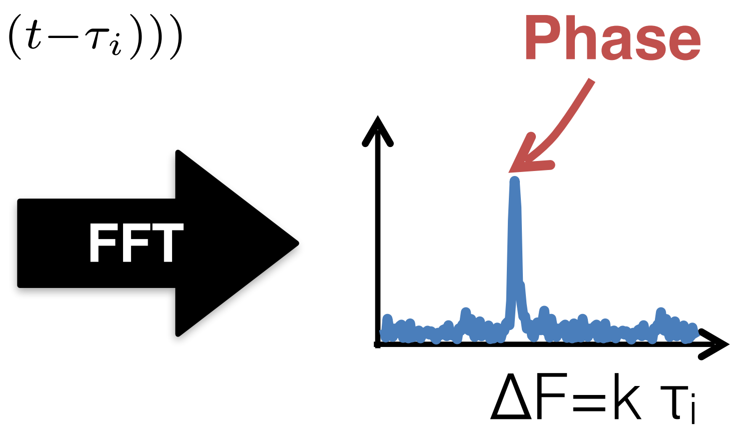

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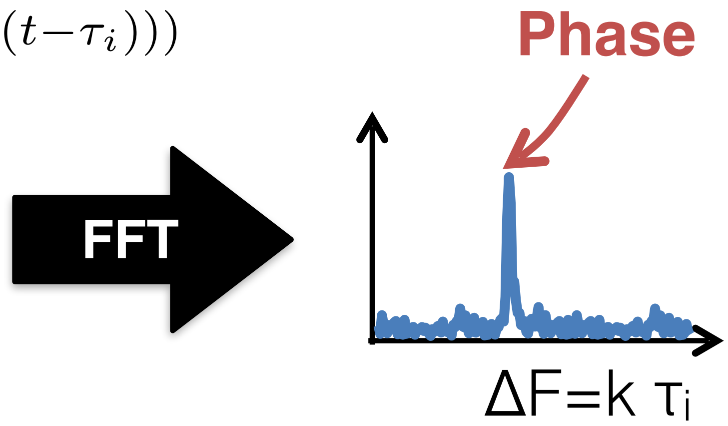

- Phase of peak = $f_0\tau_i$

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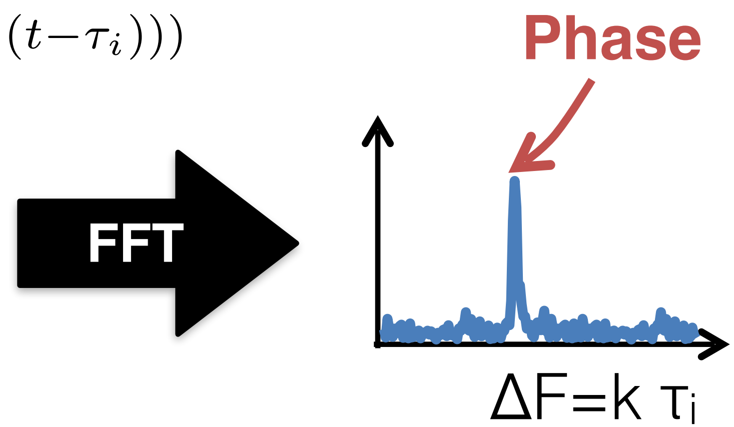

- Phase of peak = $f_0\tau_i$
  - Phase wraps around 2pi

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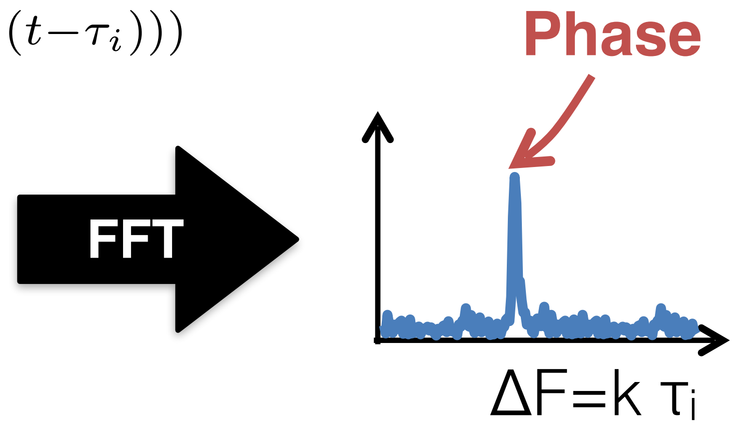

- Phase of peak = $f_0\tau_i$
  - Phase wraps around 2pi
  - Use peak position $\Delta F = k\,\tau_i$ for course estimate of τ_i

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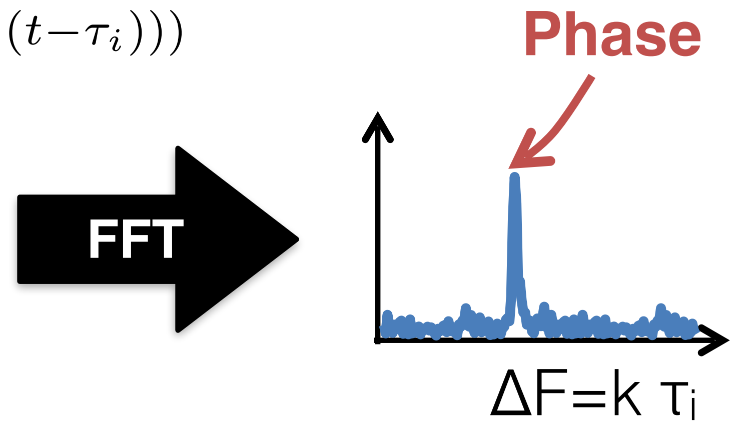


- Phase of peak = $f_0\tau_i$
  - Phase wraps around 2pi
  - Use peak position $\Delta F=k\,\tau_i$ for course estimate of τ_i
  - Use peak phase $f_0\tau_i$ for fine estimate of τ_i

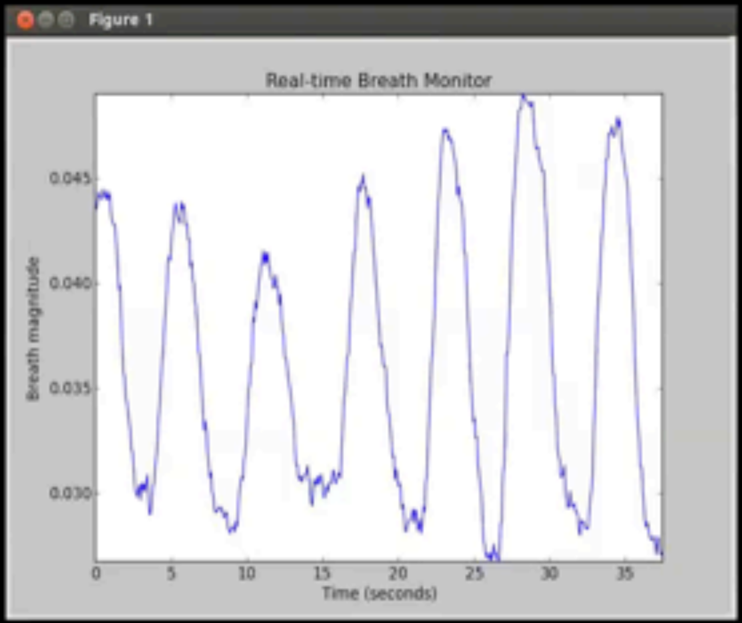
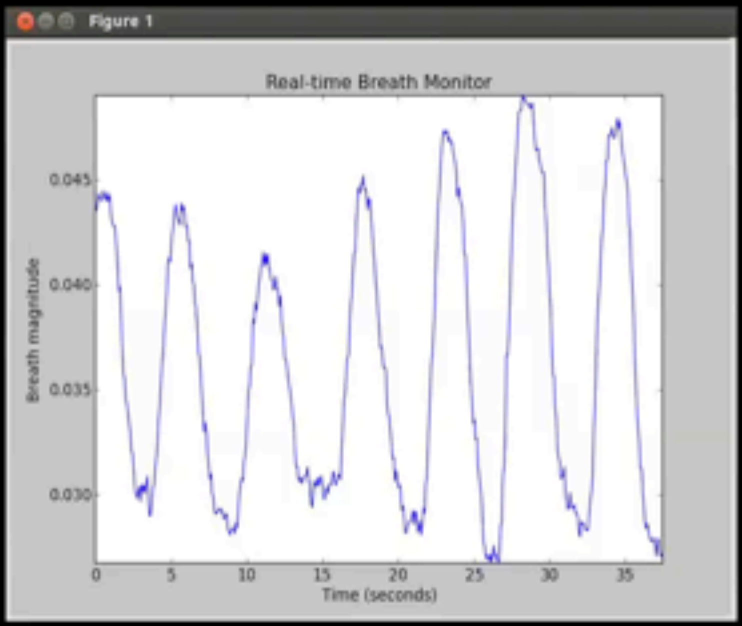


Figure 1
Real-time Breath Monitor
Breath magnitude
0.030
0.035
0.040
0.045
0
5
10
15
20
25
30
35
Time (seconds)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Breath magnitude
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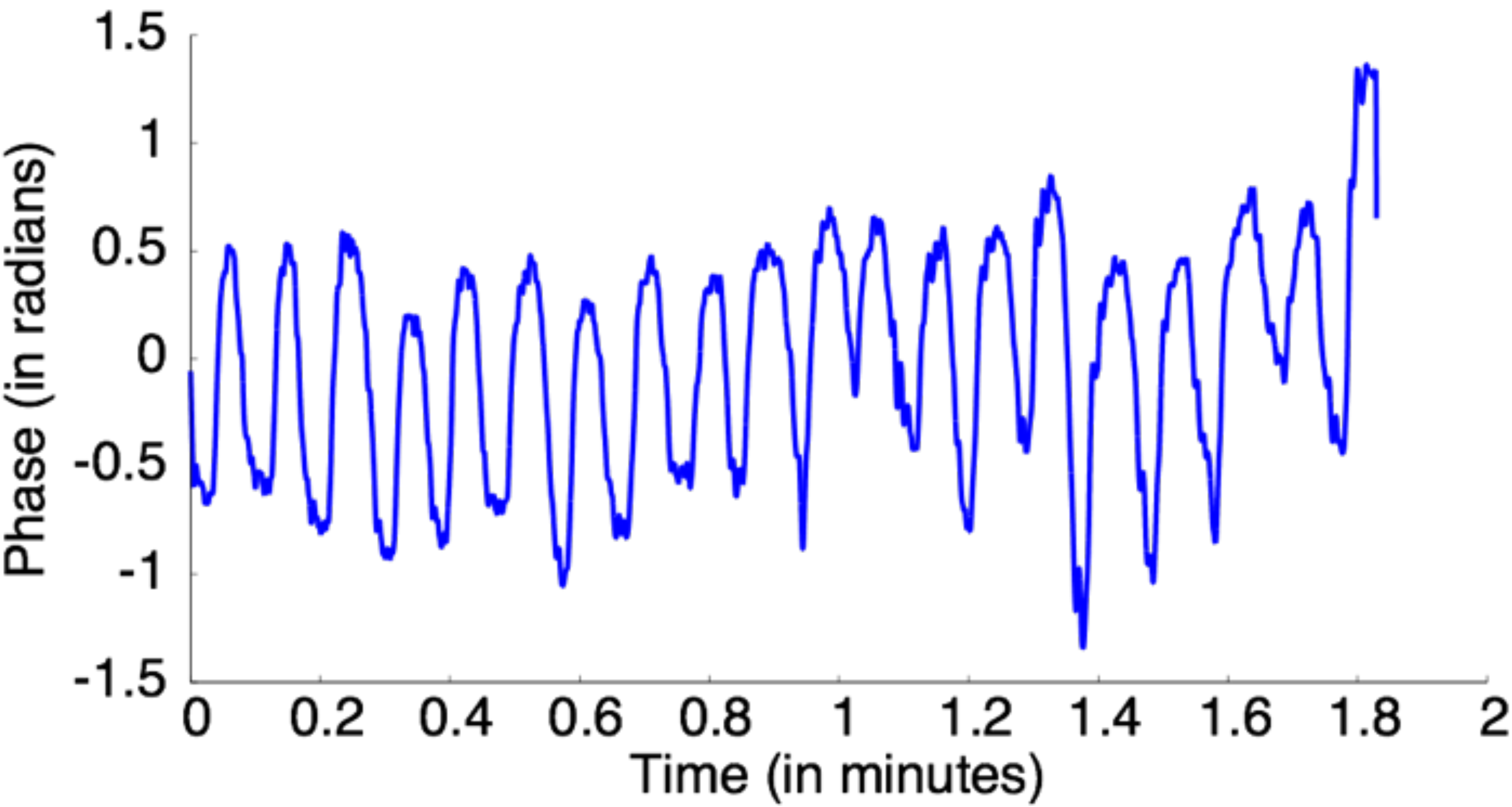
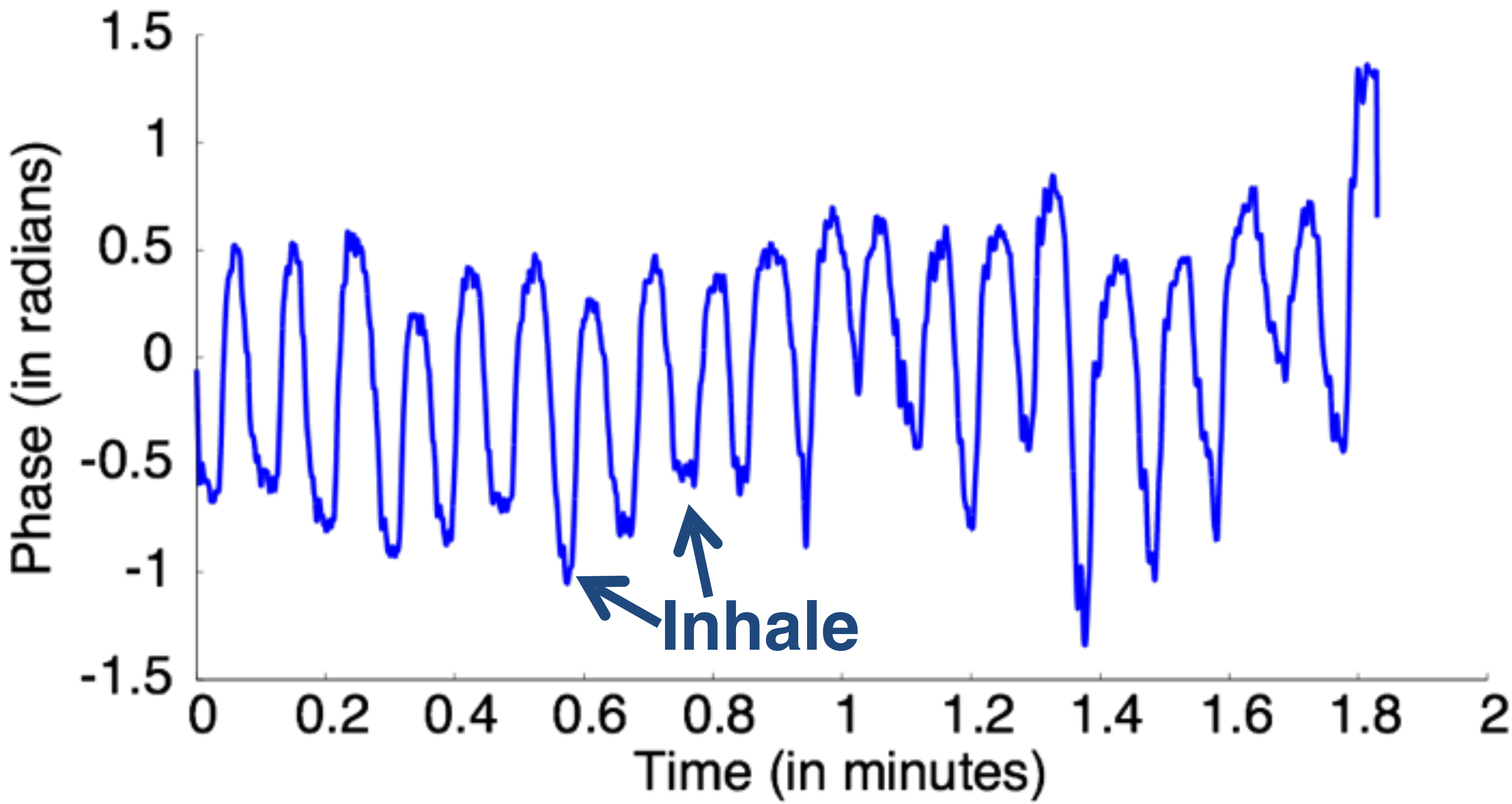
0.040
0.035
0.030
0
5
10
15
20
25
30
35
Time (seconds)

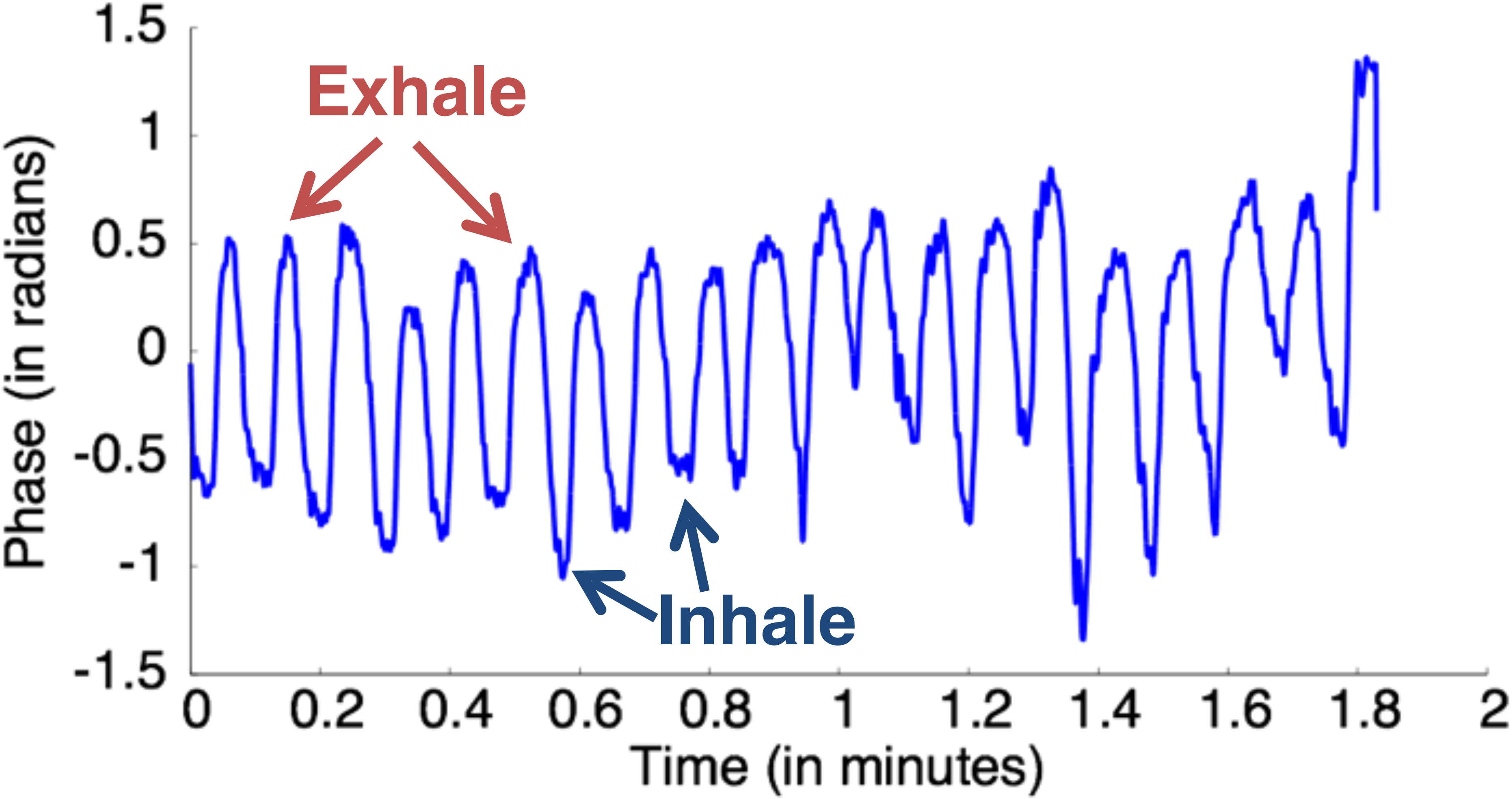
Let’s zoom in on these signals



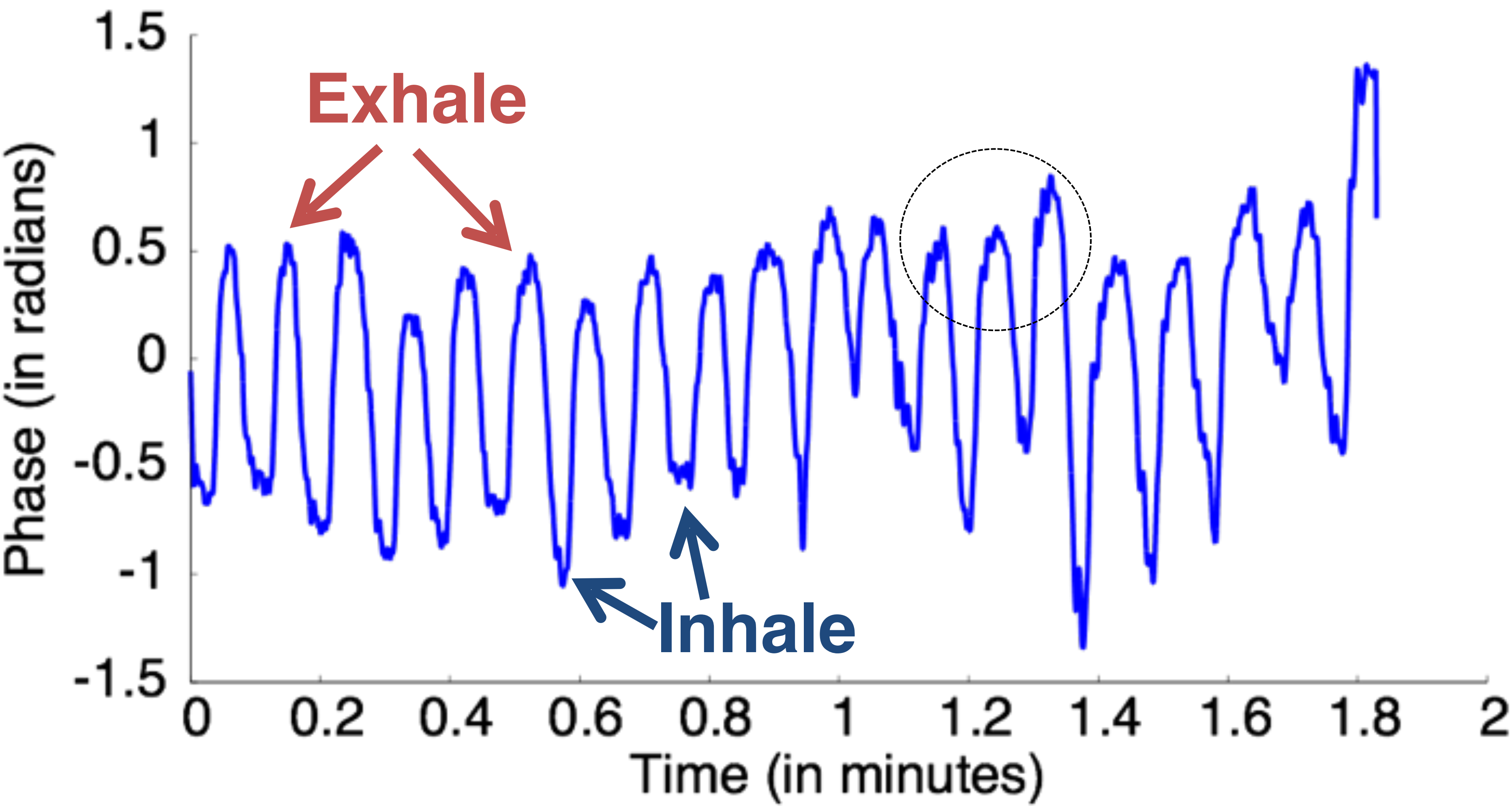
1.5
1
0.5
0
-0.5
-1
-1.5
Phase (in radians)
0
0.2
0.4
0.6
0.8
1
1.2
1.4
1.6
1.8
2
Time (in minutes)



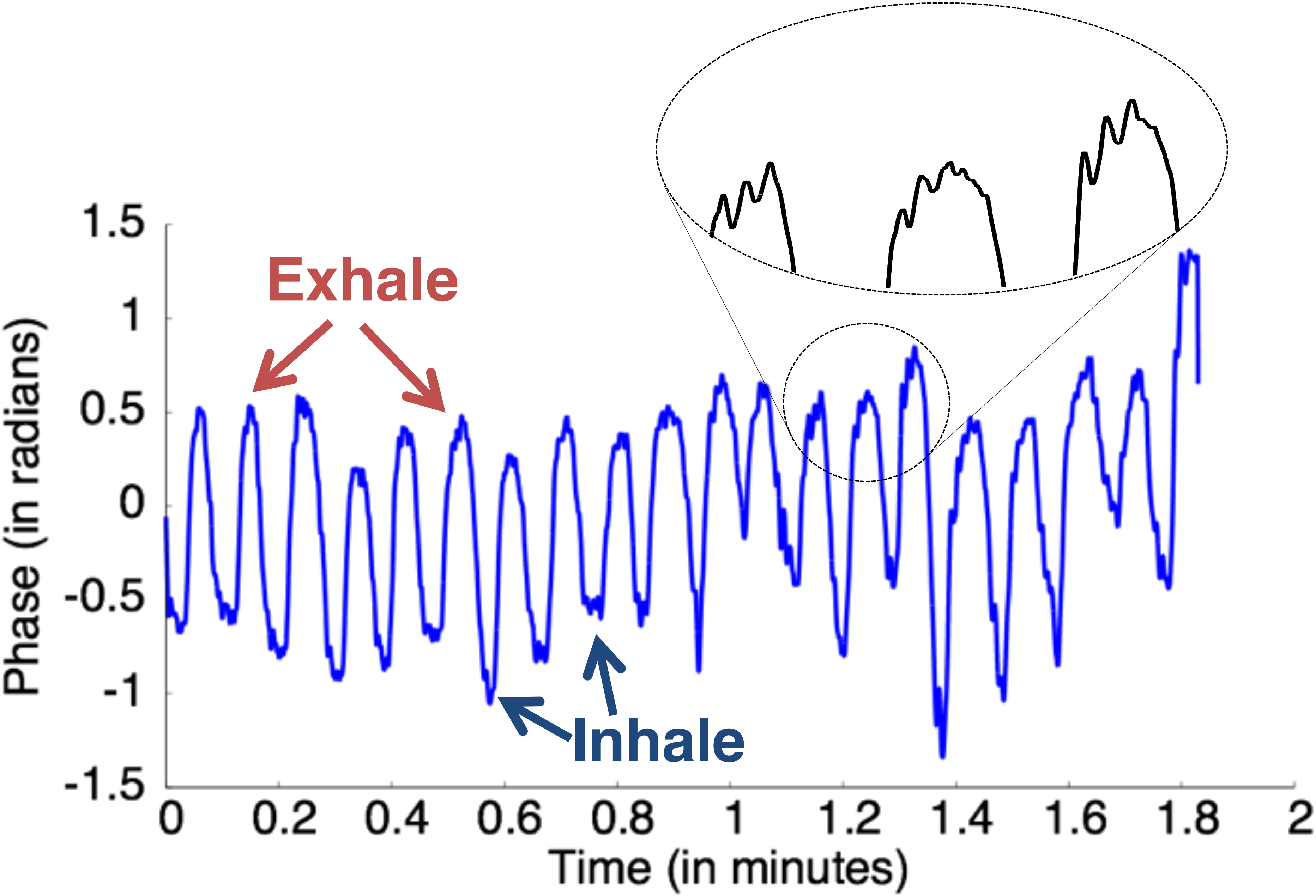
Phase (in radians)
1.5
1
0.5
0
-0.5
-1
-1.5
0
0.2
0.4
0.6
0.8
1
1.2
1.4
1.6
1.8
2
Time (in minutes)
Inhale



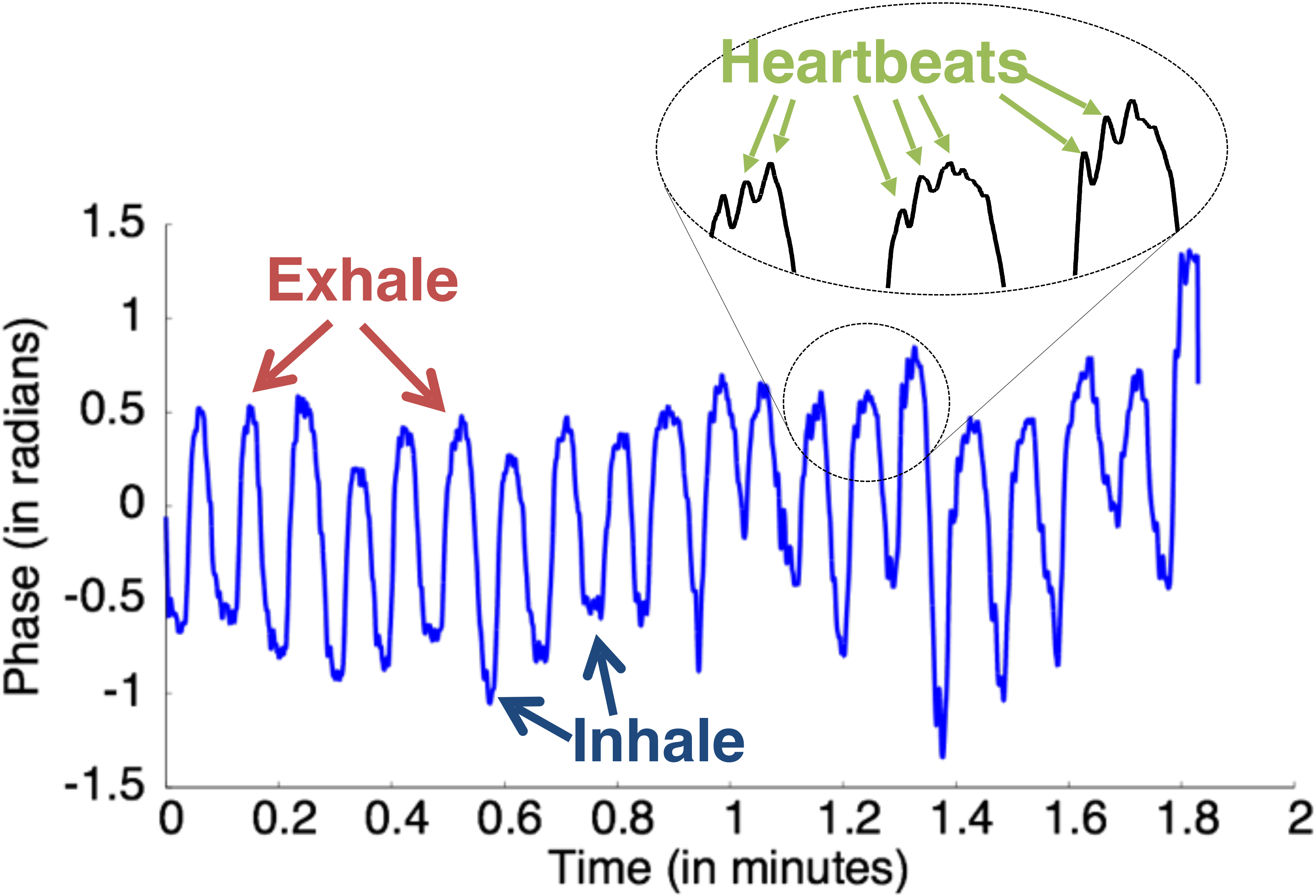
Exhale
Inhale
Phase (in radians)
1.5
1
0.5
0
-0.5
-1
-1.5
0
0.2
0.4
0.6
0.8
1
1.2
1.4
1.6
1.8
2
Time (in minutes)



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



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


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?

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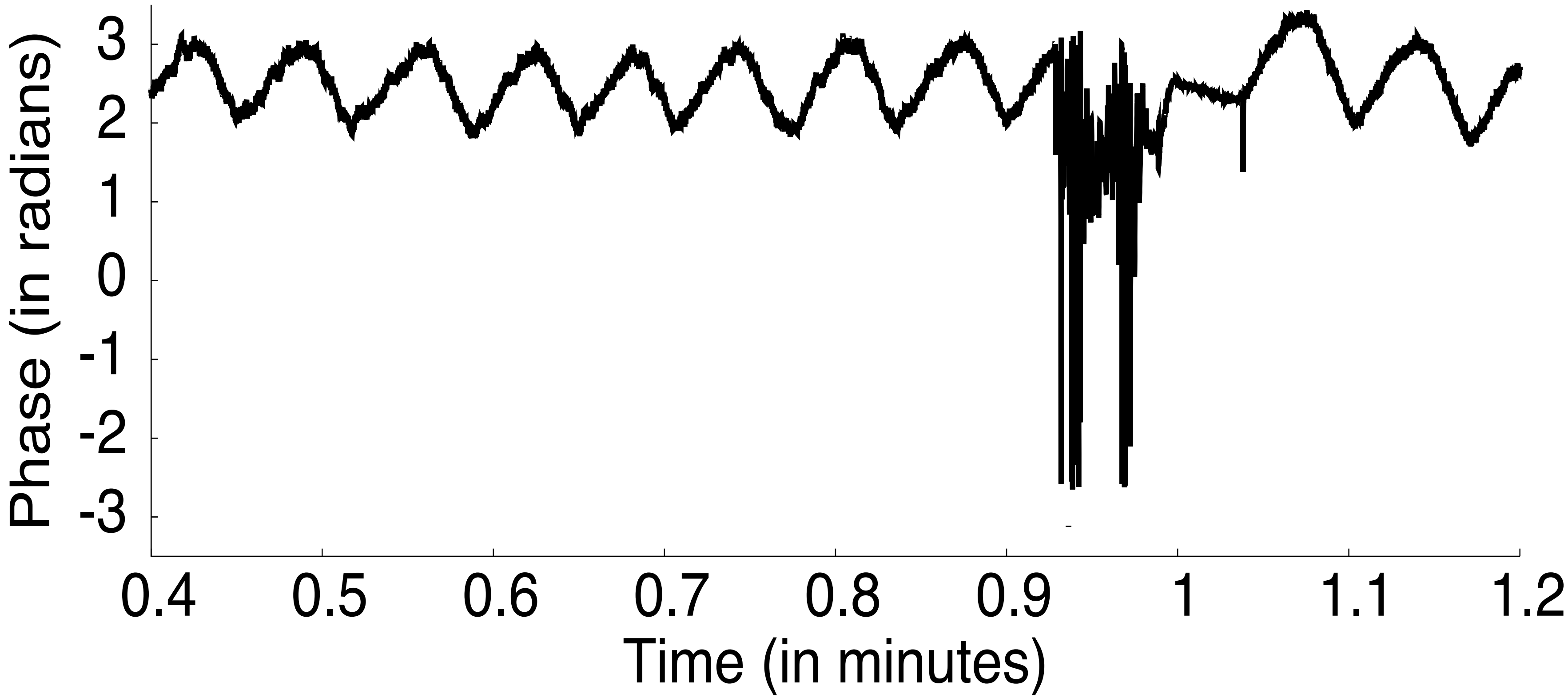

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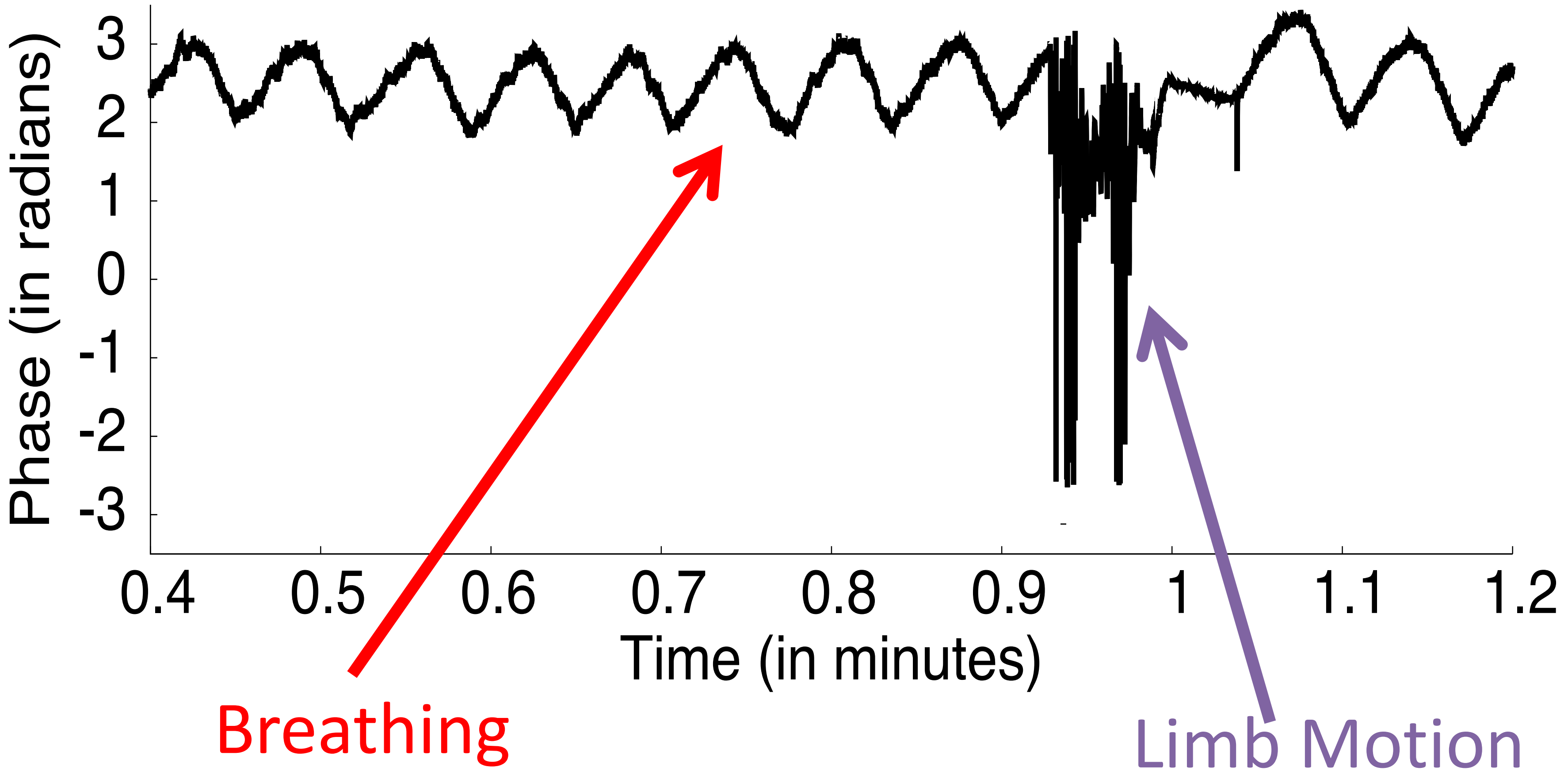
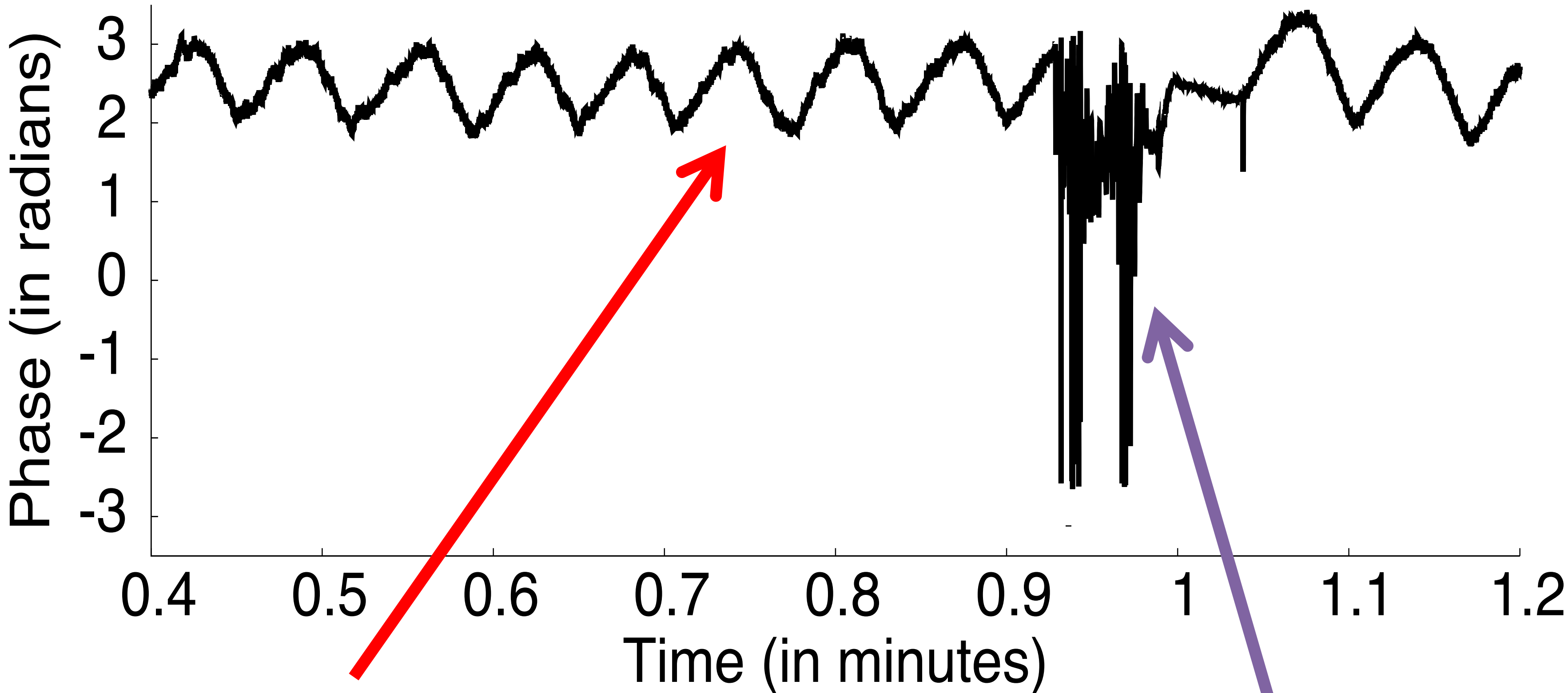


Periodic

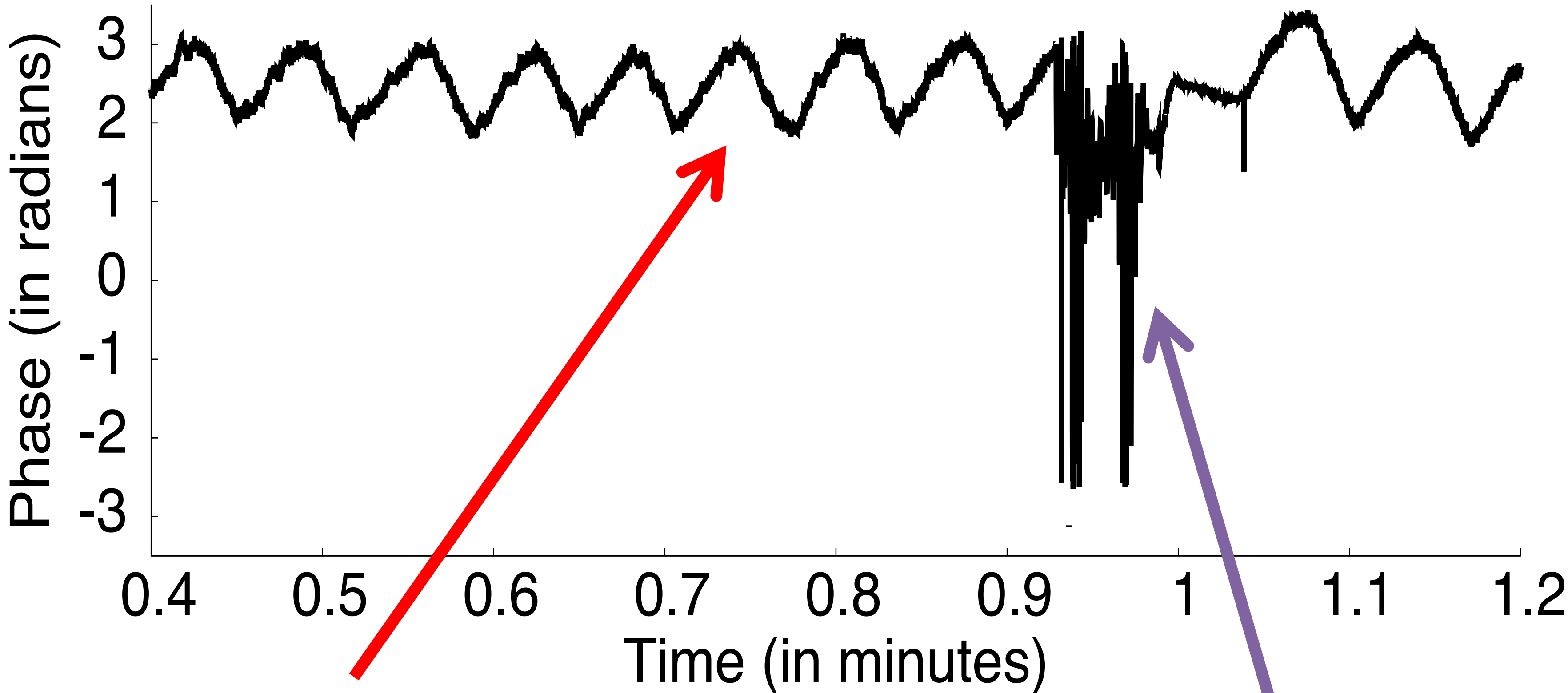
Not periodic

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?

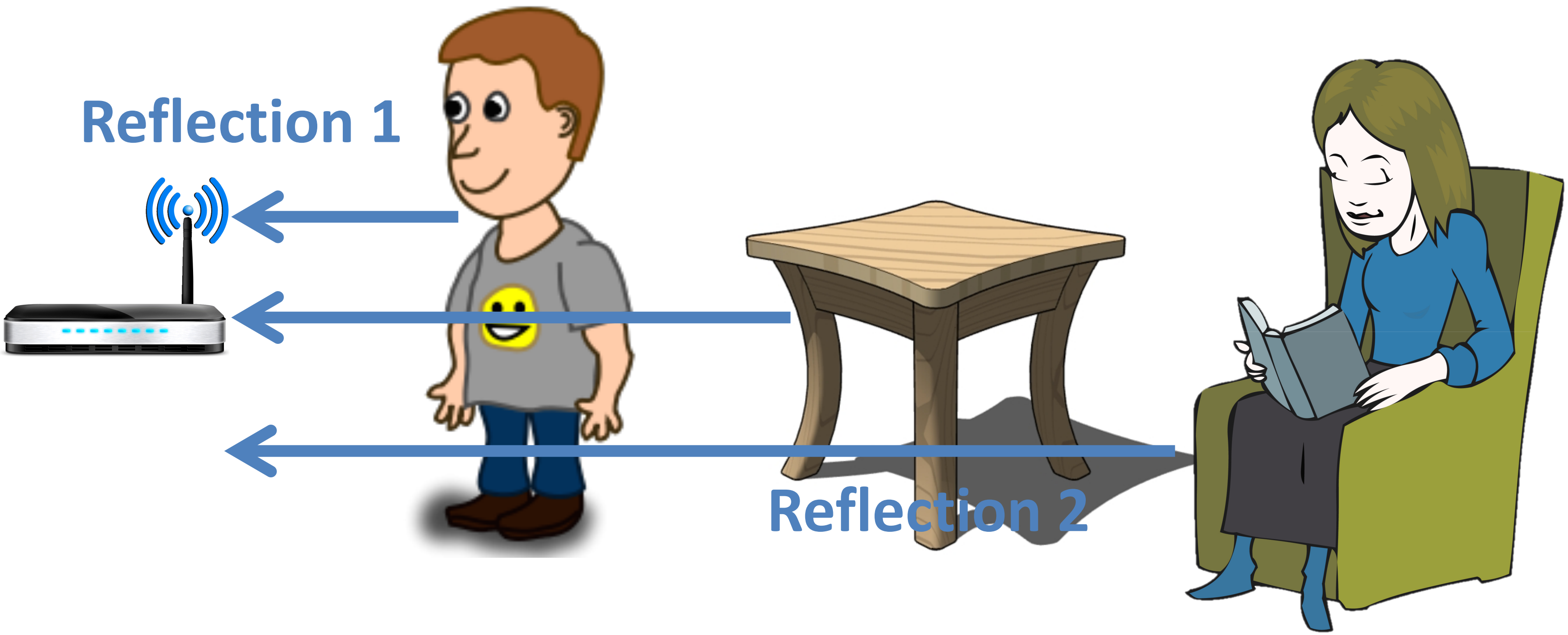


Band-pass filter the cleaned signals to extract breathing and heart rate

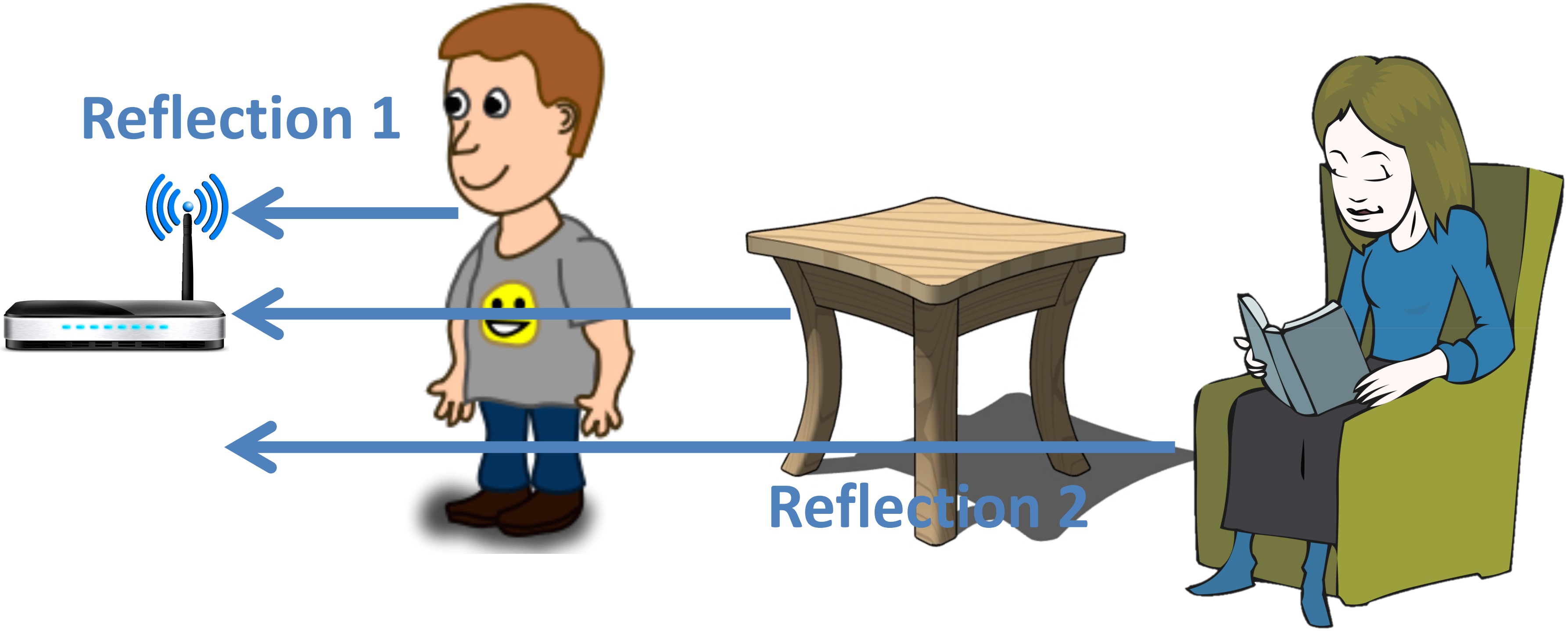
What happens with multiple users in the environment?

Reflections from different objects collide

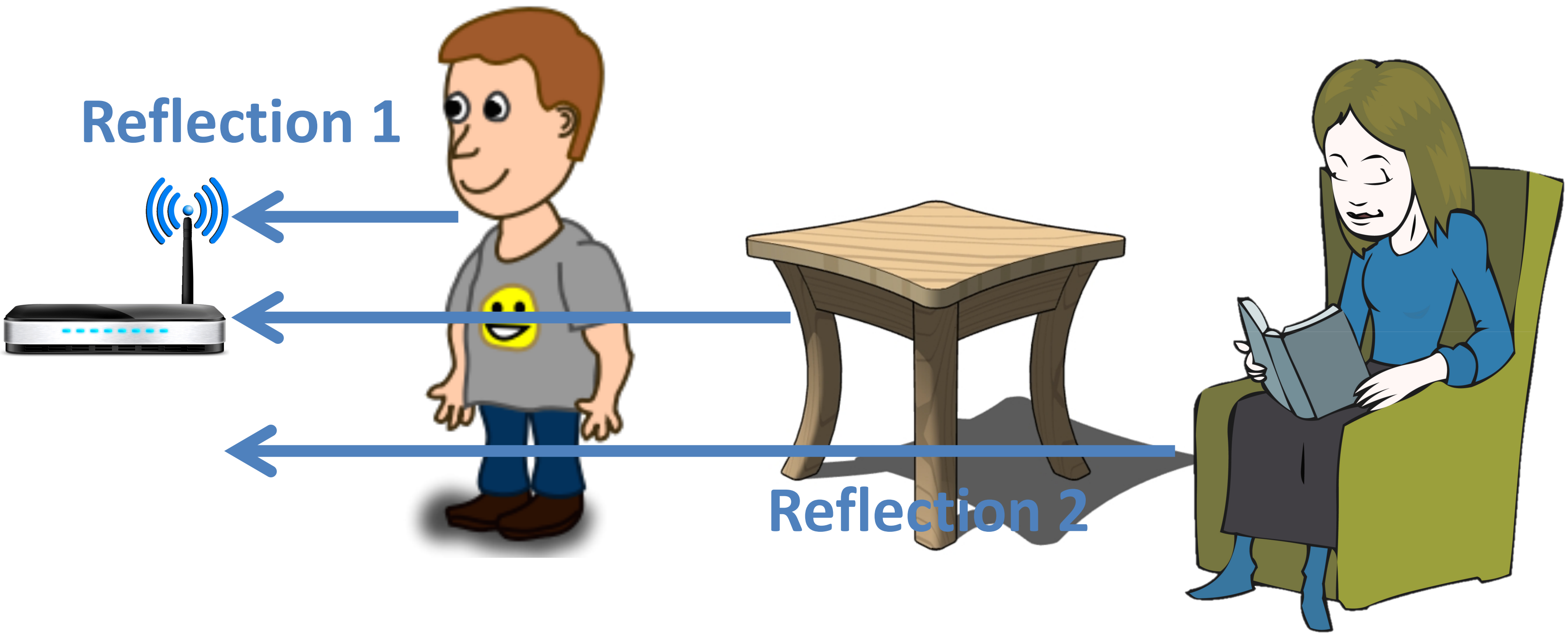
<u>Problem:</u> Phase becomes meaningless!



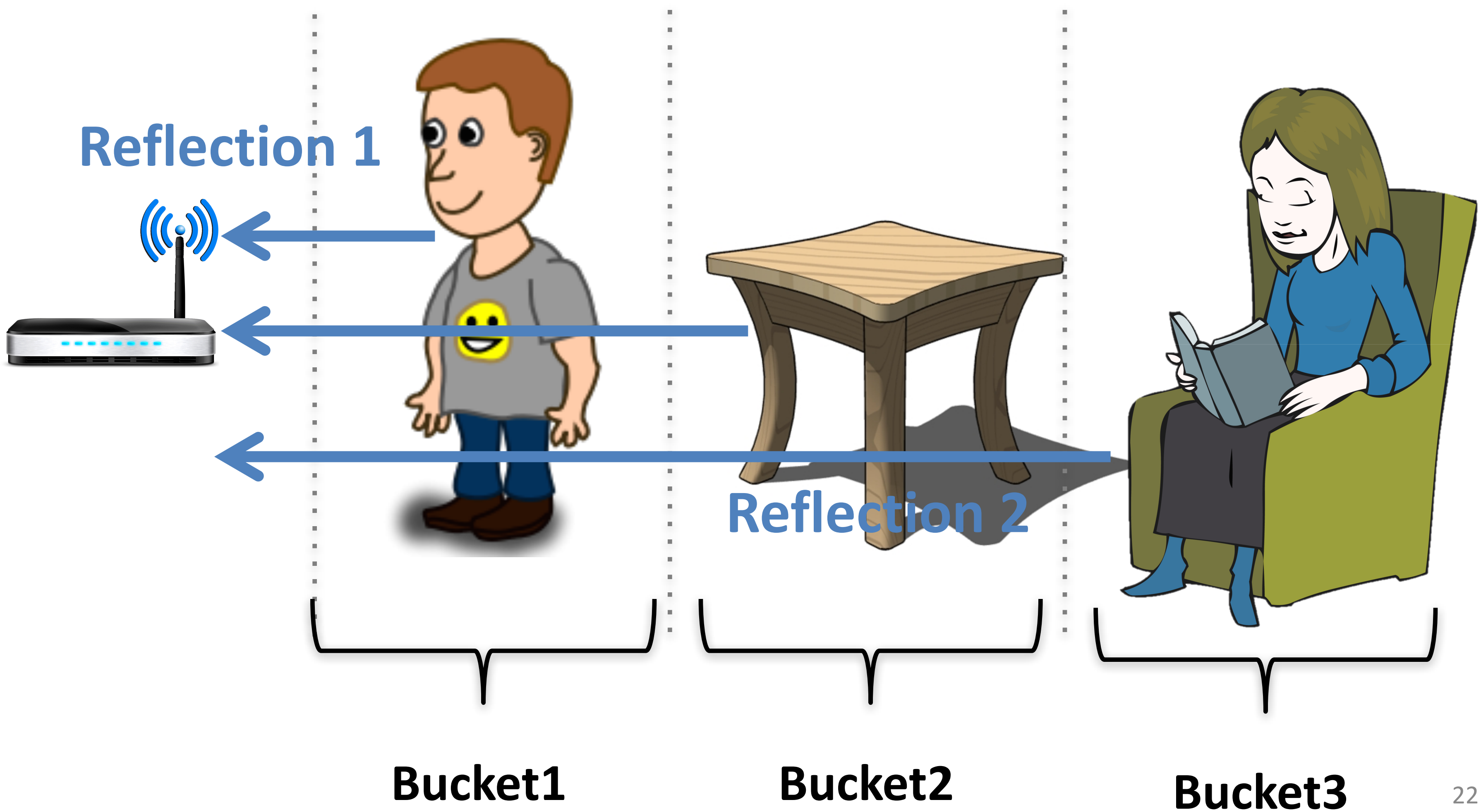
Idea: Wireless localization can be used to locate various devices



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

Baby Monitoring

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

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

Smart Homes that adapt to our mood

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

Smart Homes that adapt to our mood

Does my advisor like my work?

Graduate student

Advisor

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

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

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Is the date going well!

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

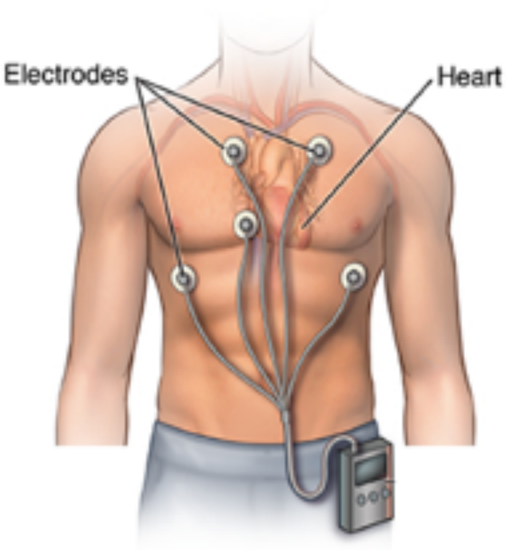
Combating Depression

Is the date going well!

Existing approaches measure vital signs

Existing approaches measure vital signs

- Use ECG to get very accurate heartbeats



Emotion recognition using wireless signals

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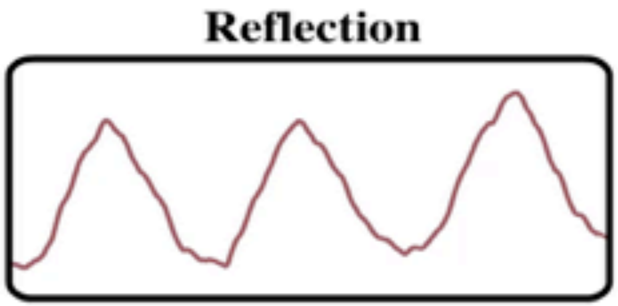
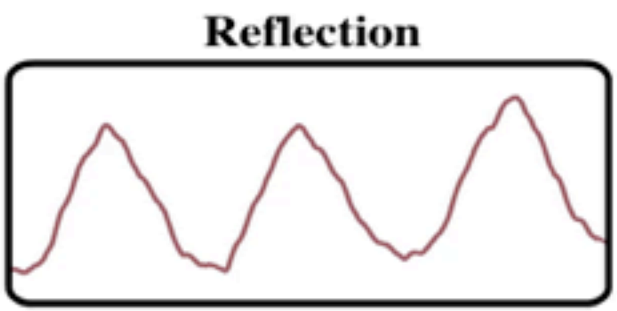
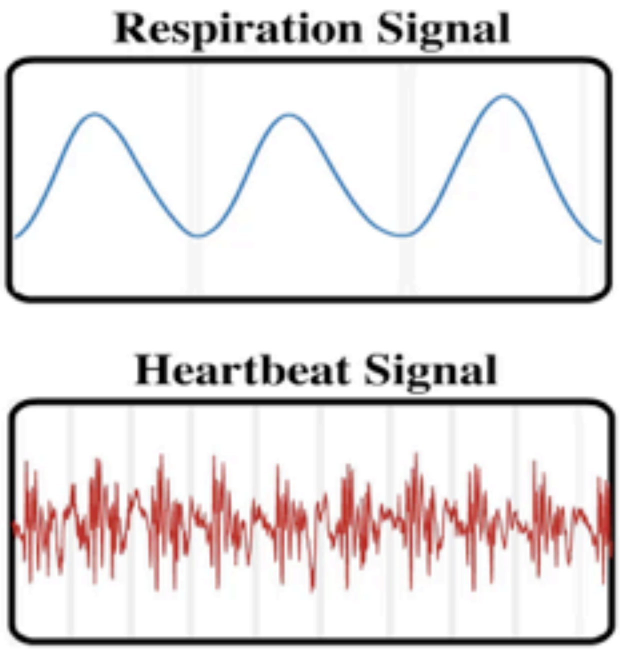


Emotion recognition using wireless signals





Key challenge: Inter-Beat Interval (IBI)

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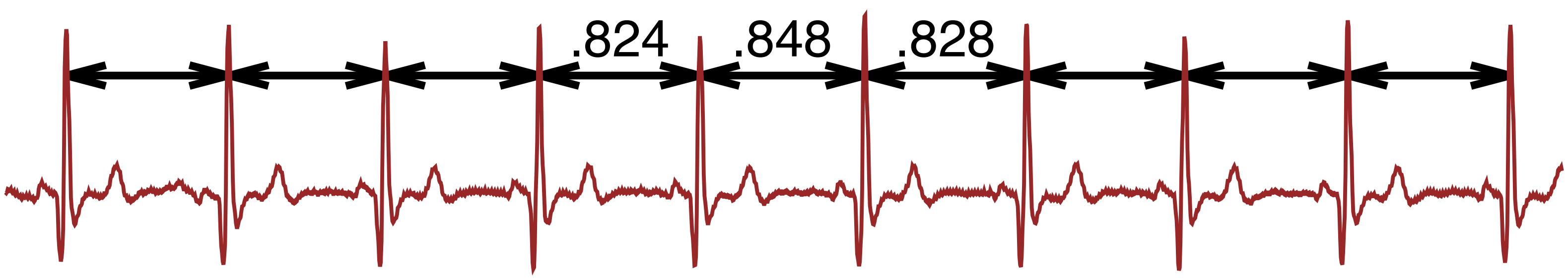
- Emotion recognition needs accurate measurements of the length of every single heartbeat



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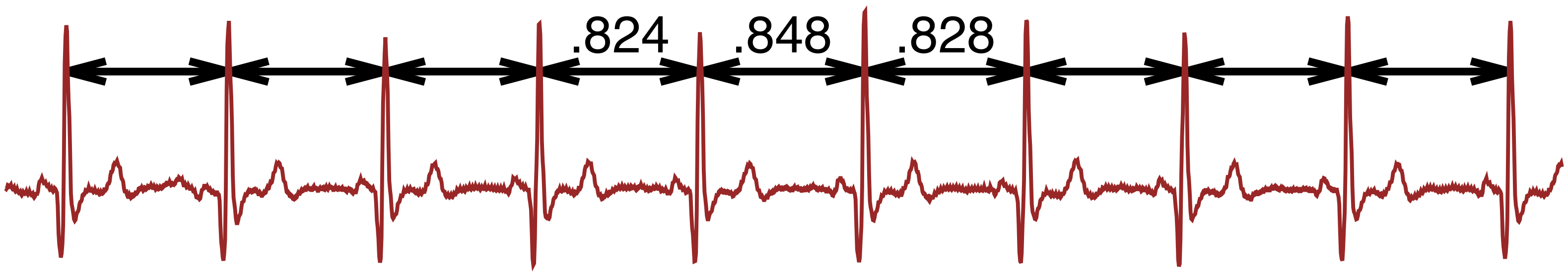


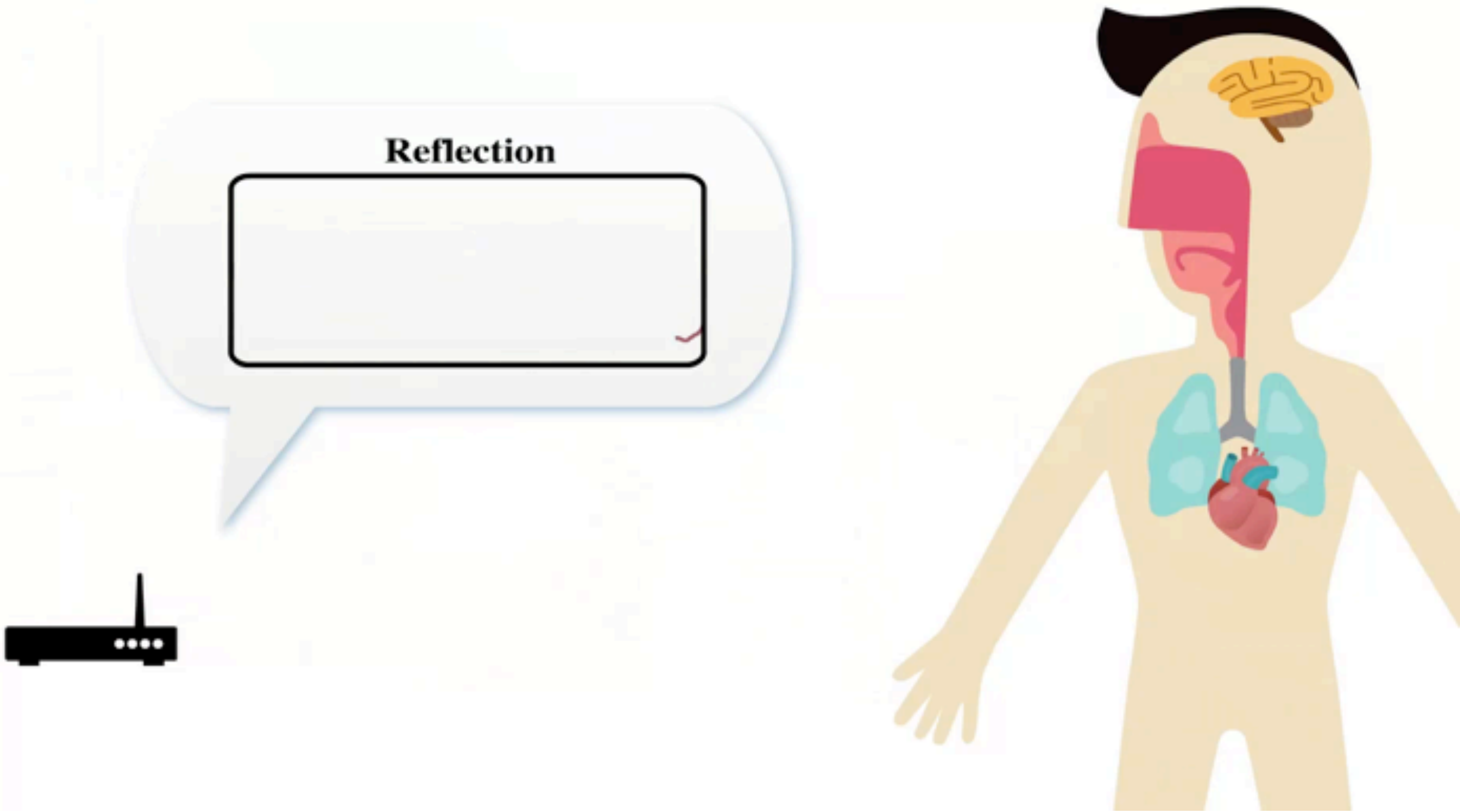
We need to extract IBI with accuracy over 99%

Input signal

Wireless reflection of the human body

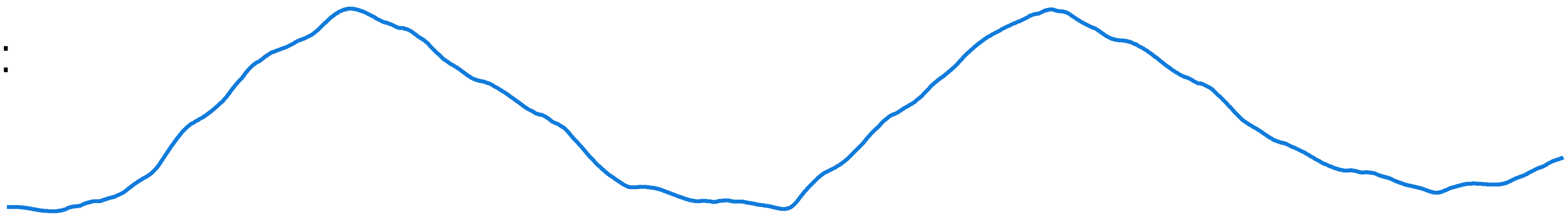
Input signal

Wireless reflection of the human body



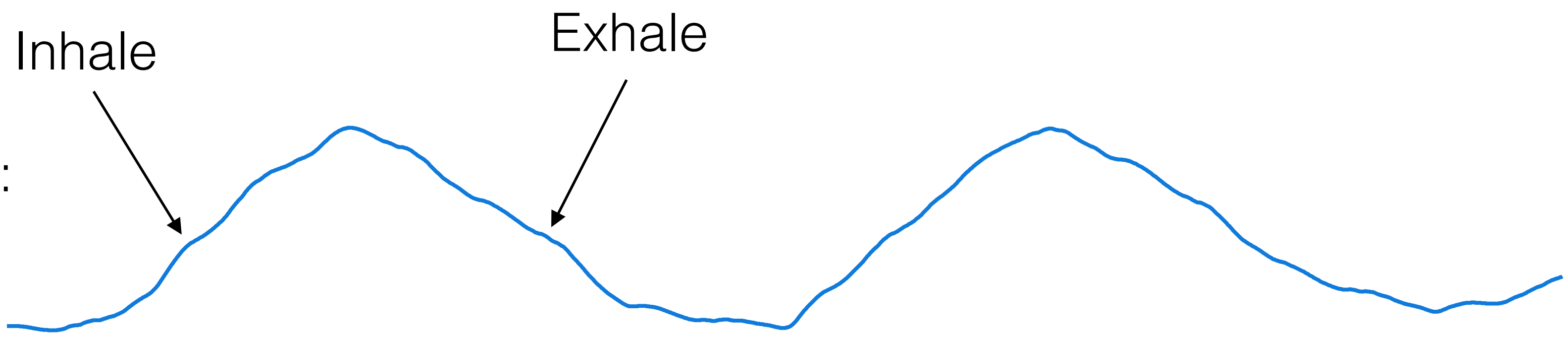
Input signal

Our signal:



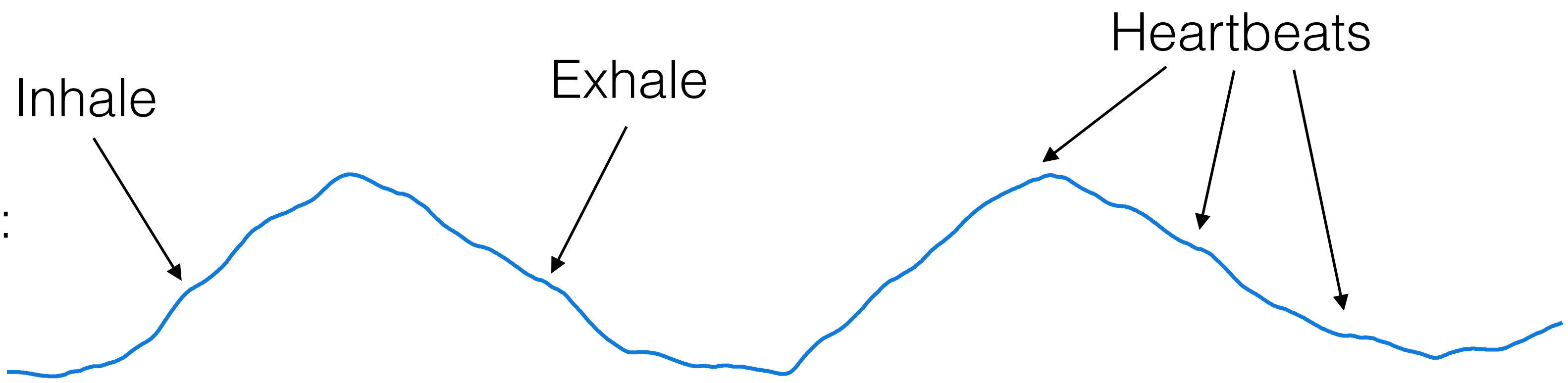
Input signal

Our signal:

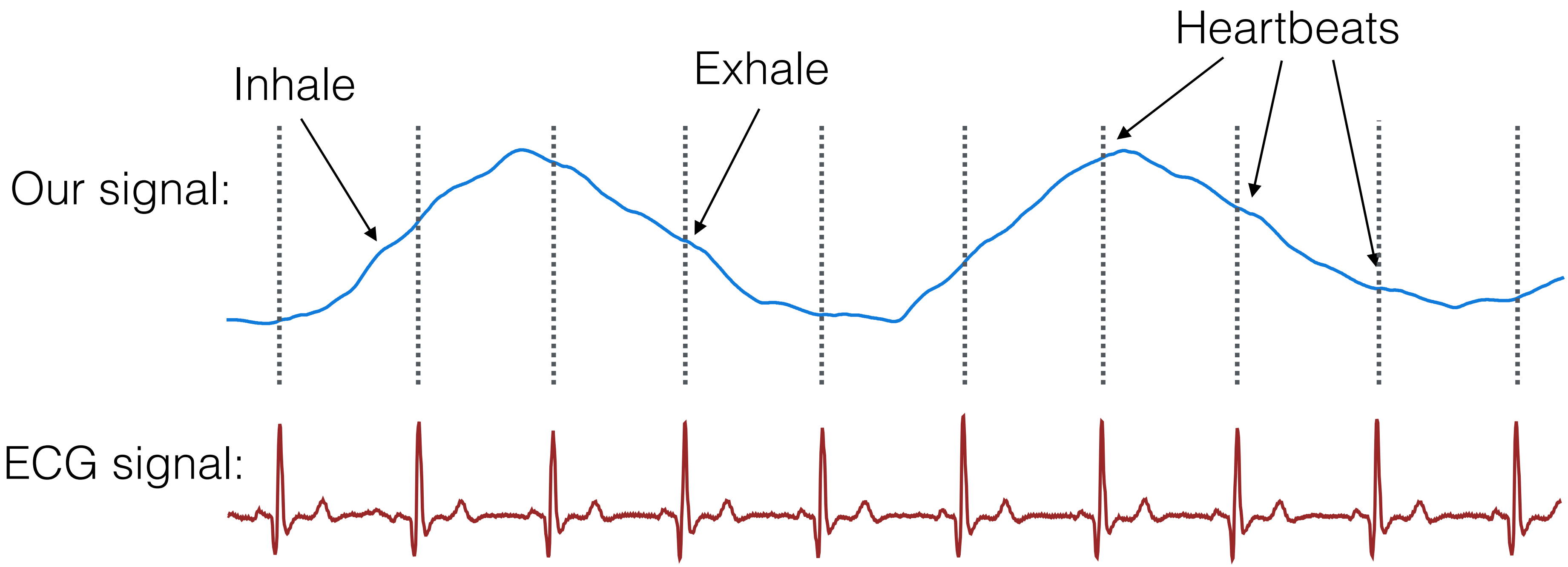


Input signal

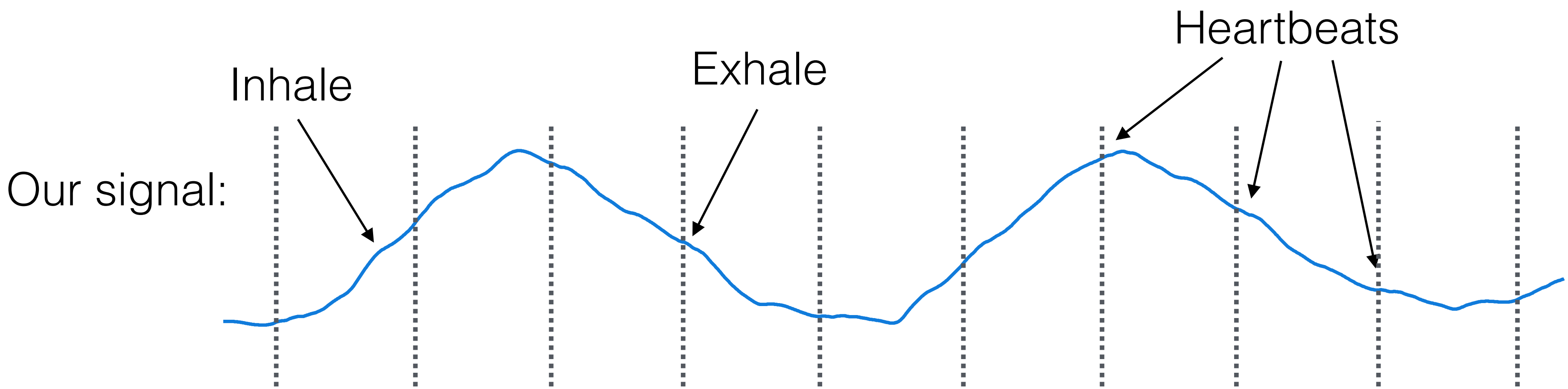
Our signal:



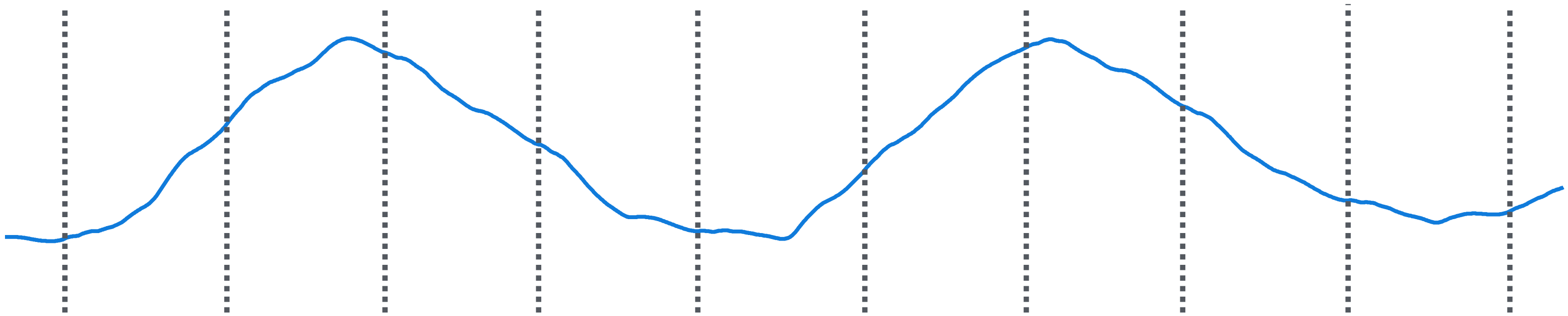
Input signal



Input signal

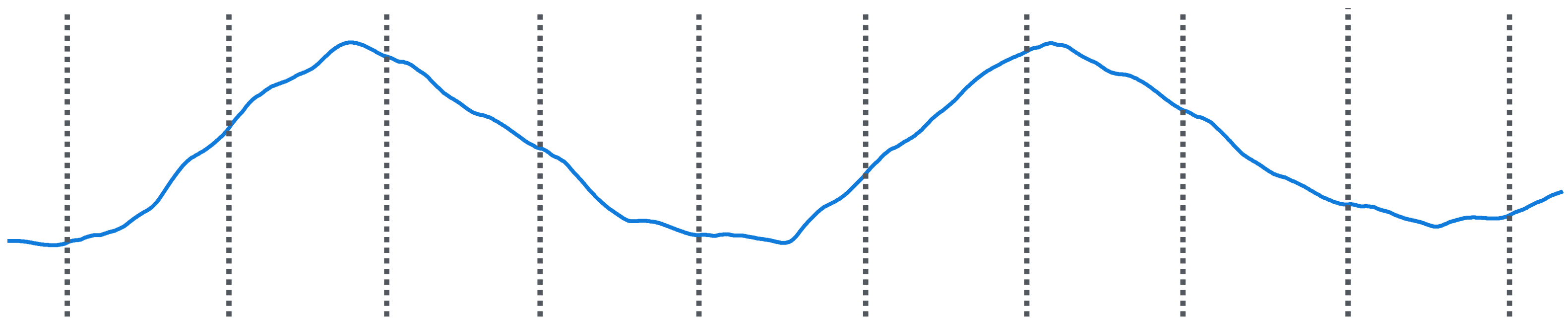


Step 1: Remove breathing signal



- Breathing masks heartbeats

Step 1: Remove breathing signal

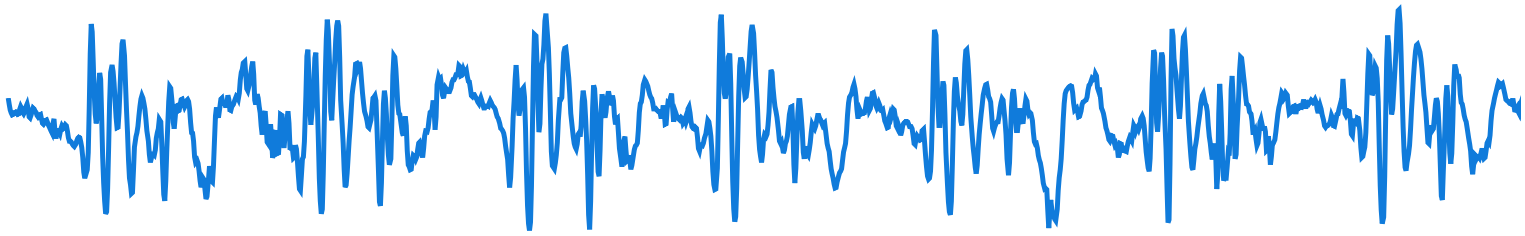


- Breathing masks heartbeats
- We use acceleration filter
  - Heartbeat involves rapid contraction of muscle
  - Breathing is slow and steady

Heartbeat signal

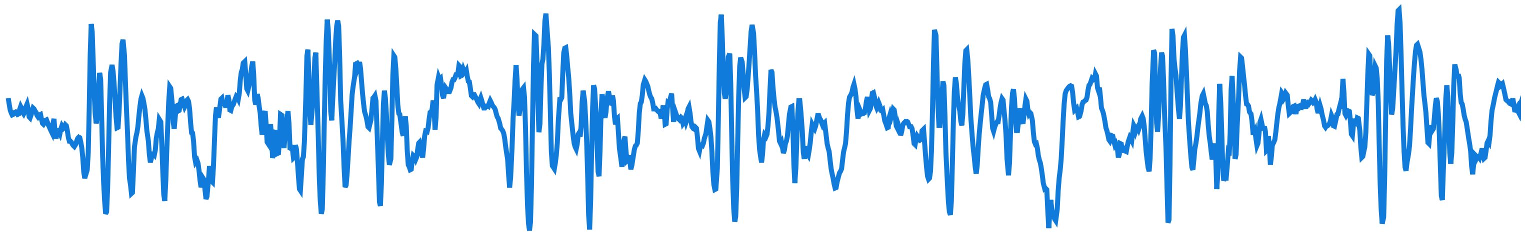
Heartbeat signal

- Output of acceleration filter

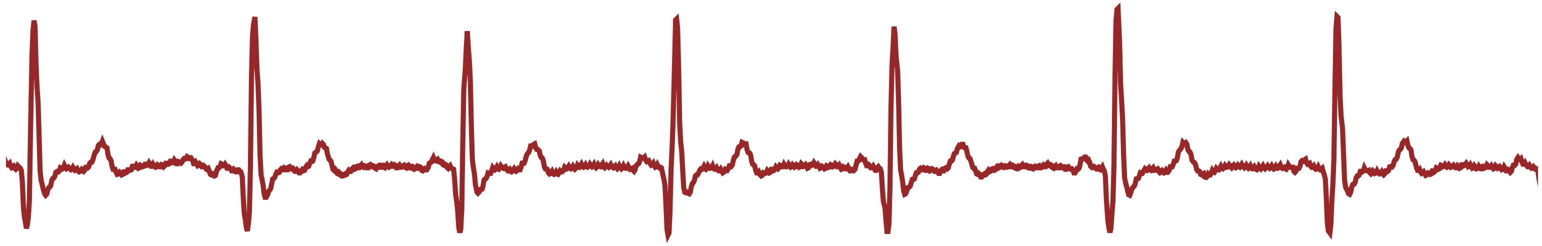


Heartbeat signal

- Output of acceleration filter

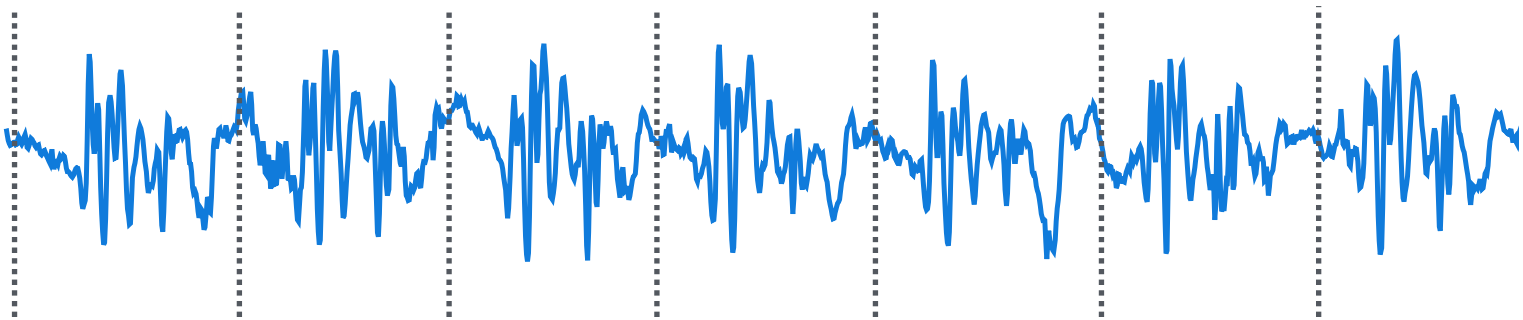


- ECG signal



Heartbeat signal

- Output of acceleration filter



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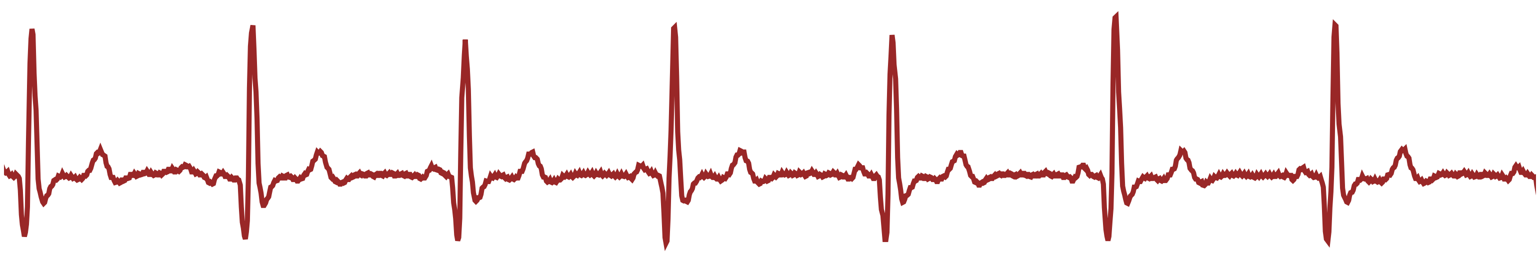

Heartbeat signal

- Other typical examples:

Heartbeat signal

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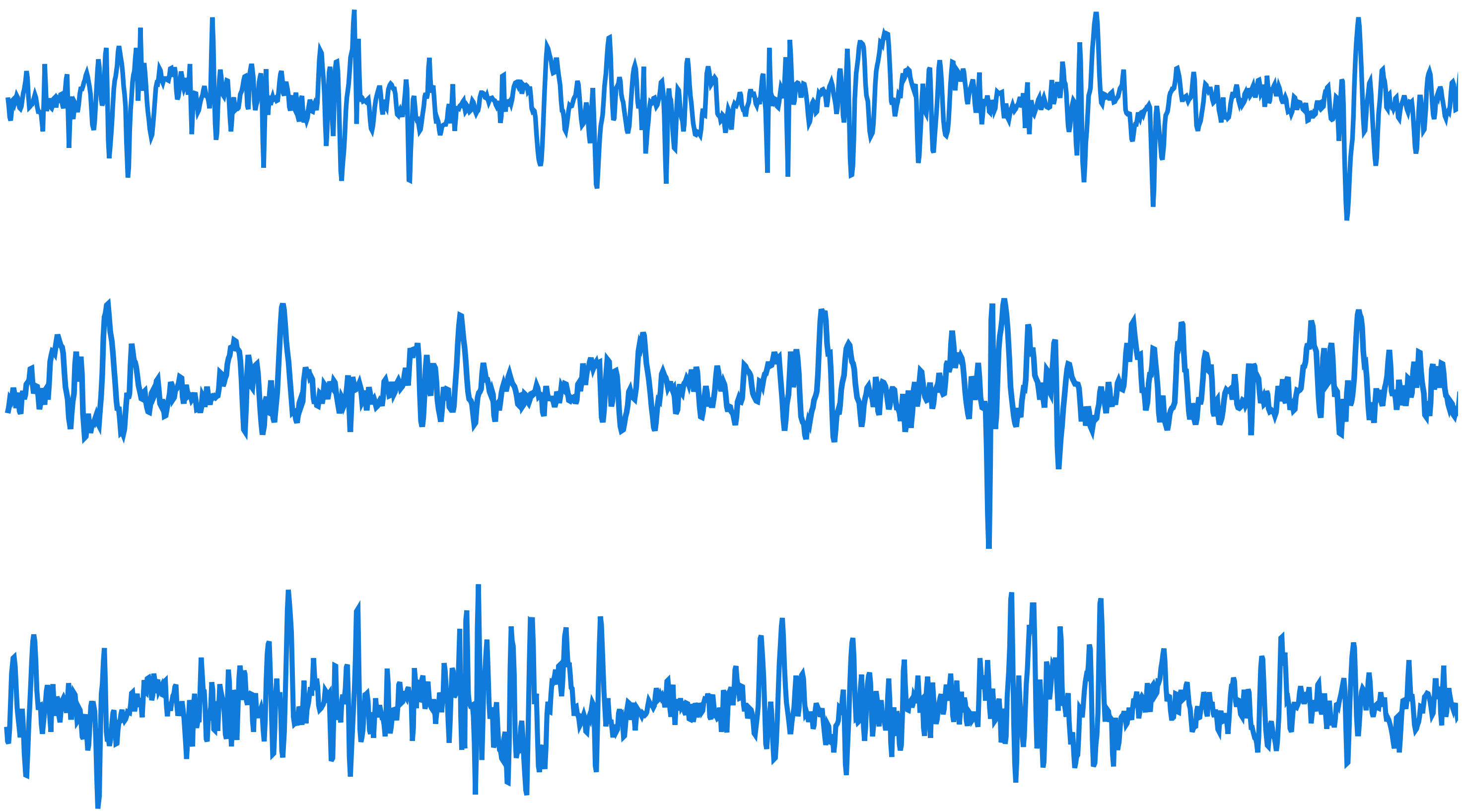

Heartbeat signal

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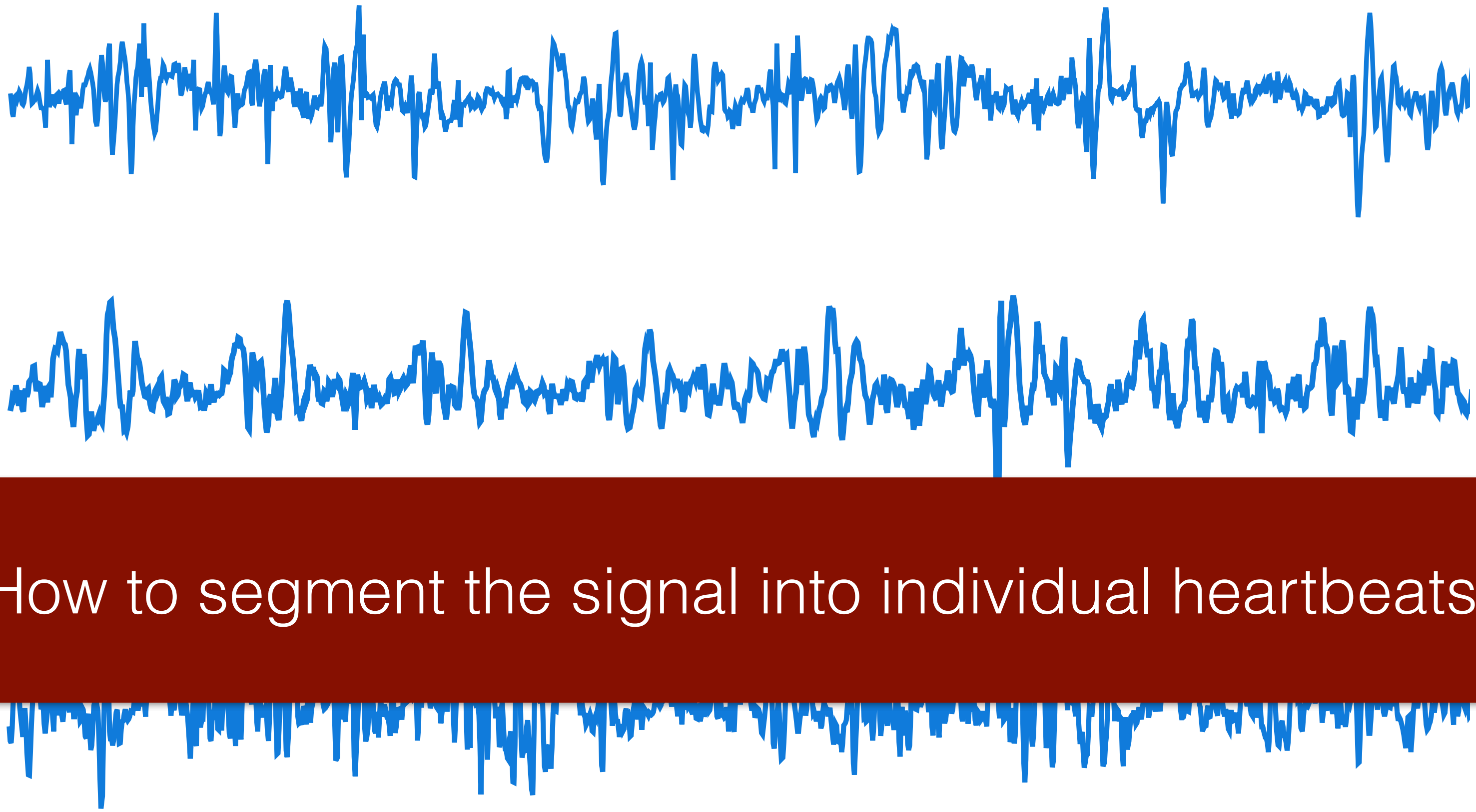

How to segment the signal into individual heartbeats?

Step 2: Heartbeat segmentation

Step 2: Heartbeat segmentation

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

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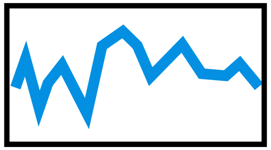
- If we can somehow discover the template, then we can segment into individual heartbeats

Step 2: Heartbeat segmentation

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

Random template:



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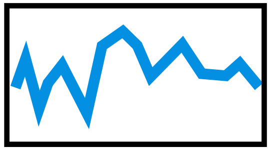

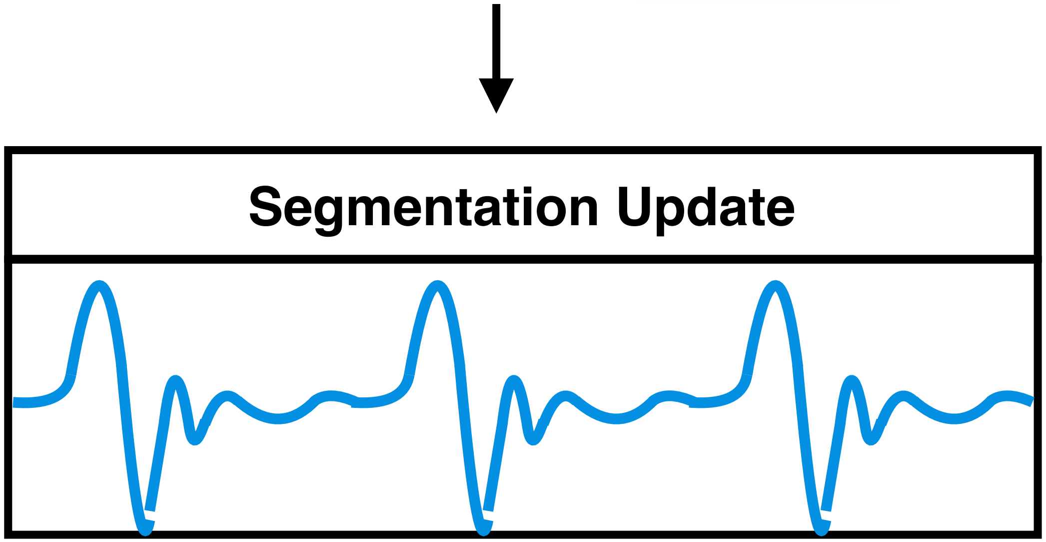

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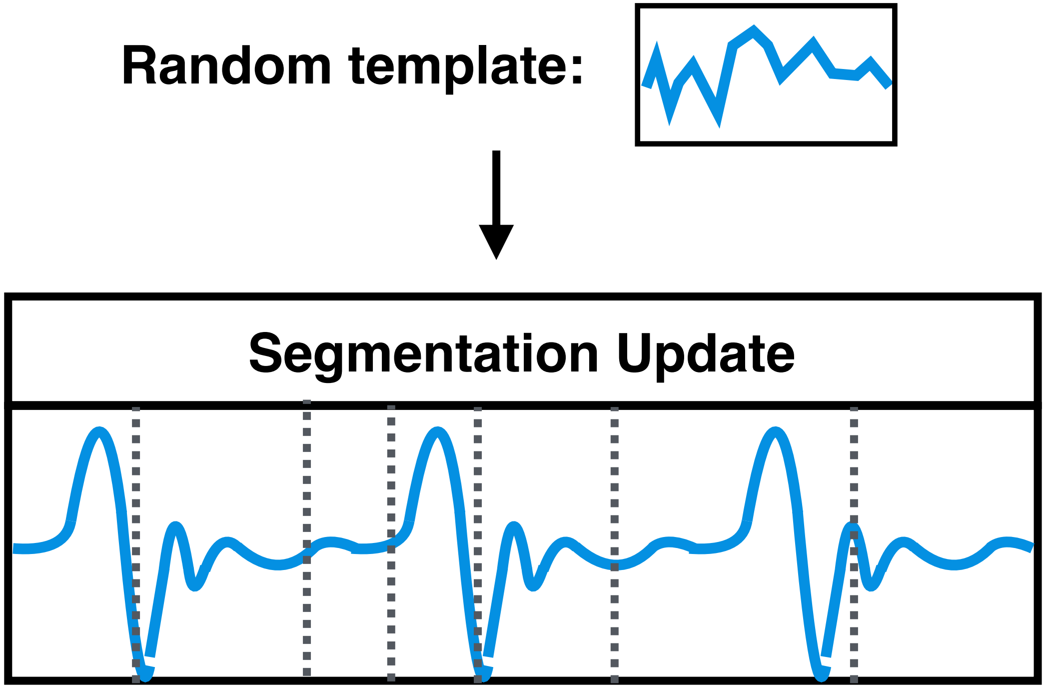

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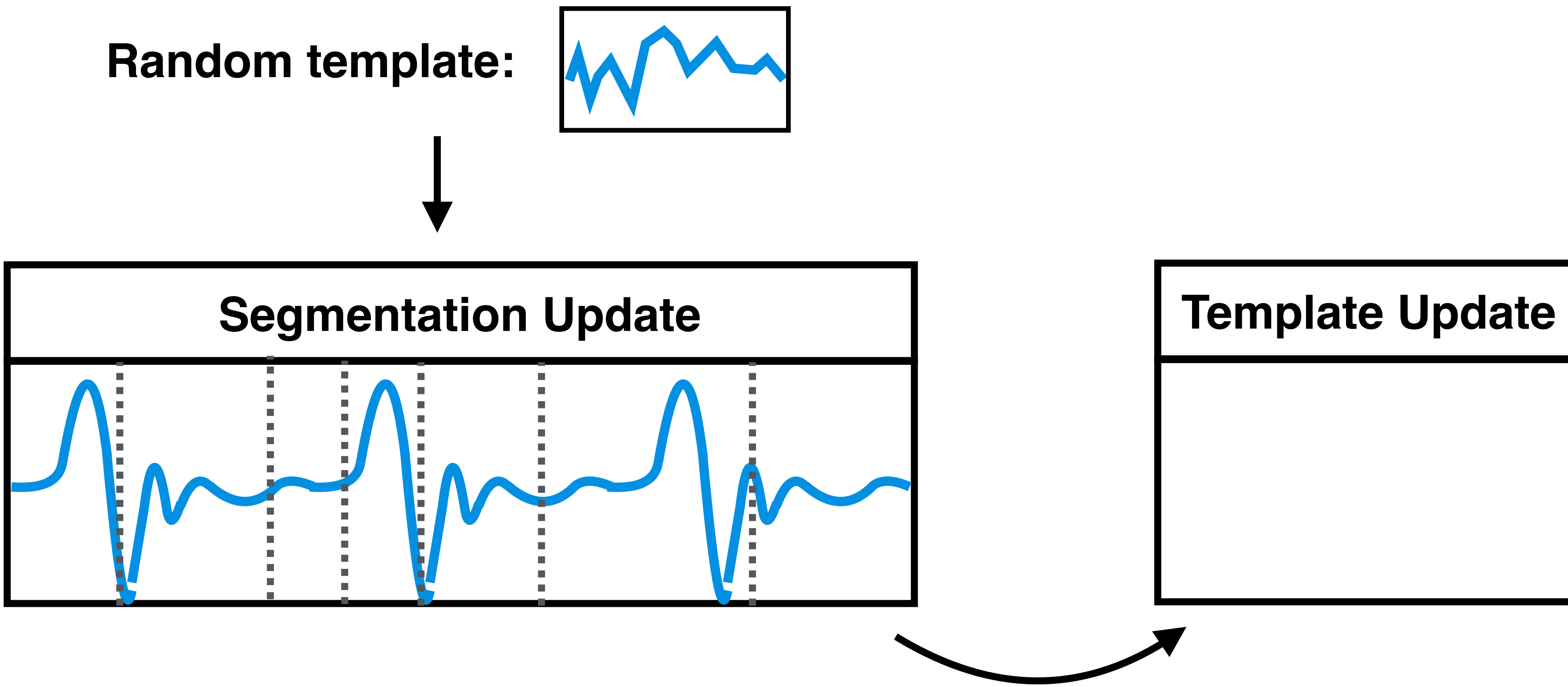

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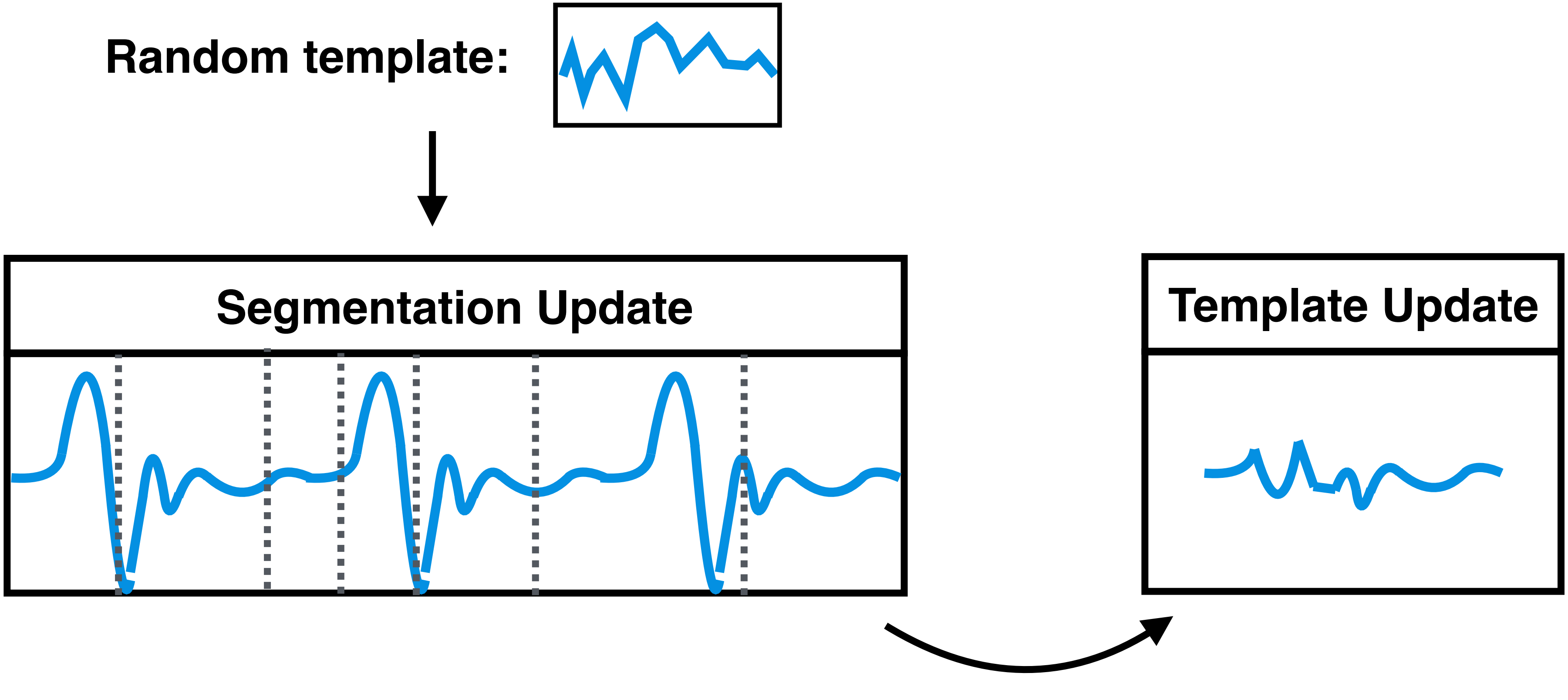

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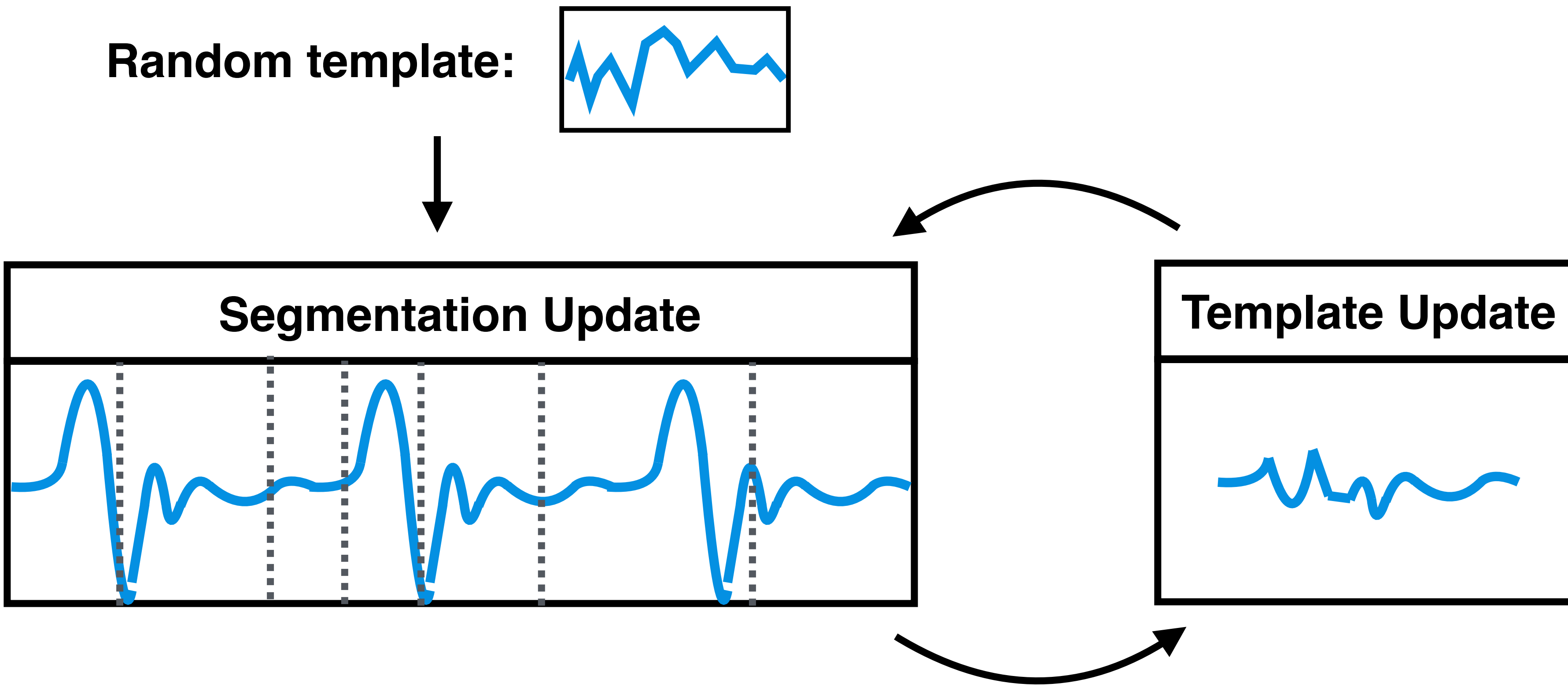

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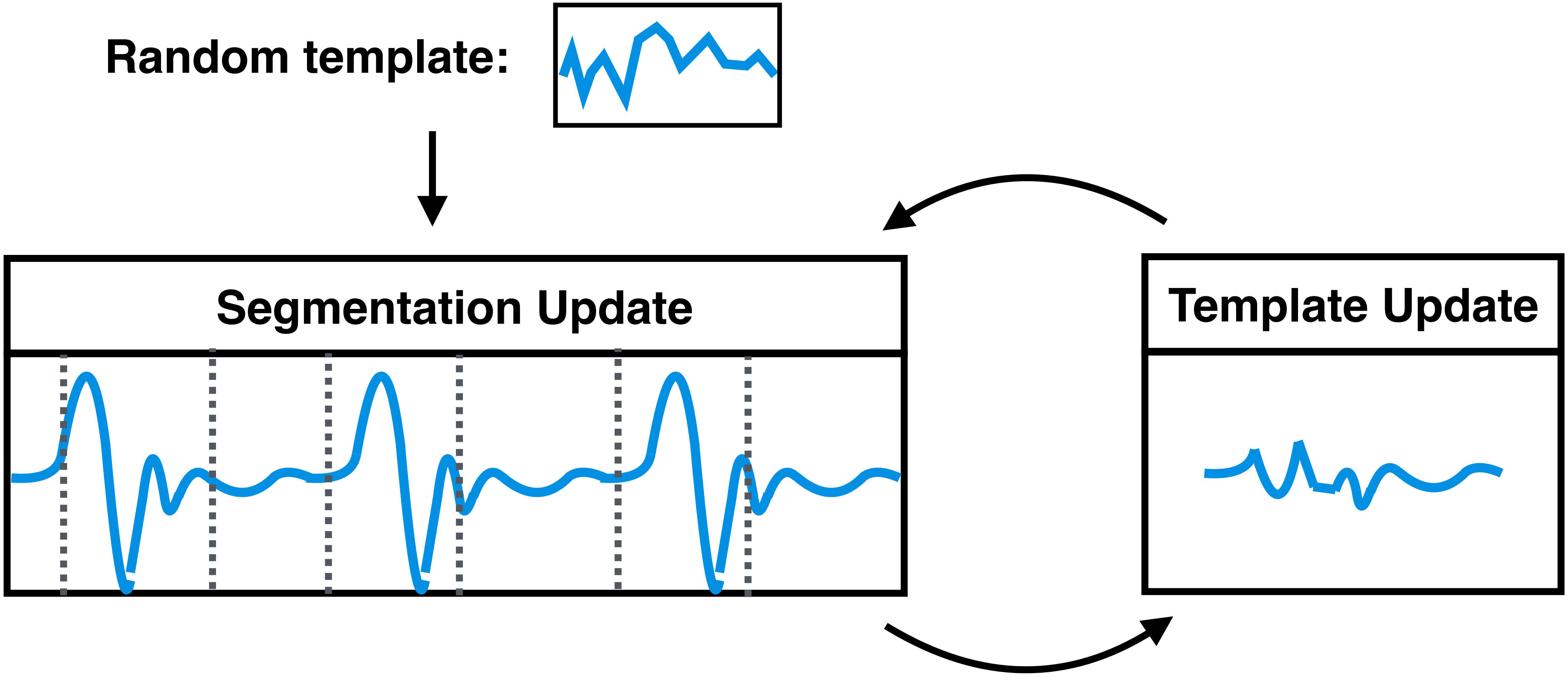

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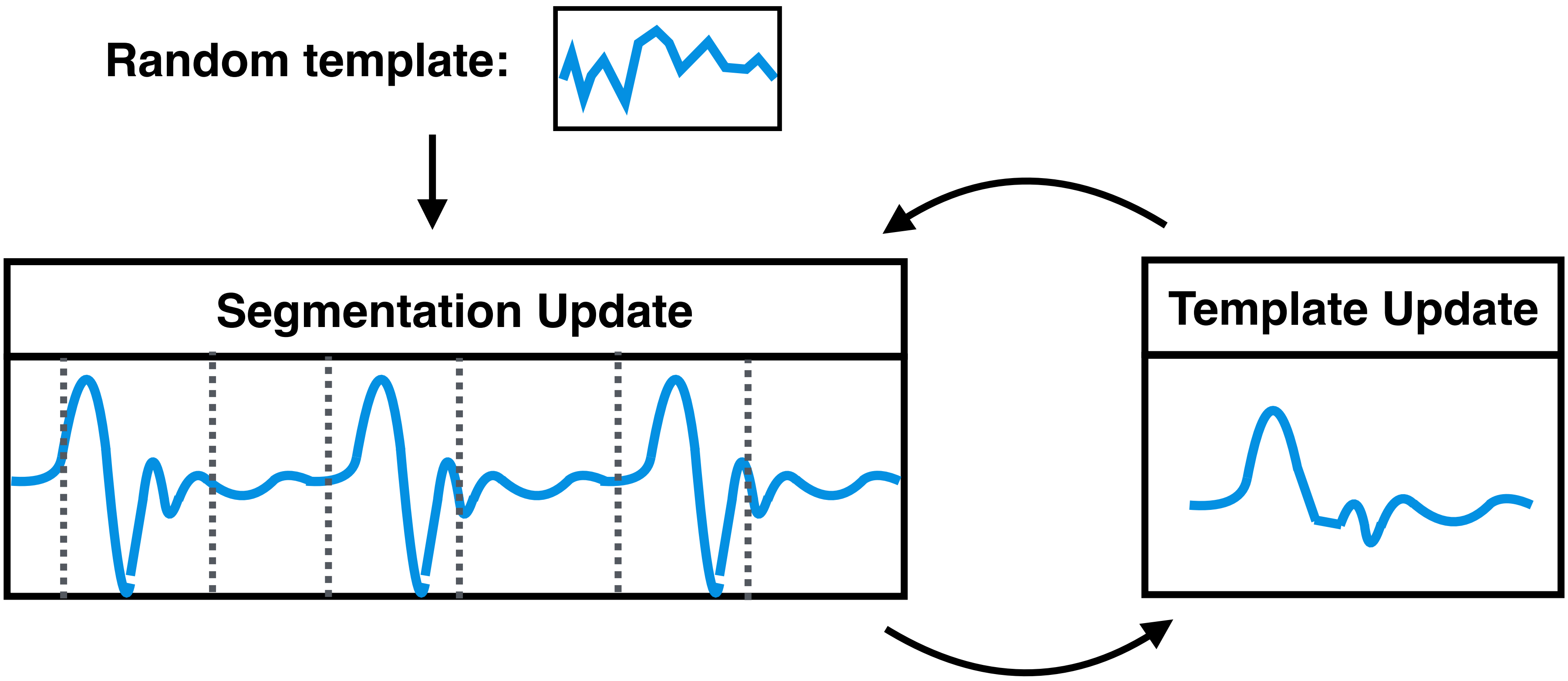

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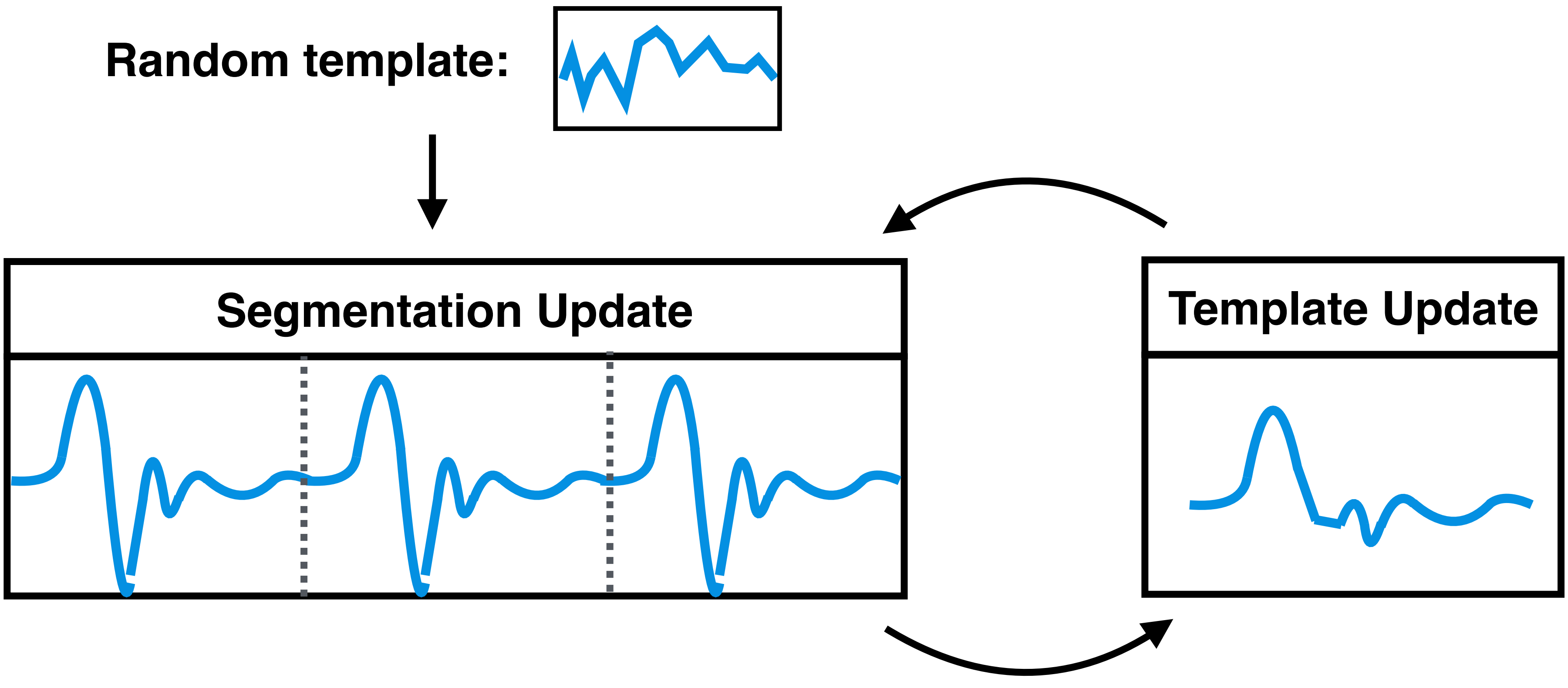

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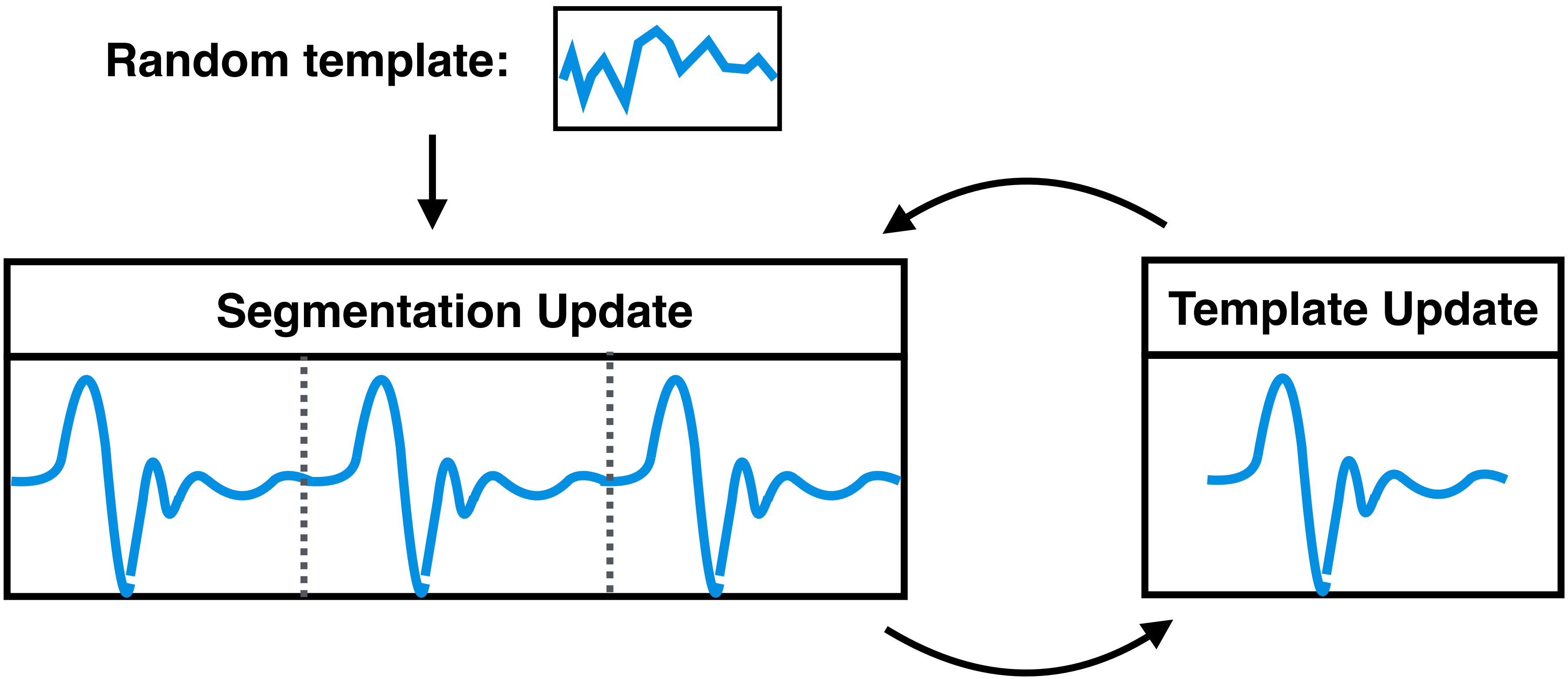

Caveat: Shrinking & Expanding

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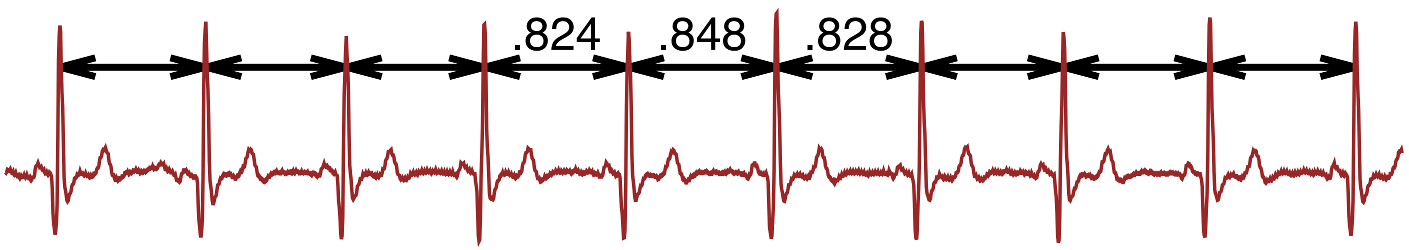
- IBI are not always the same



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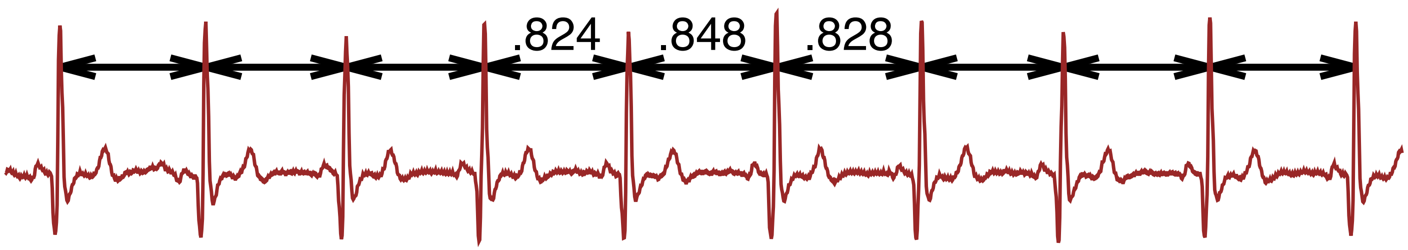

- Template subject to shrink and expanding
  - Linear warping

Algorithm

Need to recover both segmentation and template

Algorithm

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- 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

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segmentation template warping

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

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(dynamic programming)	(weighted least squares)

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Example run

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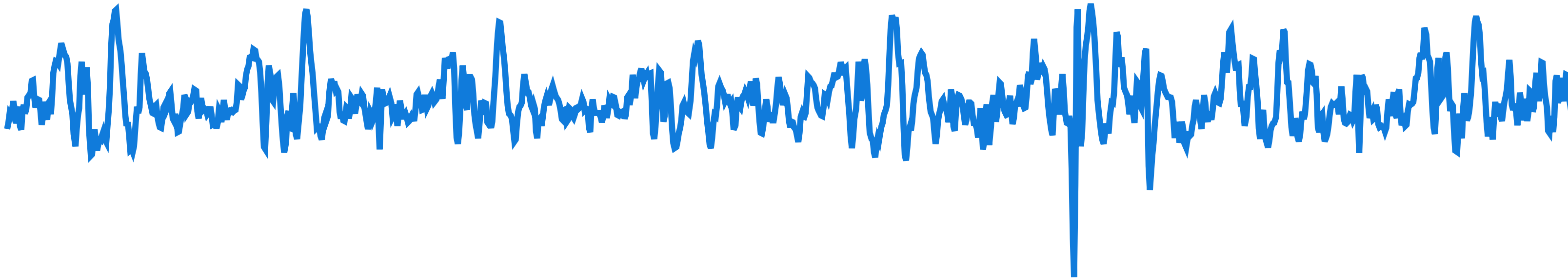
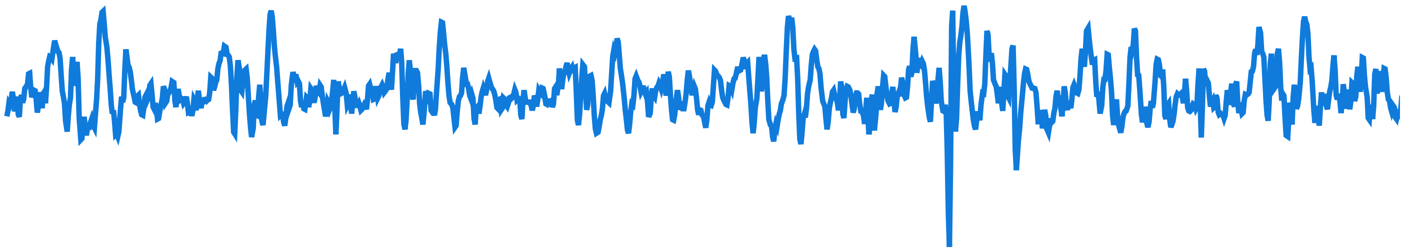


Example run

Iteration 1:



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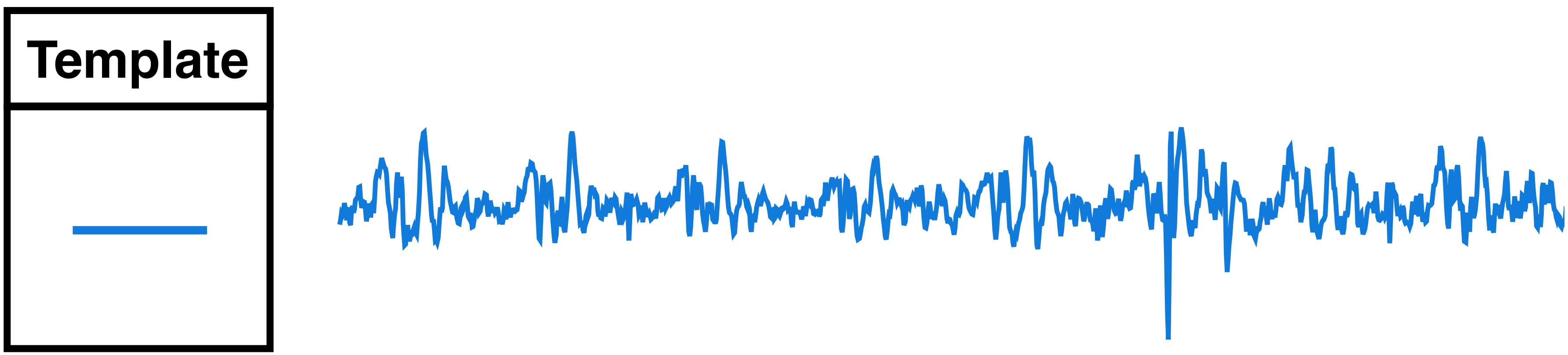

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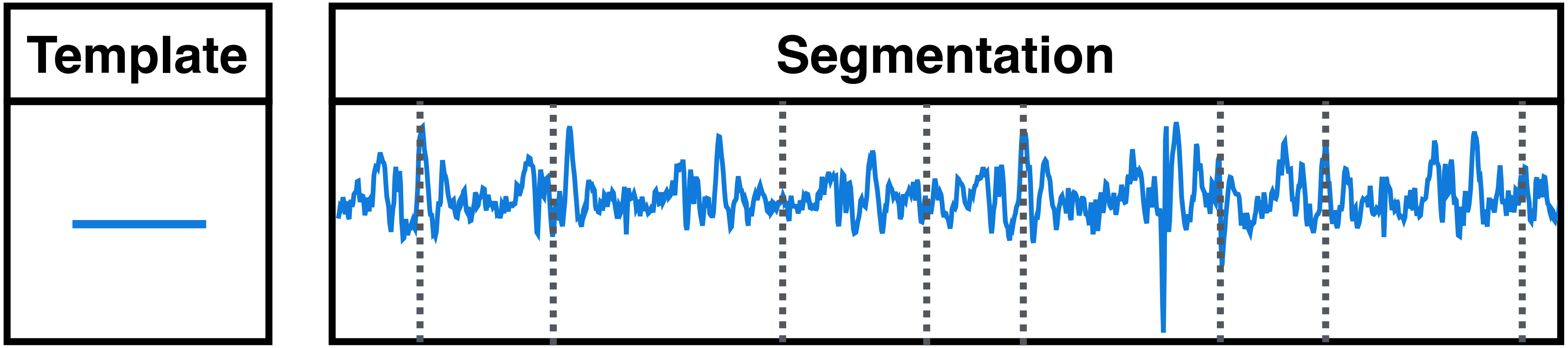
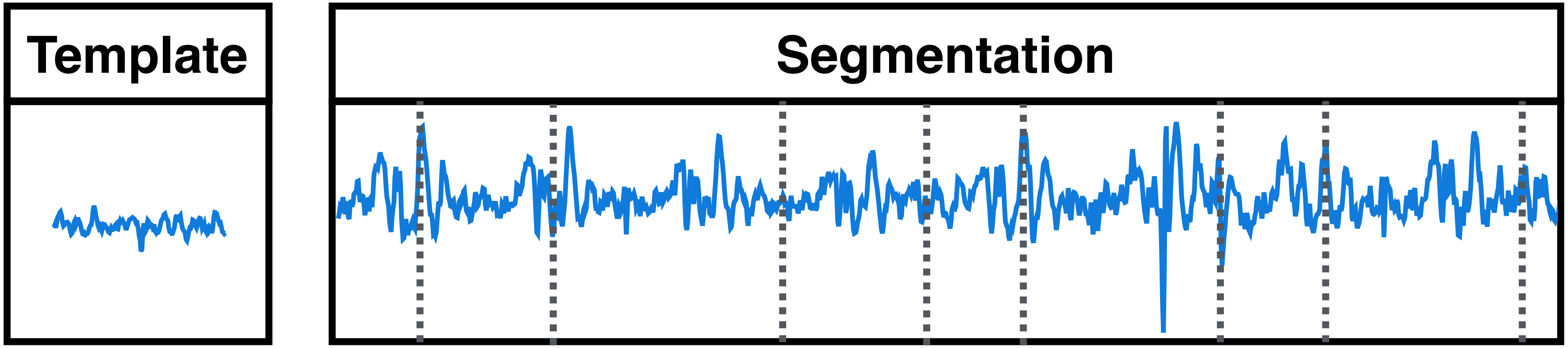


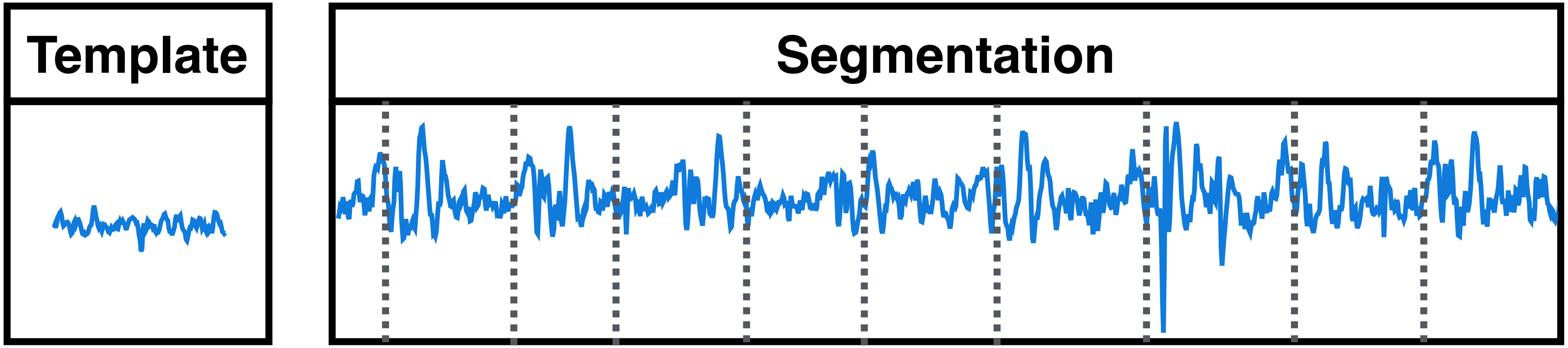
Example run

Iteration 2:



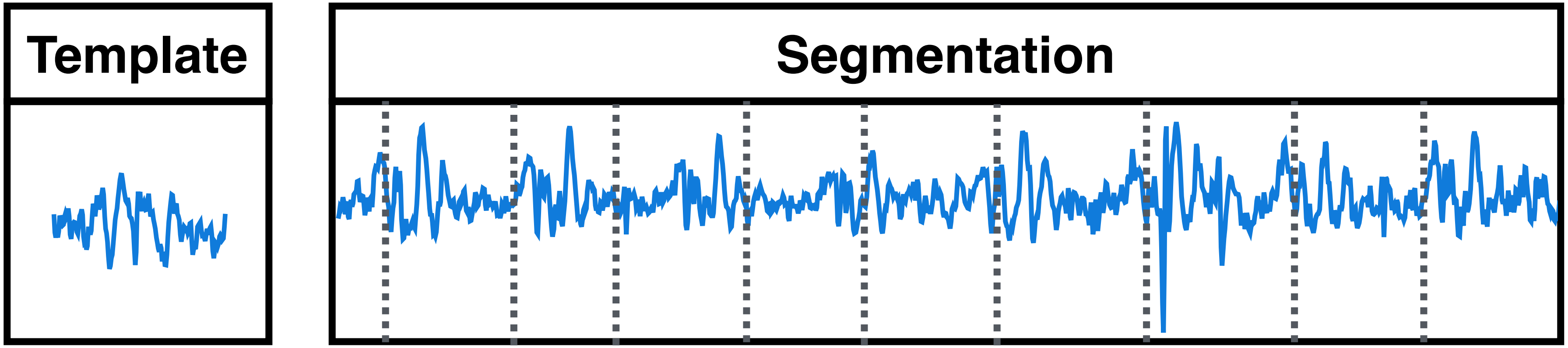
Example run

Iteration 2:



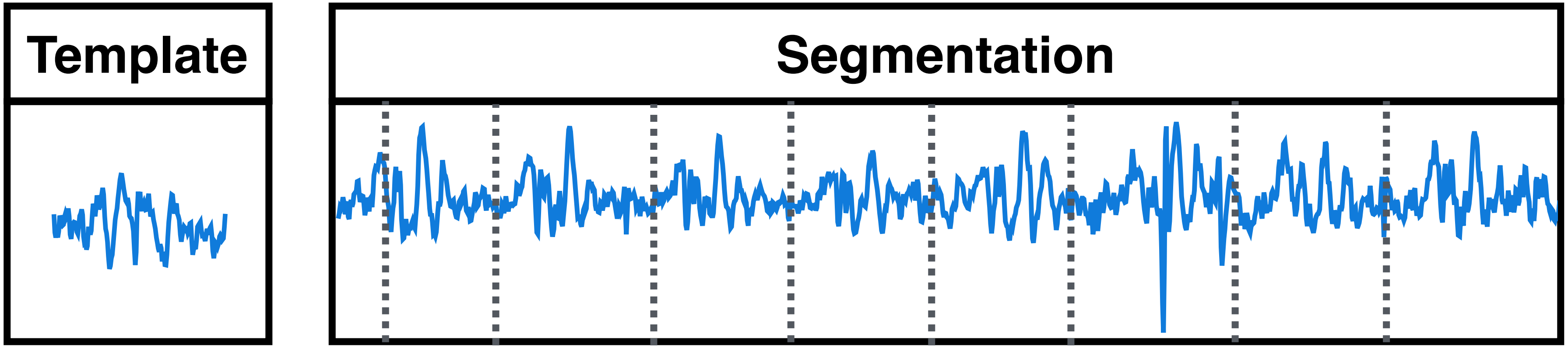
Example run

Iteration 3:



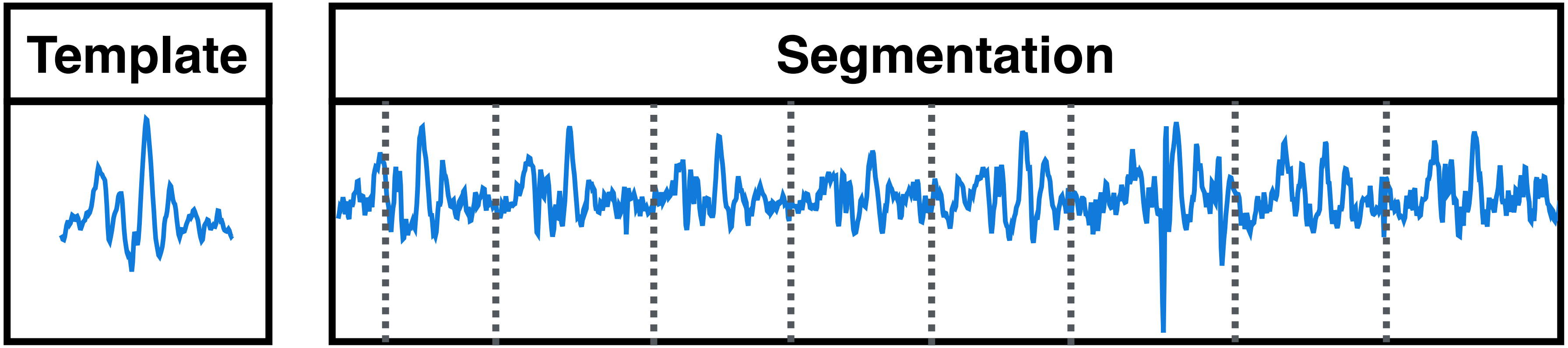
Example run

Iteration 3:



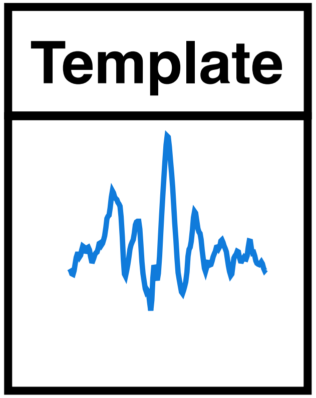
Example run

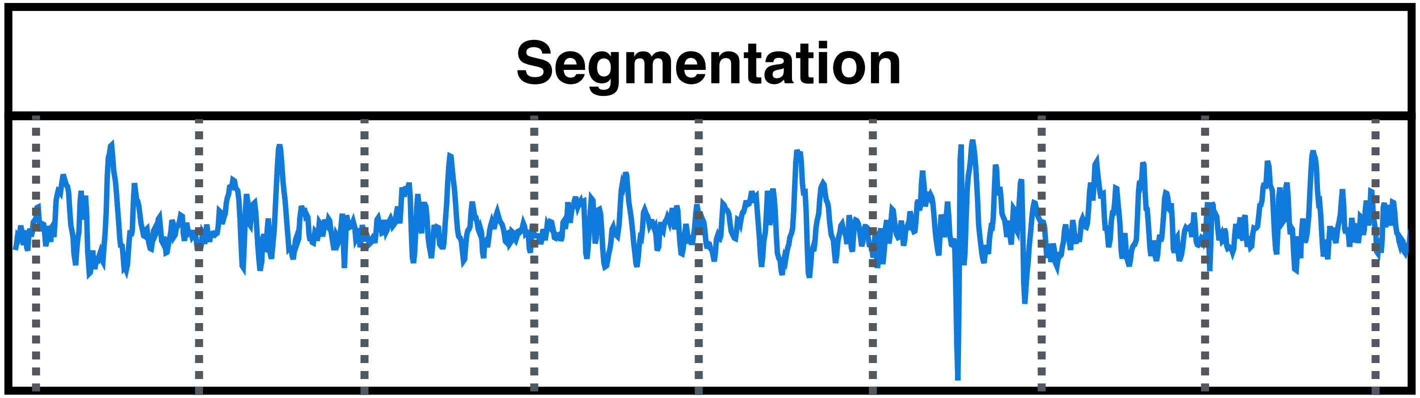
Iteration 7:



Example run

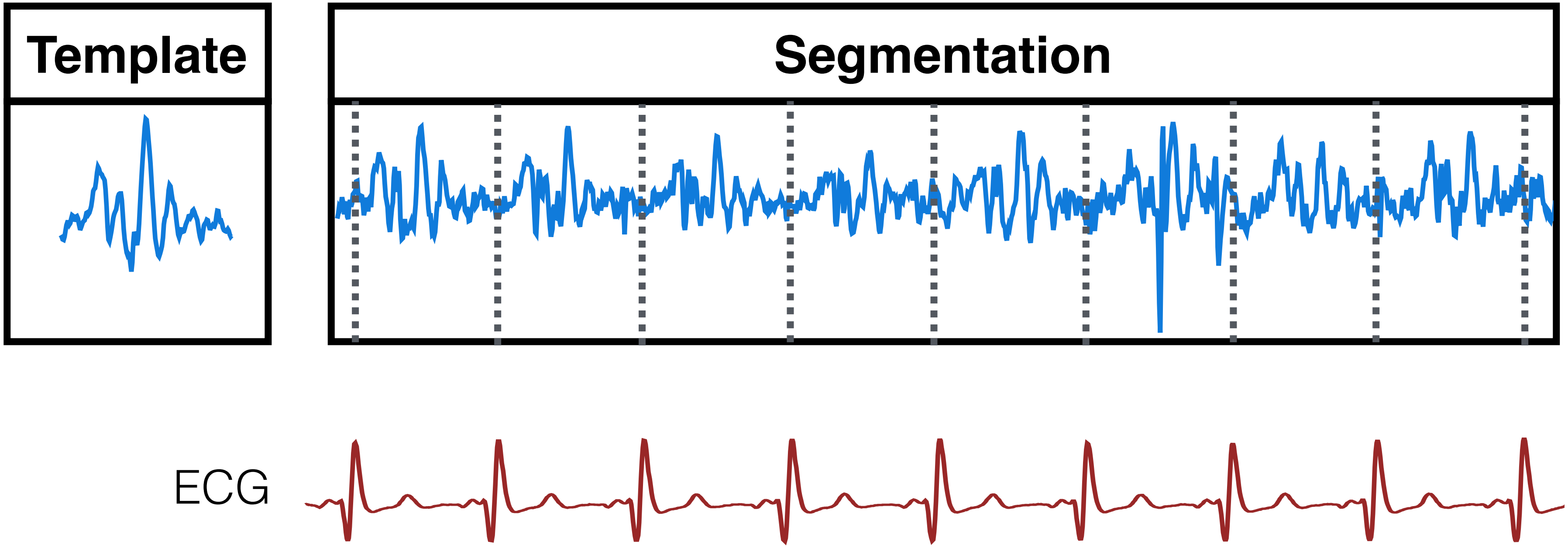
Iteration 7:





Example run

Iteration 7:



From vital signs to emotions

Physiological Features for Emotion Recognition

Physiological Features for Emotion Recognition

- 37 Features similar to ECG-based methods

Physiological Features for Emotion Recognition

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  - Variability of IBI

Physiological Features for Emotion Recognition

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

Emotion Classification

Emotion Classification

- Recognize emotion using physiological features

Emotion Classification

- Recognize emotion using physiological features
- Used L1-SVM classifier

Emotion Classification

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

Emotion Model

Emotion Model

- Standard 2D emotion model

Emotion Model

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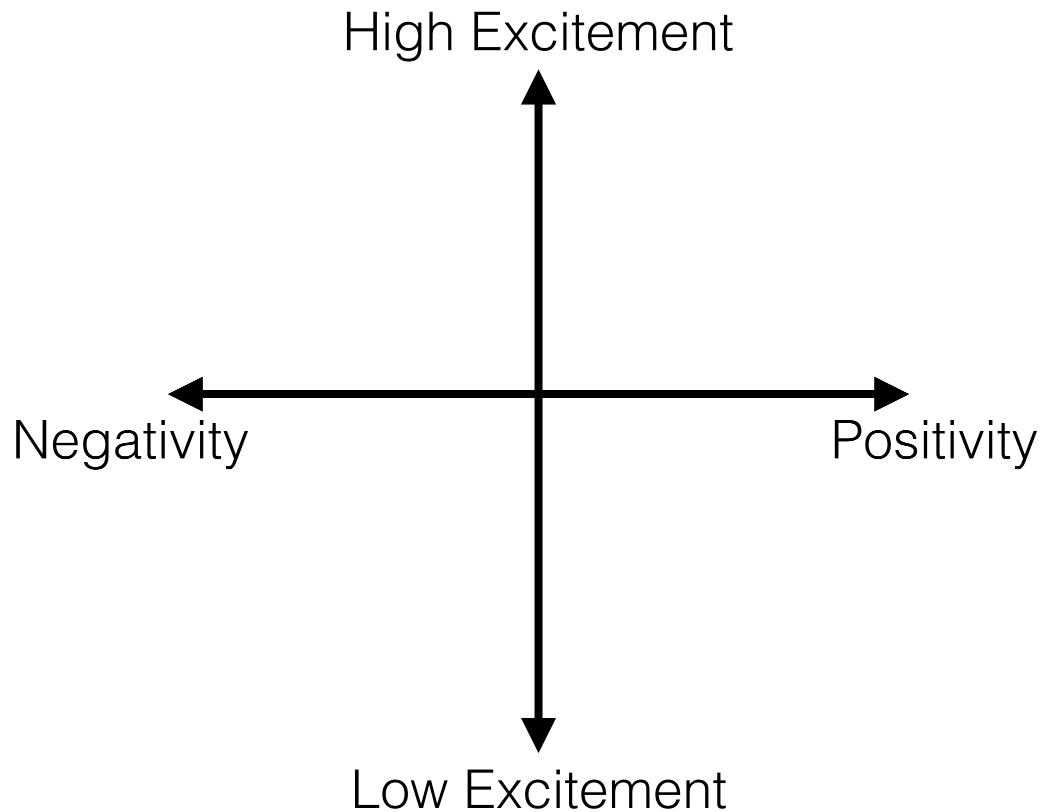
Emotion Model

- Standard 2D emotion model



Emotion Model

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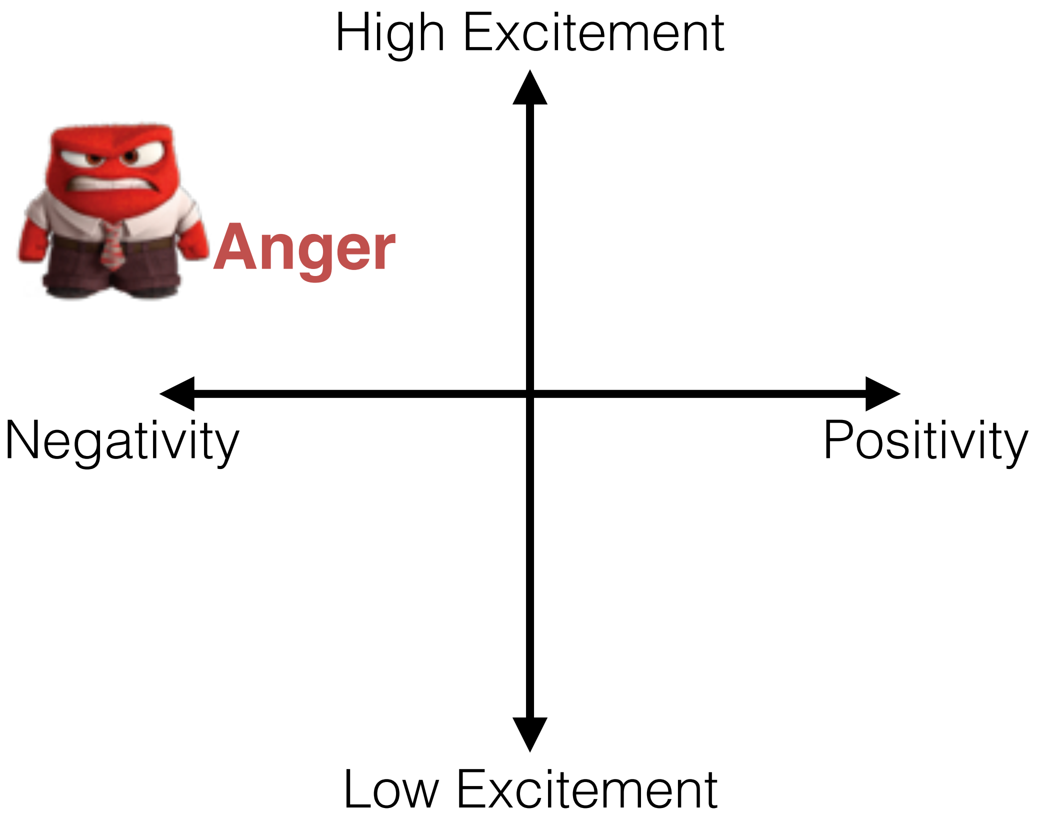

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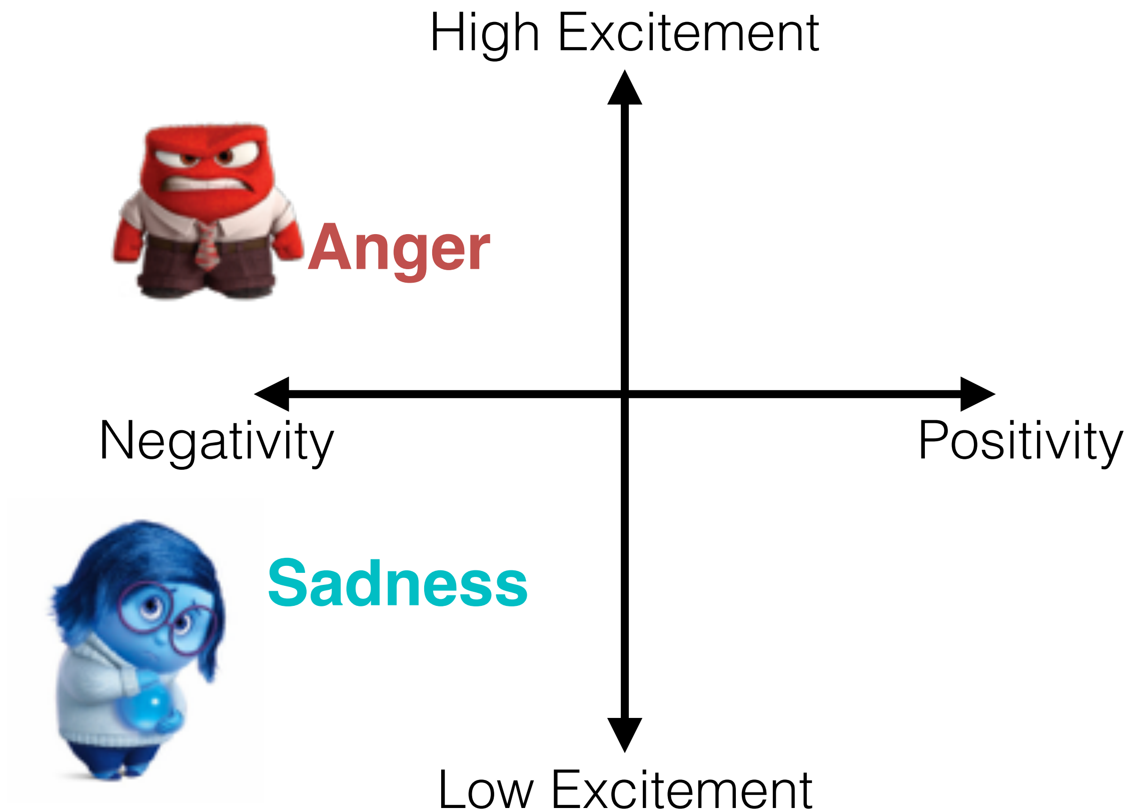

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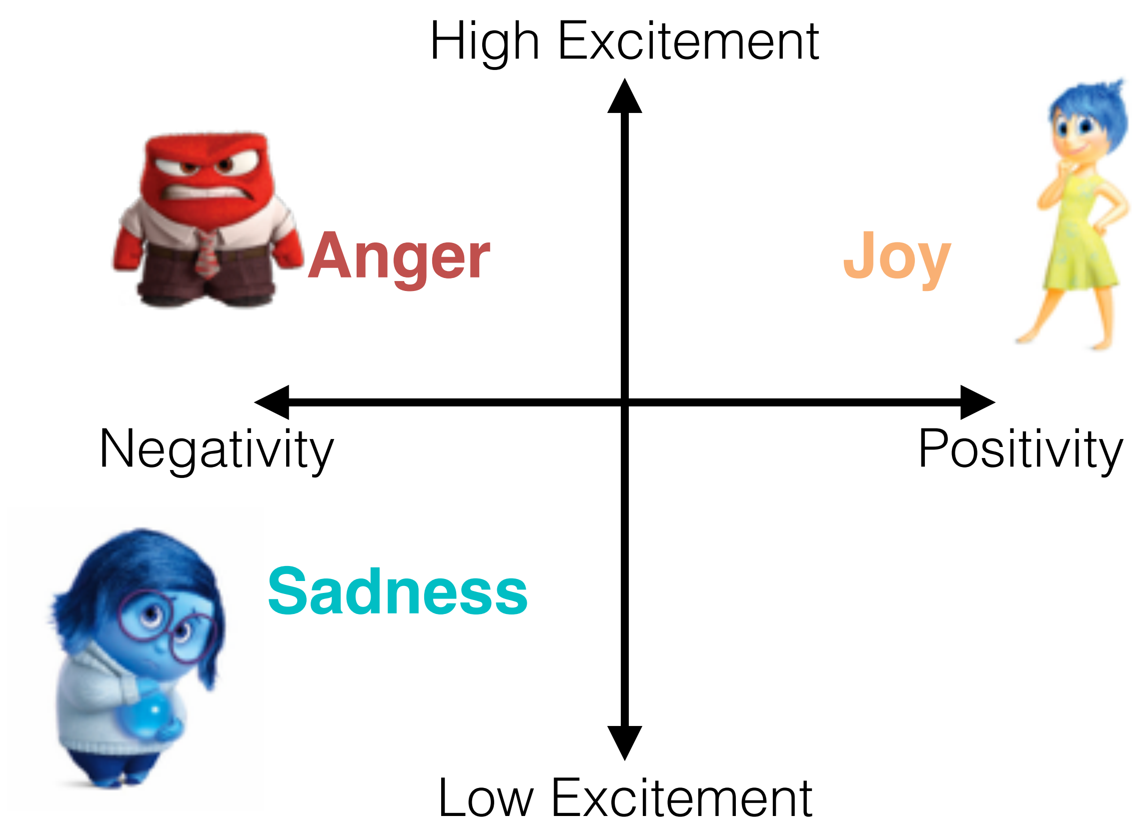

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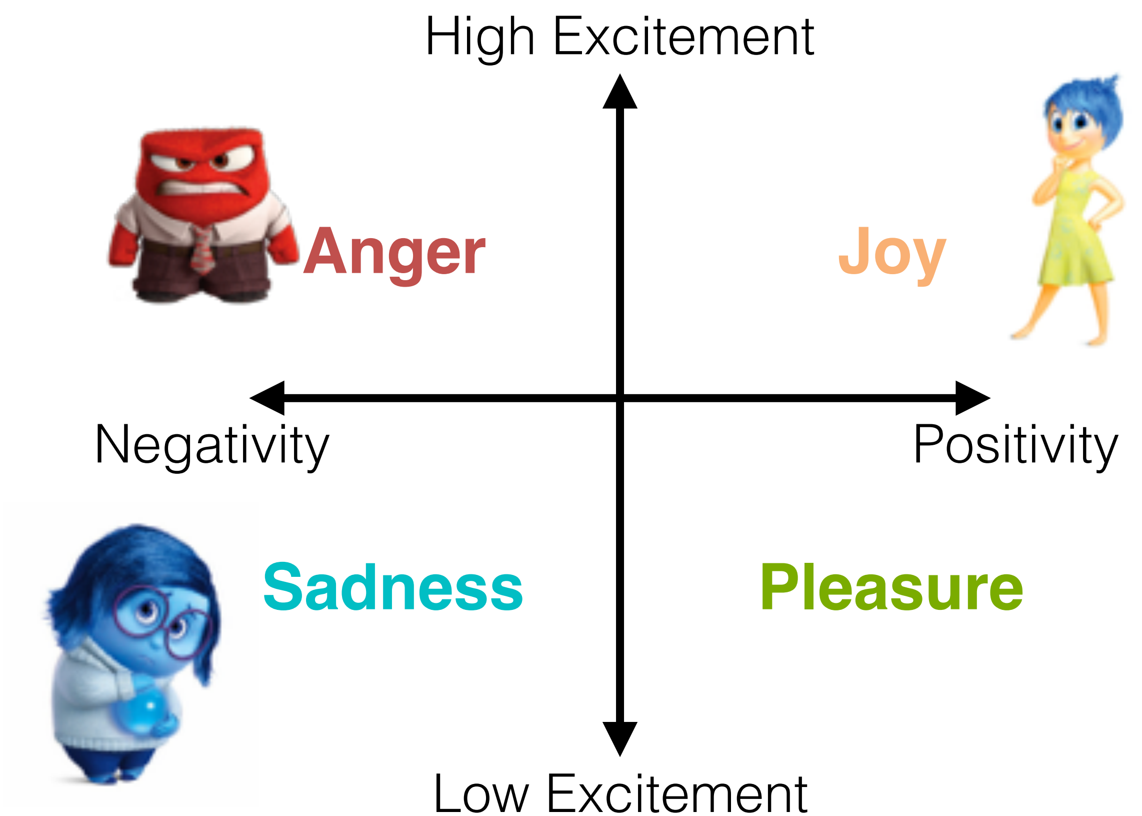
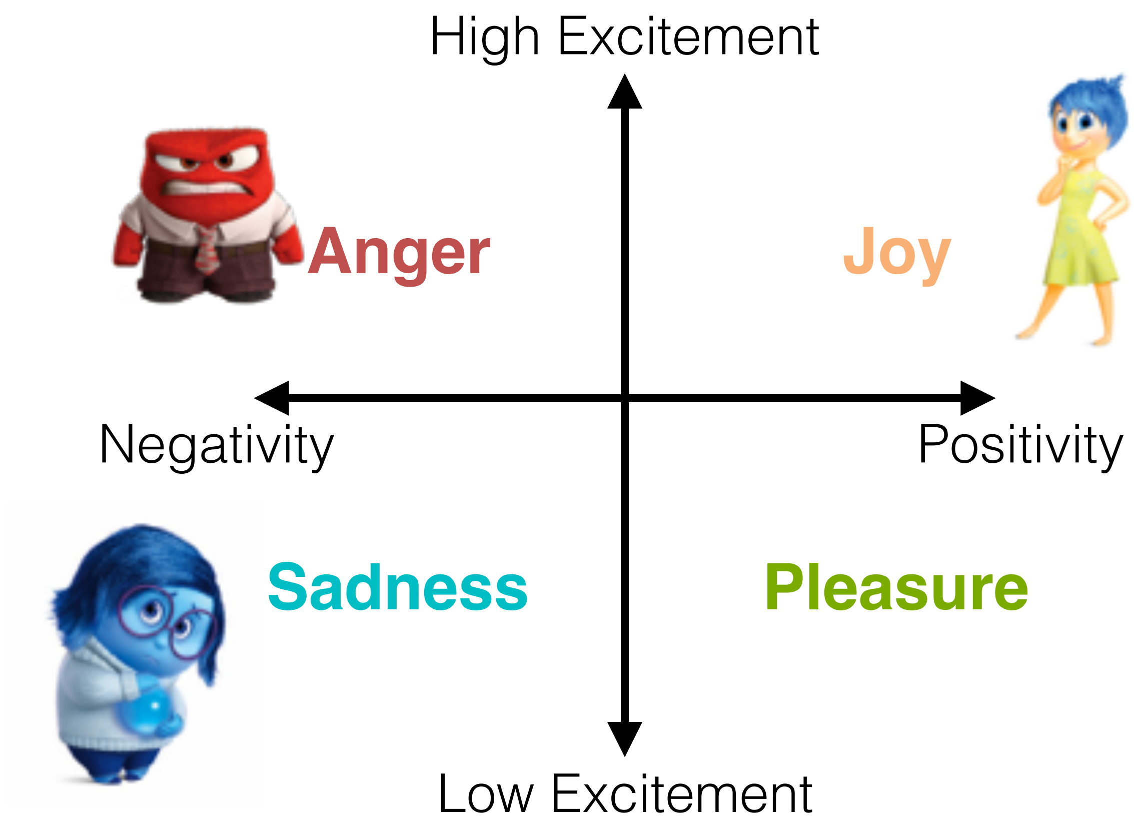


Emotion Model

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



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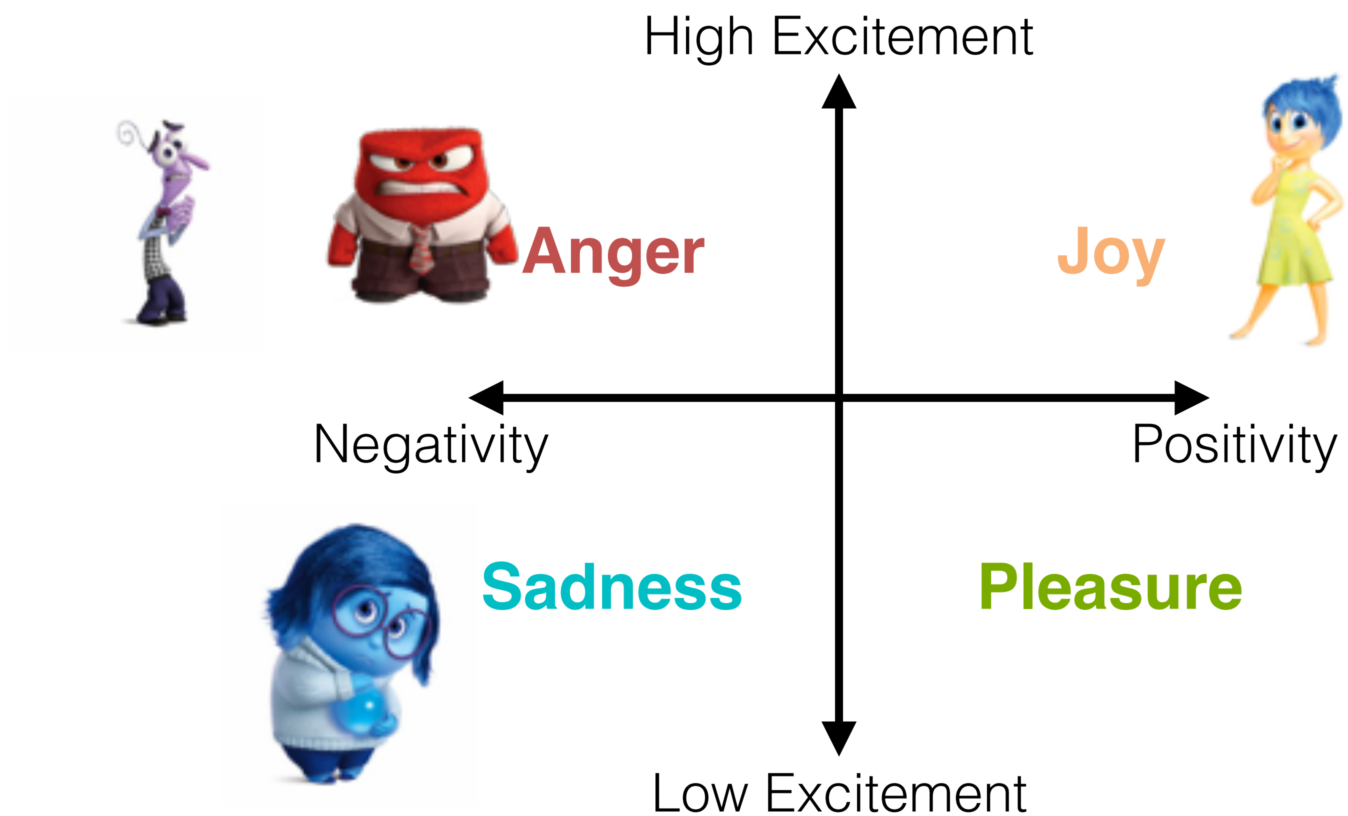

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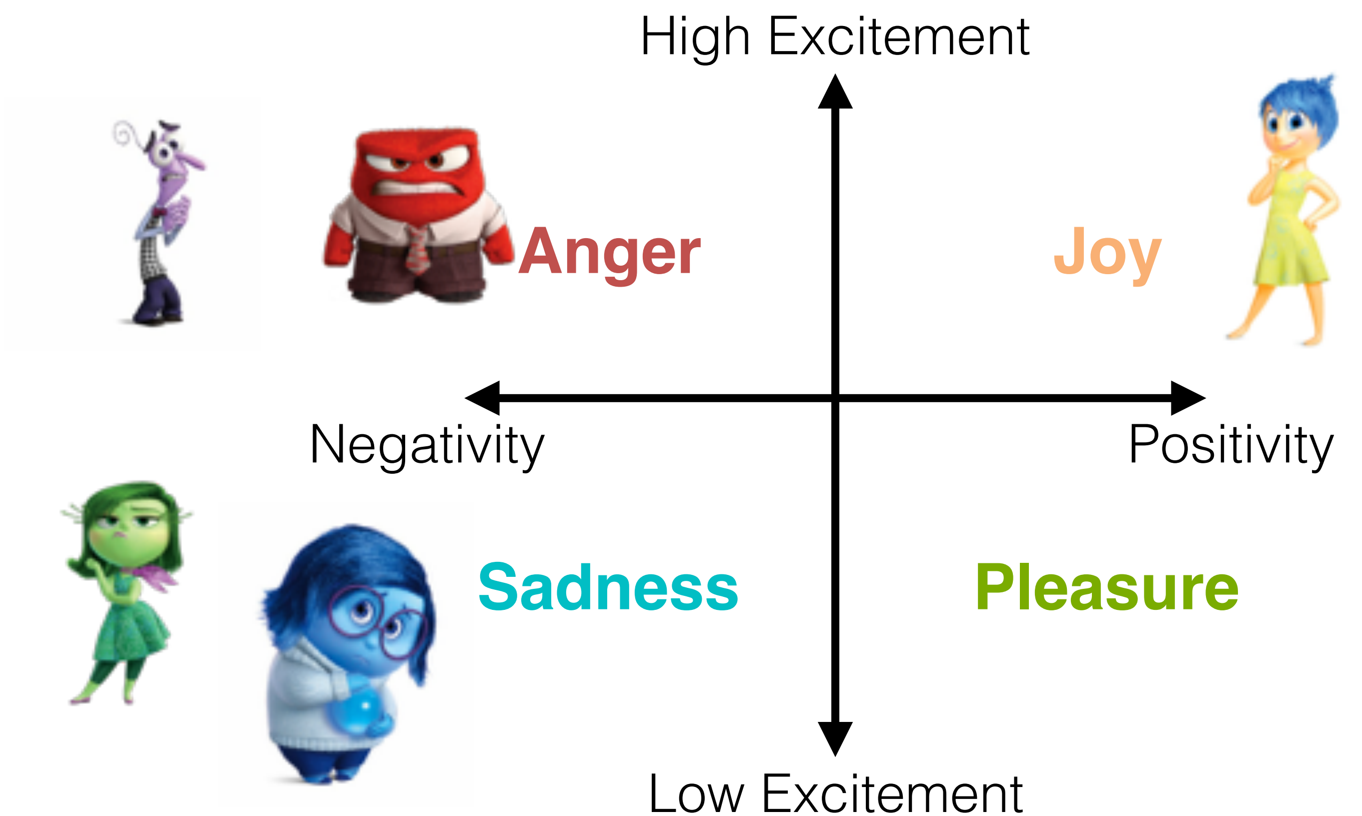
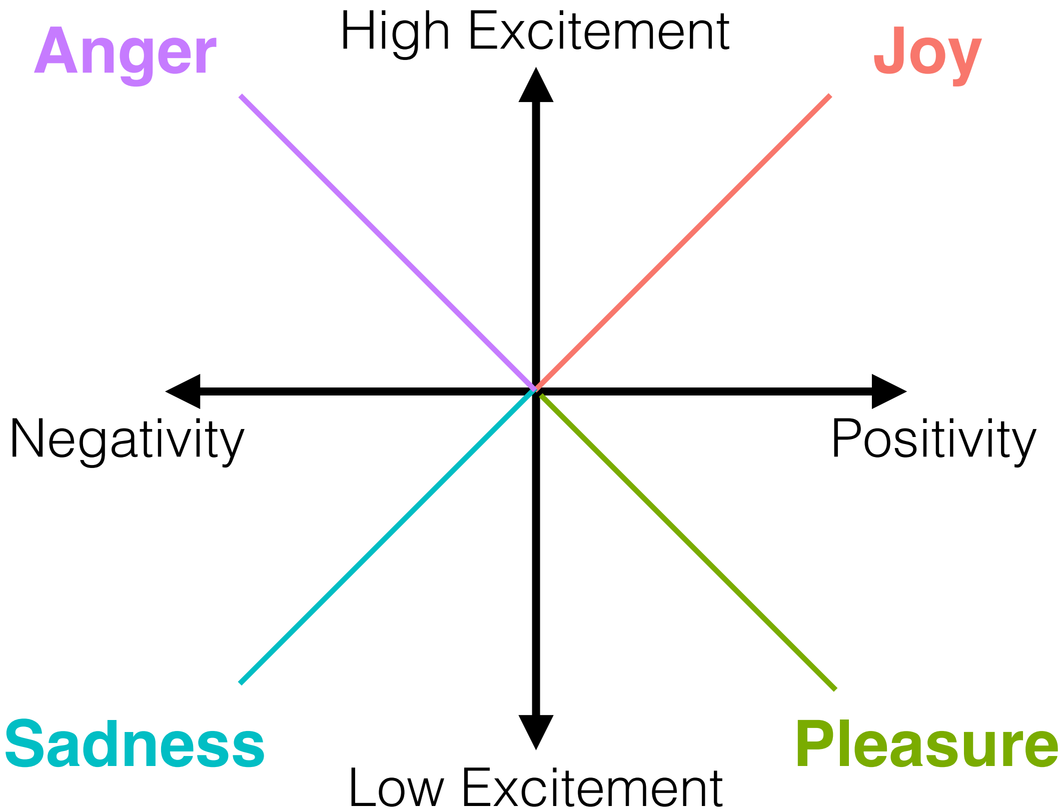
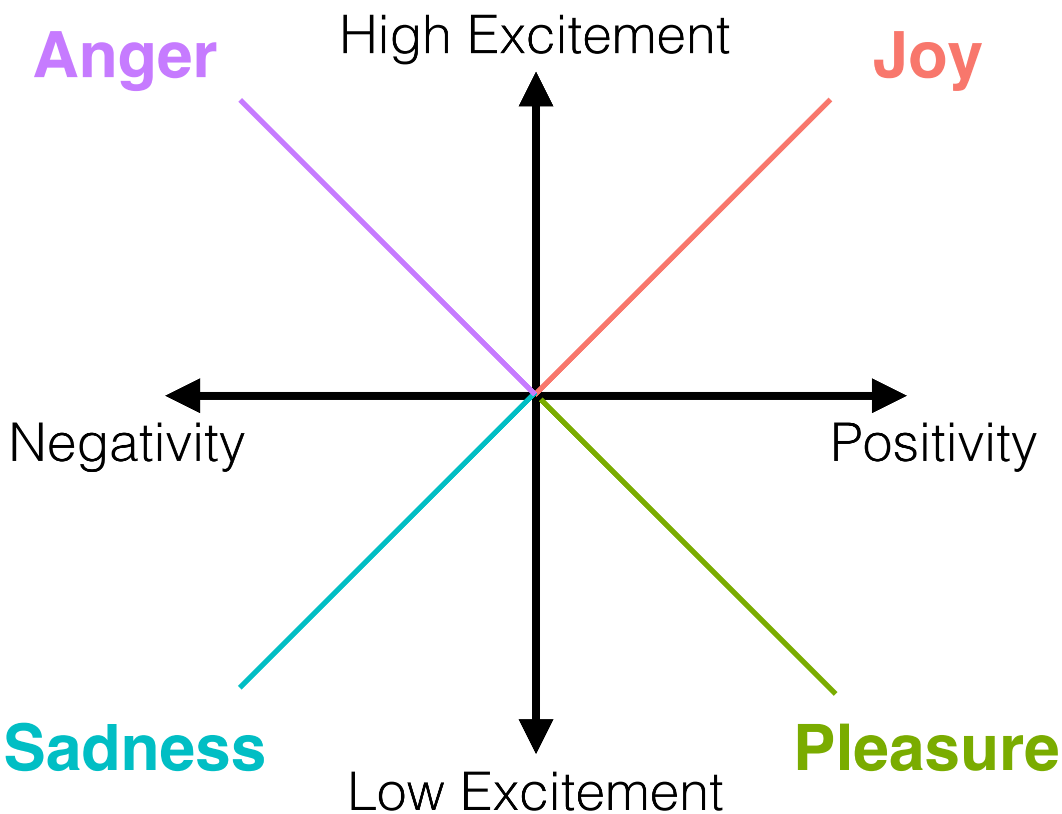


Does it detect emotion accurately?



Person-dependent Classification

- Train and test on the same person



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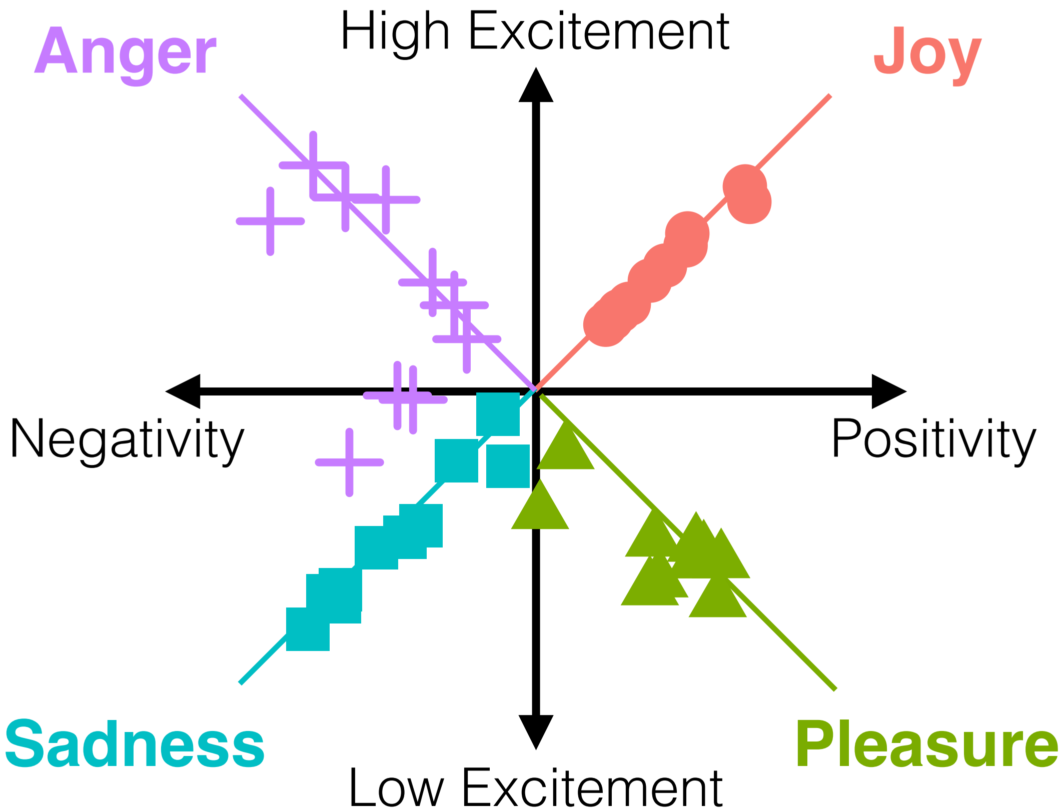

Person-dependent Classification

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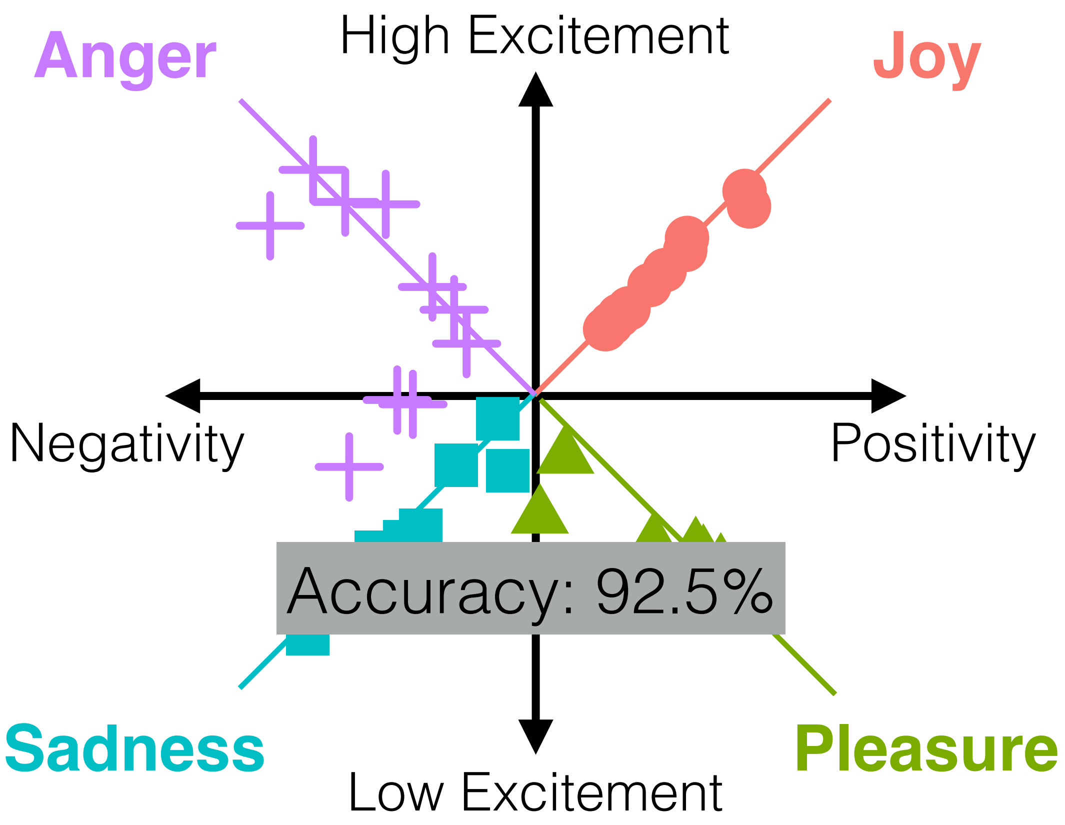

Person-independent Classification

- Train and test on the different person

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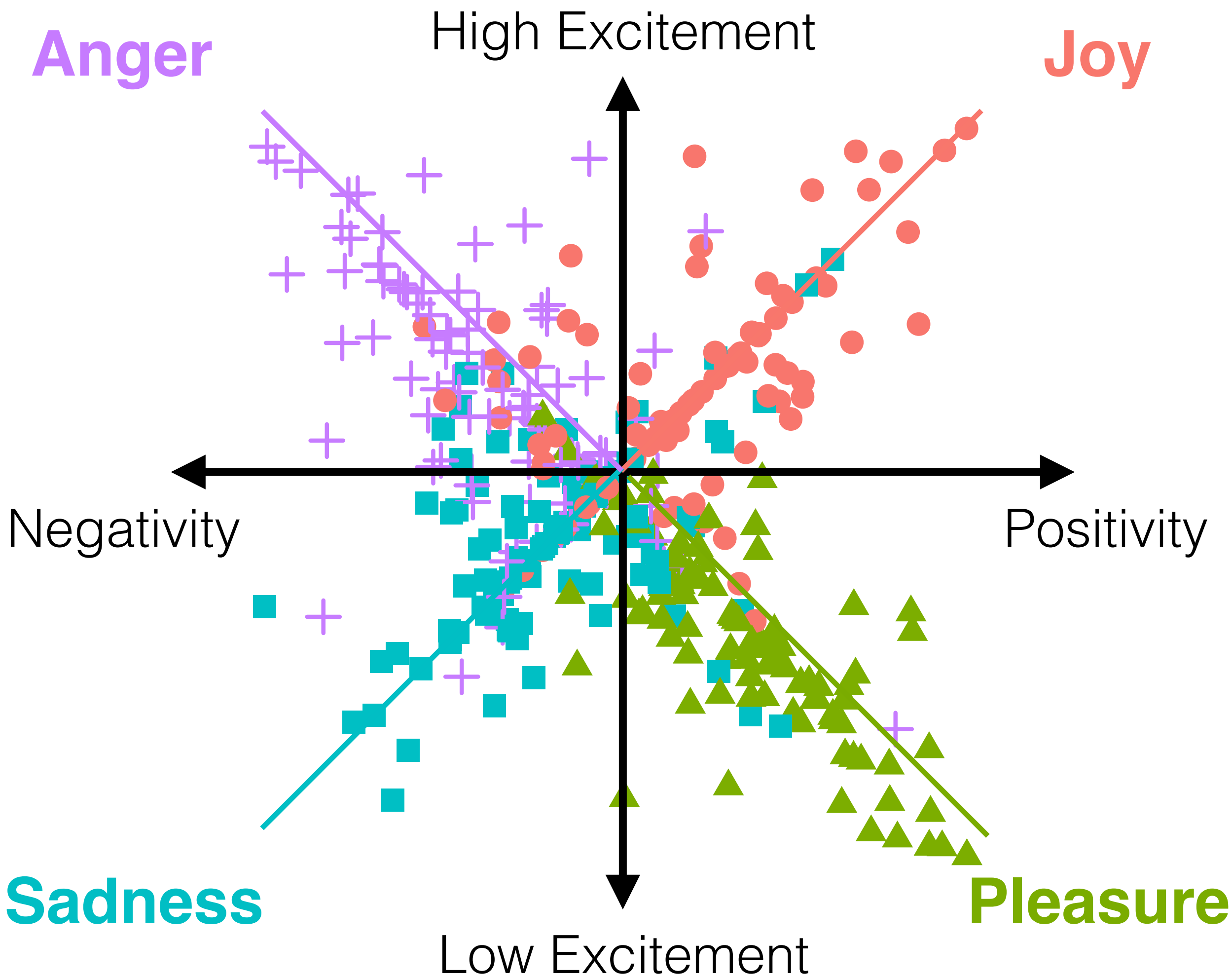
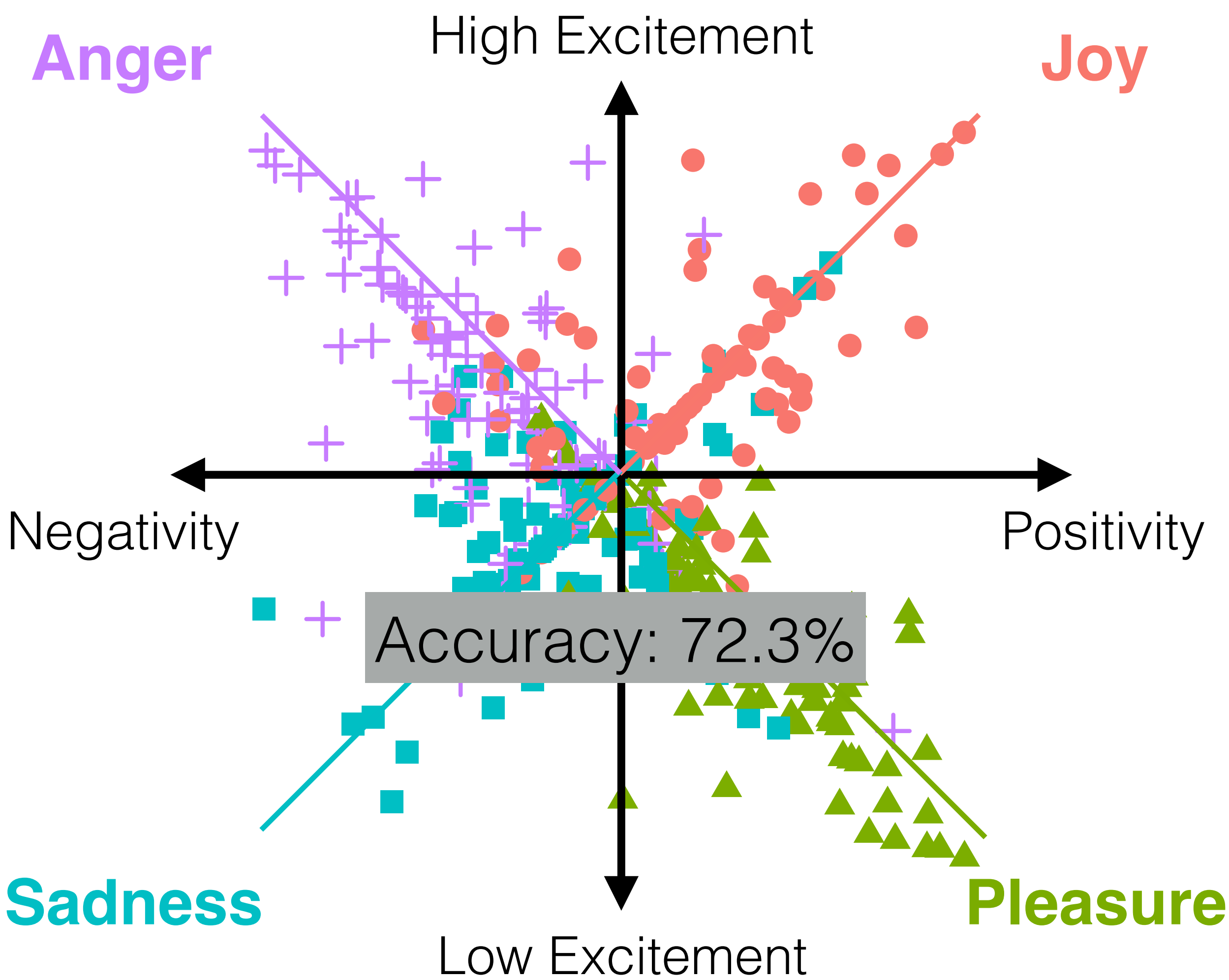
- Train and test on the different person



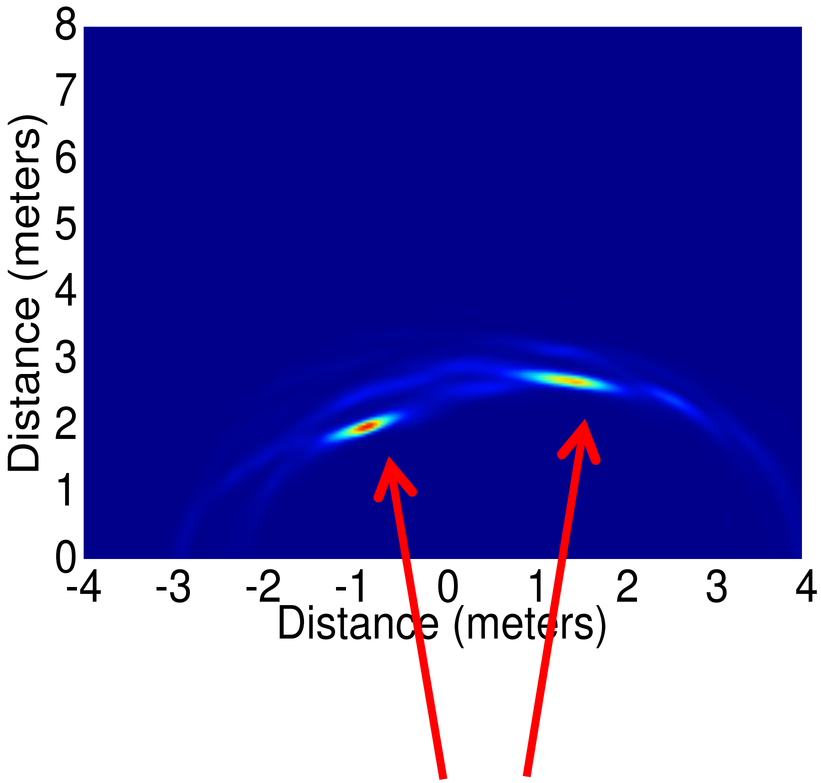
Person-independent Classification

- Train and test on the different person



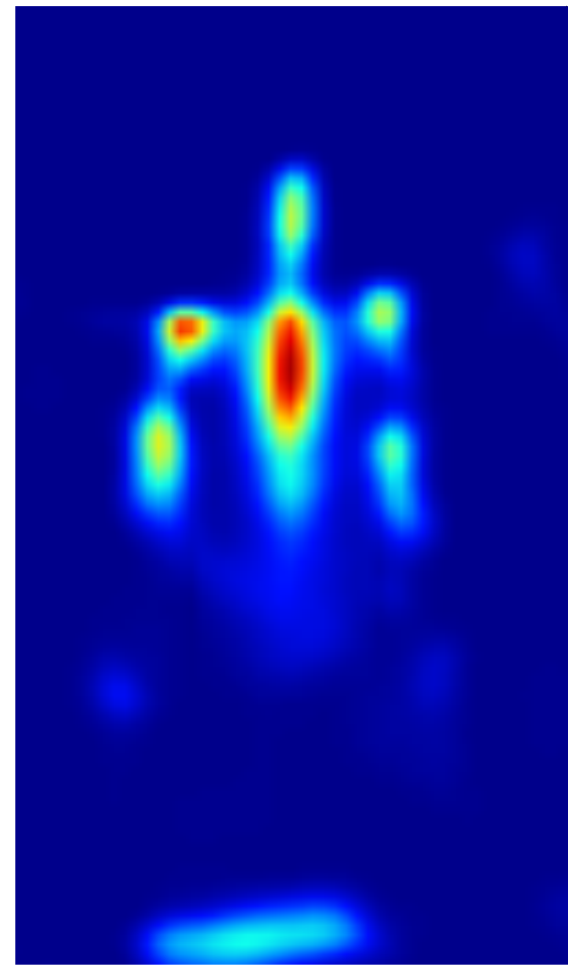
RF Imaging

People are points

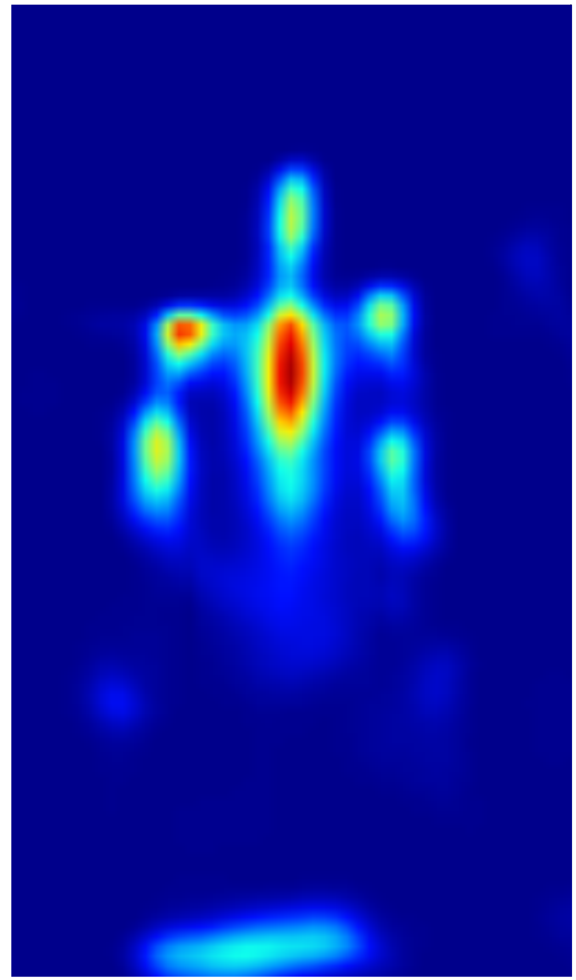


Localize the two users

Want a silhouette



Capturing a Coarse Human Silhouette



Traditional Imaging

RF Imaging

Traditional Imaging

Cannot image through occlusions like walls

RF Imaging

✚ Walls are transparent and can image through them

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

Traditional Imaging

Cannot image through occlusions like walls

Form 2D images using lenses

Get a reflection from all points: can image all the body

RF Imaging

+ Walls are transparent and can image through them

− No lenses at these frequencies

− No reflections from most points: all reflections are specular

RF Imaging

- + Walls are transparent and can image through them
- − No lenses at these frequencies
- − 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

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

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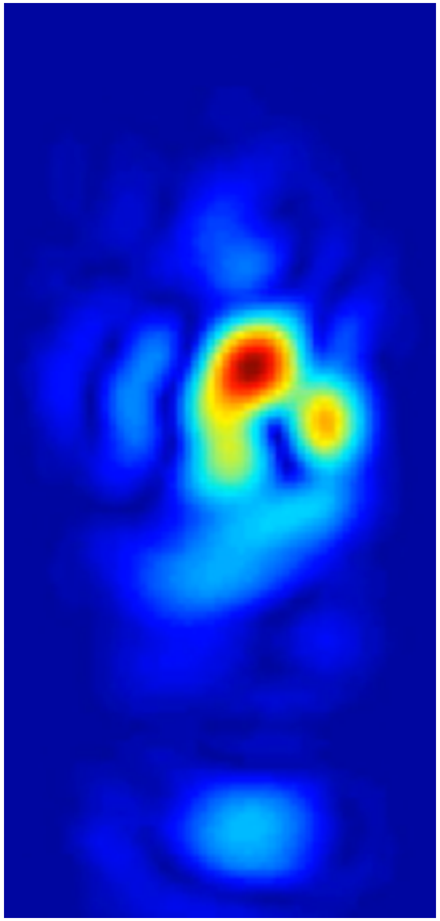
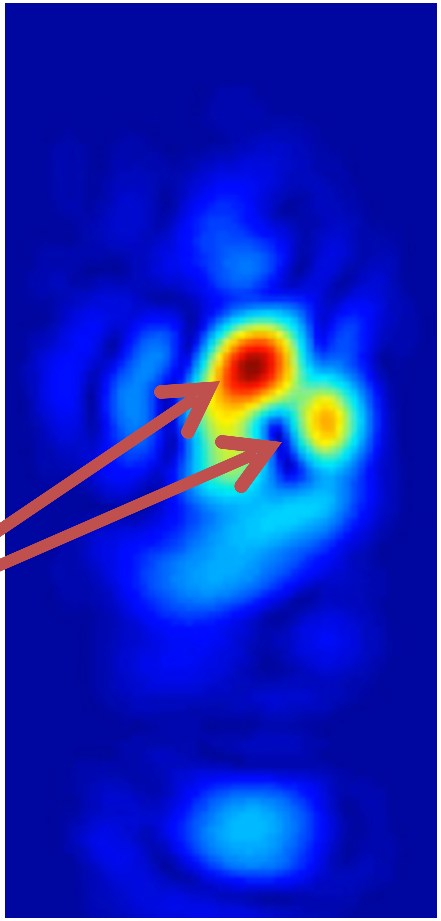
Output of 3D RF Scan



Challenge: We only obtain blobs in space

Output of 3D RF Scan



Blobs of reflection power

<u>Challenge:</u> We only obtain blob in space

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At frequencies that traverse walls, human body parts are specular (pure mirror)

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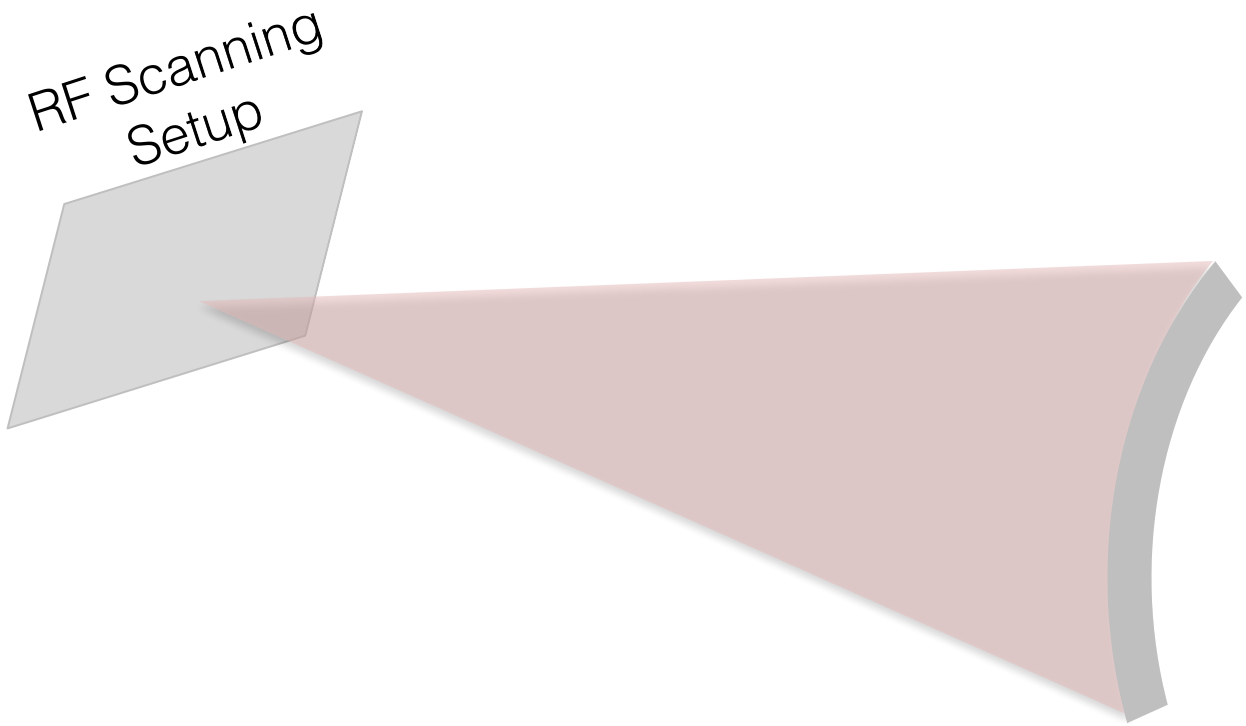

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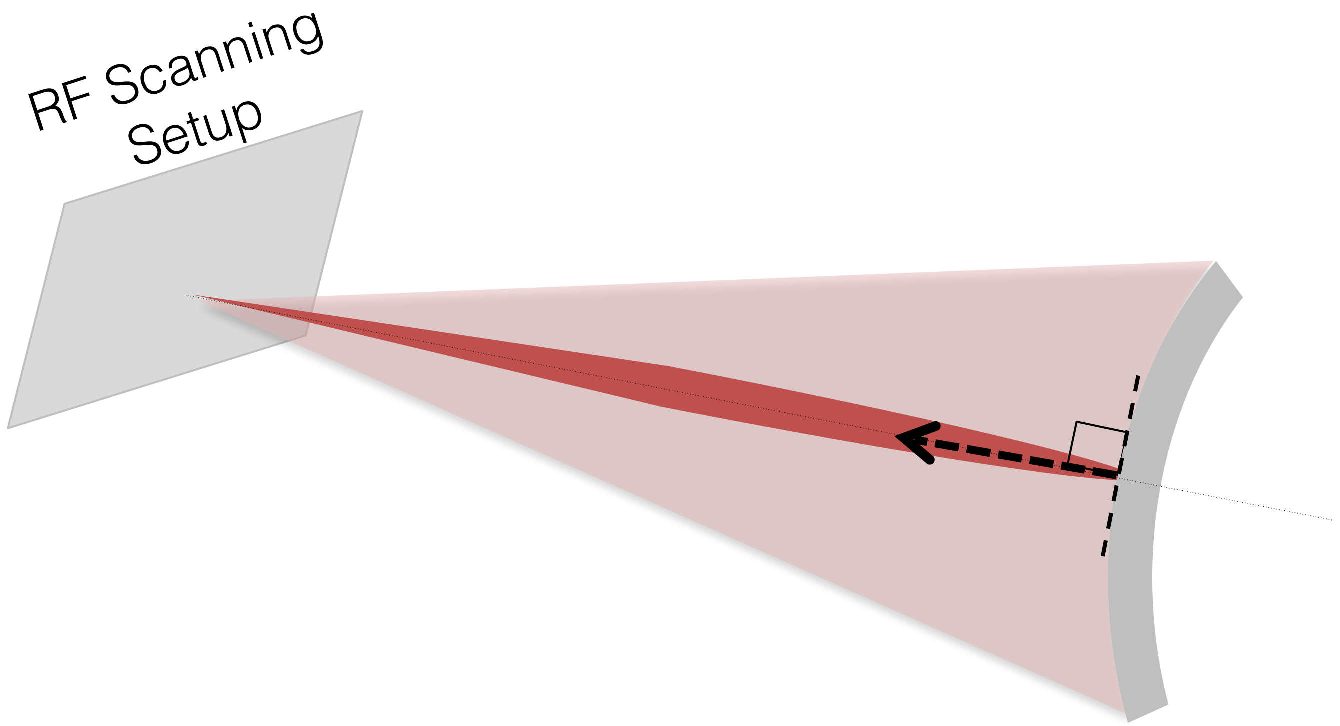
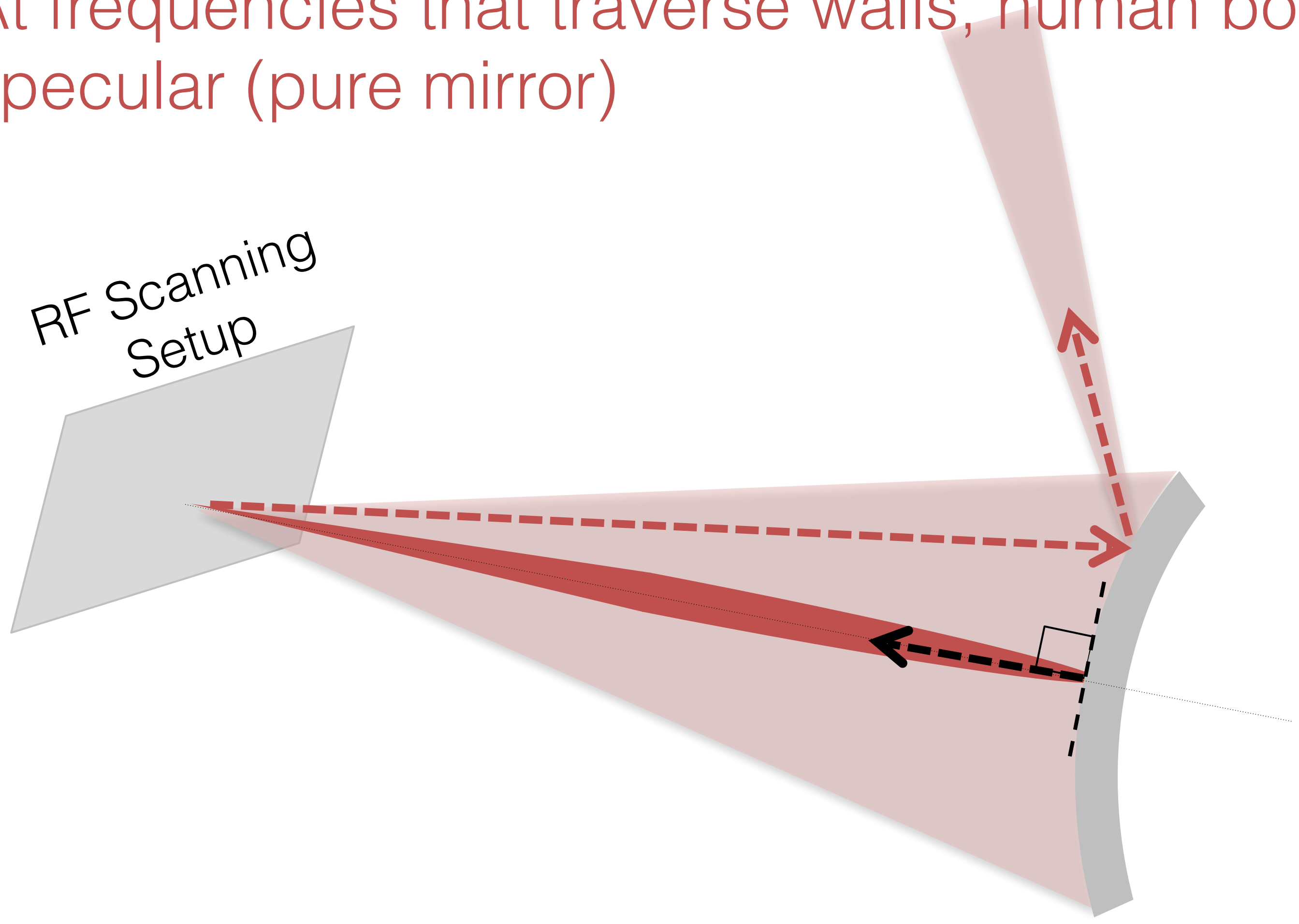
At frequencies that traverse walls, human body parts are specular (pure mirror)



Challenge: We only obtain blob in space

At frequencies that traverse walls, human body parts are specular (pure mirror)



Challenge: We only obtain blob in space

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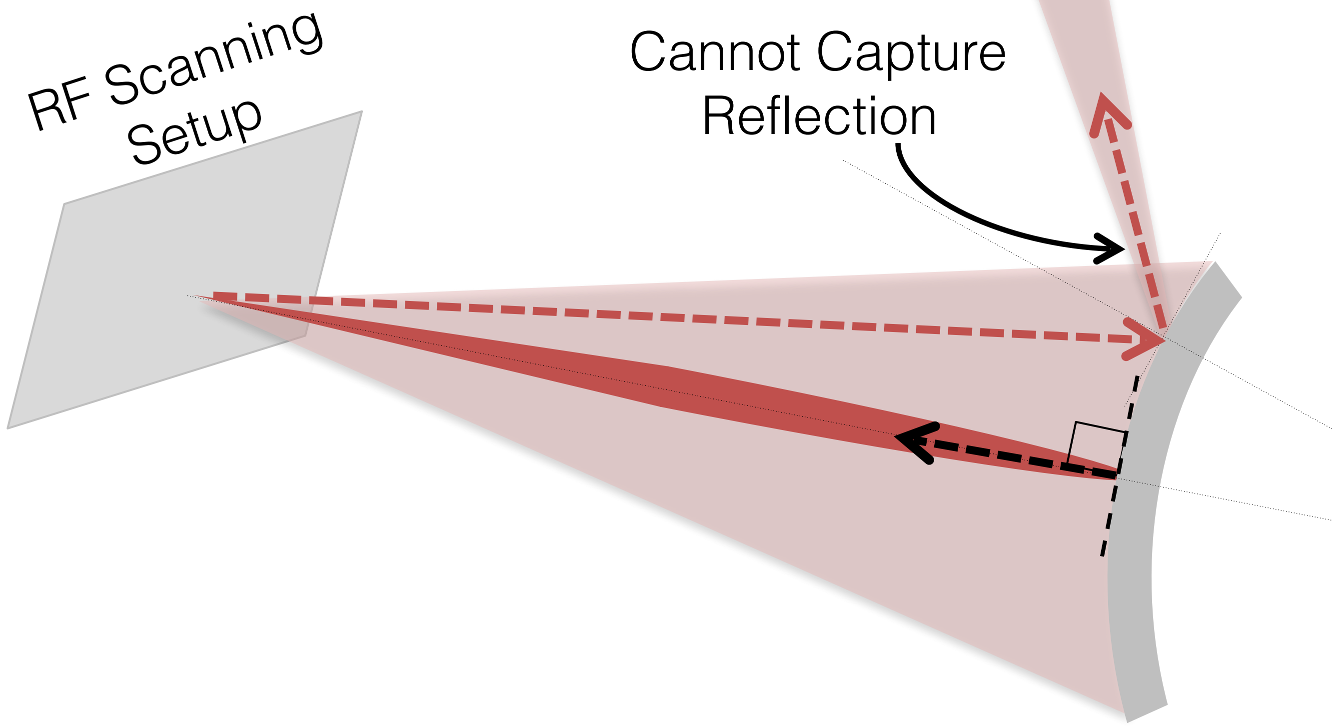
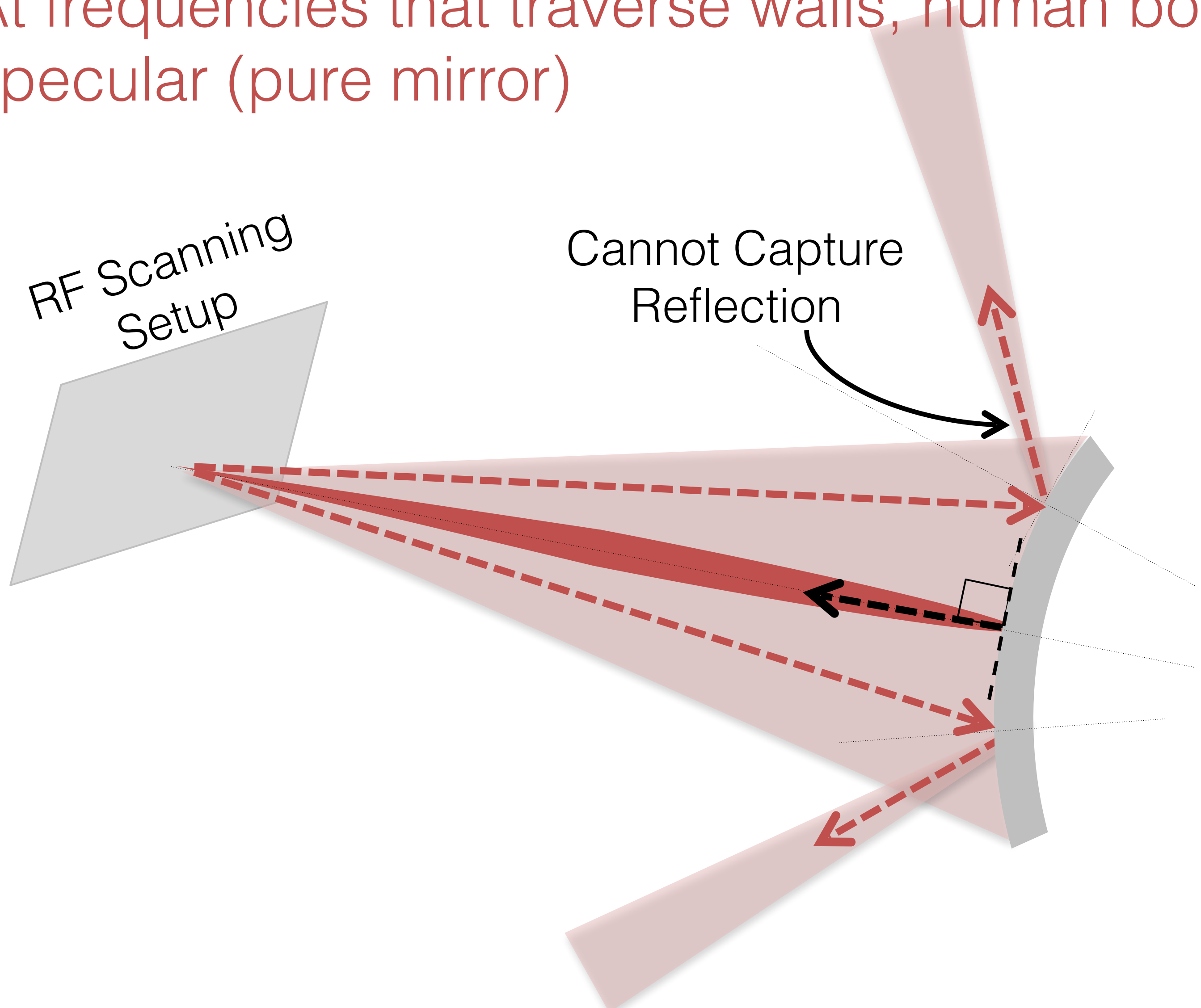
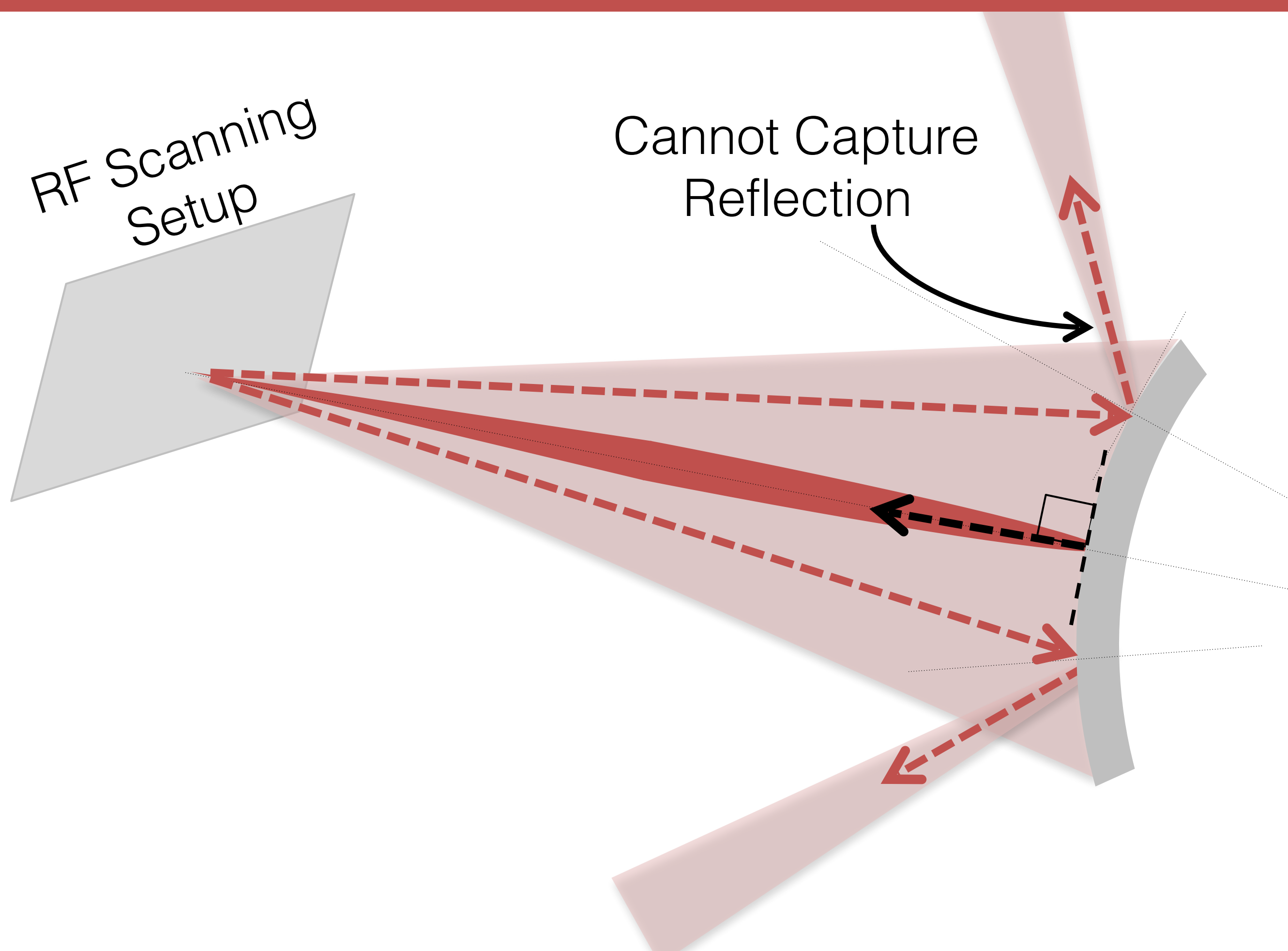


Challenge: We only obtain blob in space

At frequencies that traverse walls, human body parts are specular (pure mirror)



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



Solution Idea: Exploit Human Motion and Aggregate over Time

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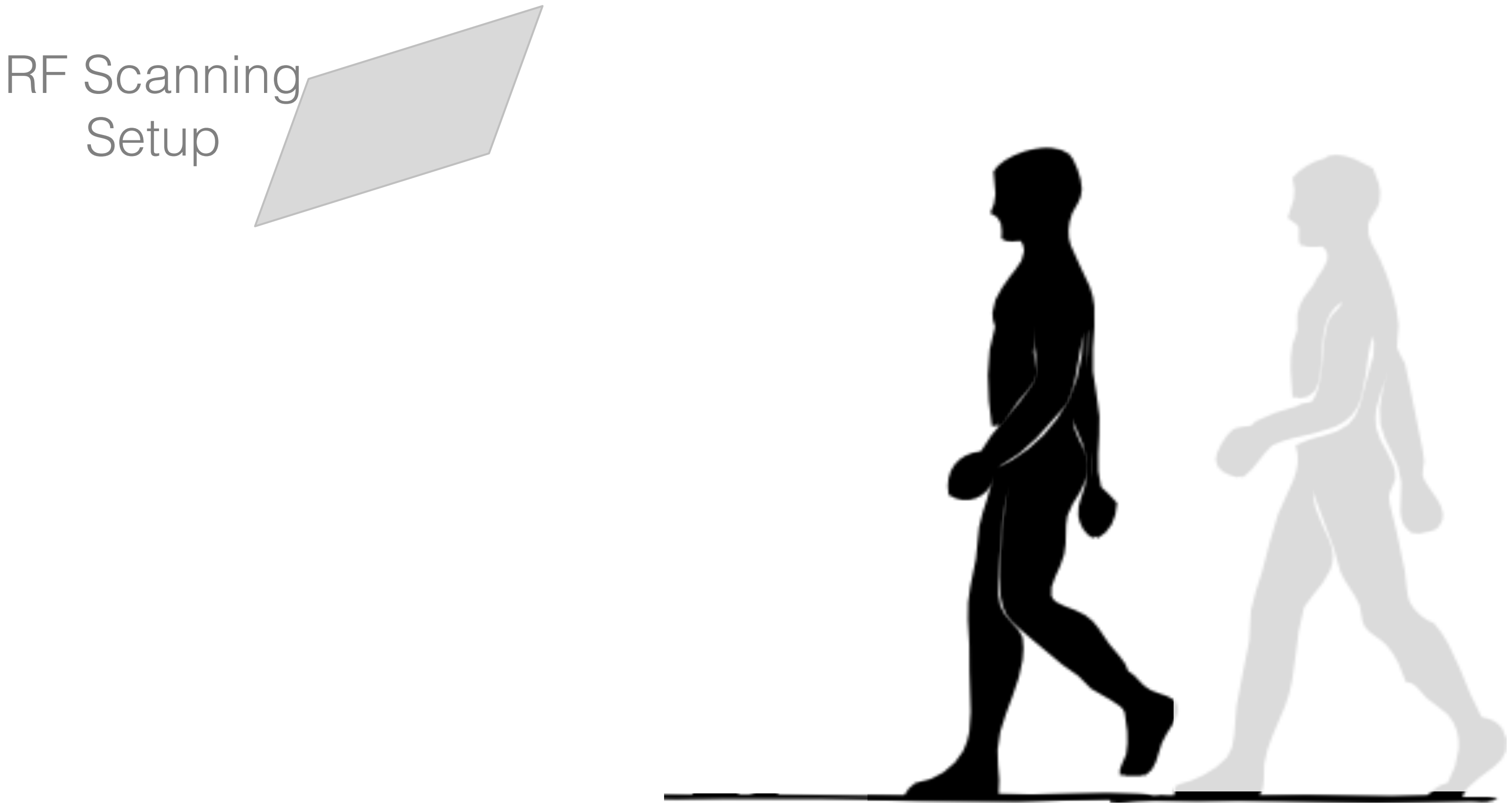

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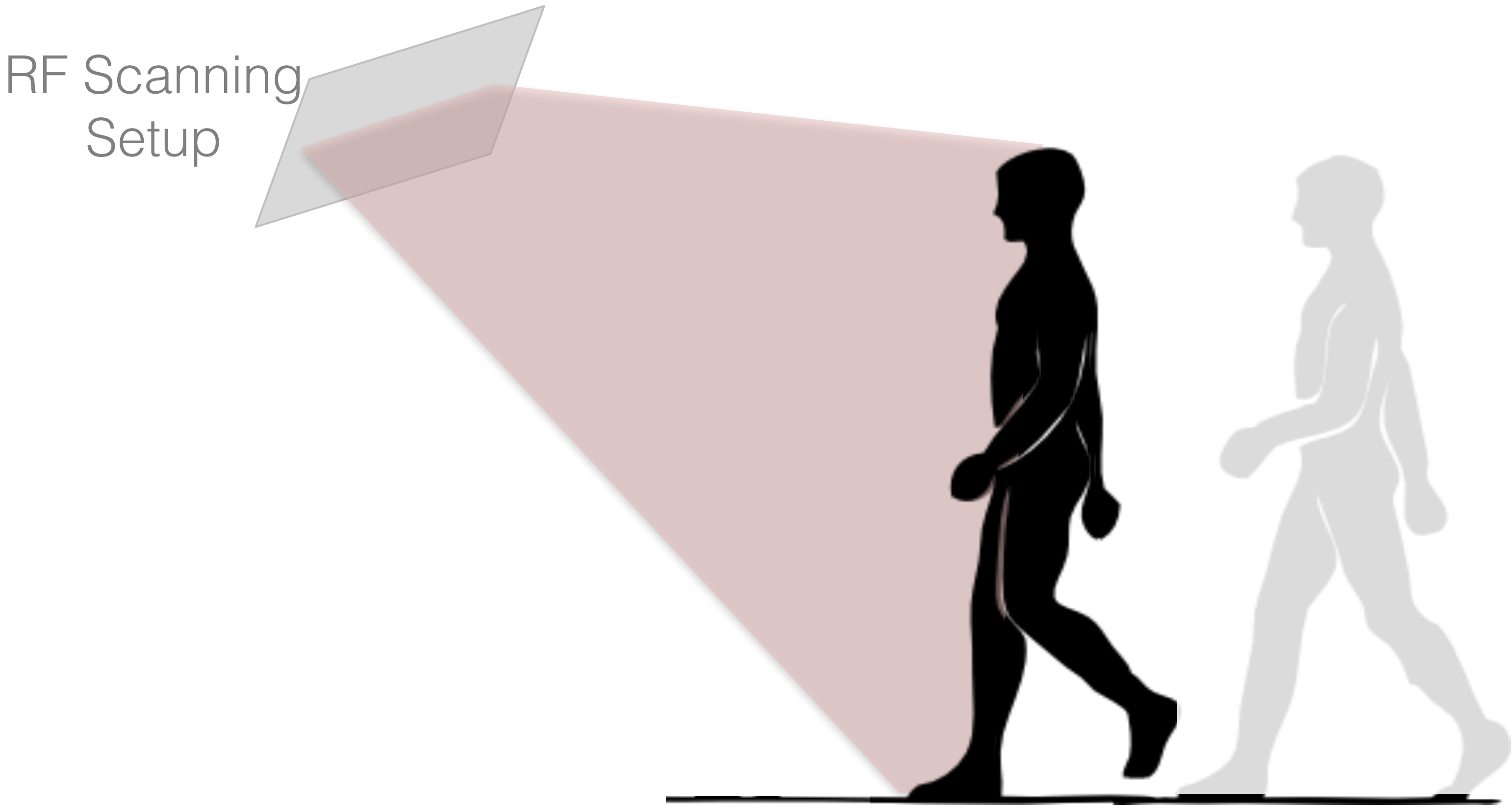

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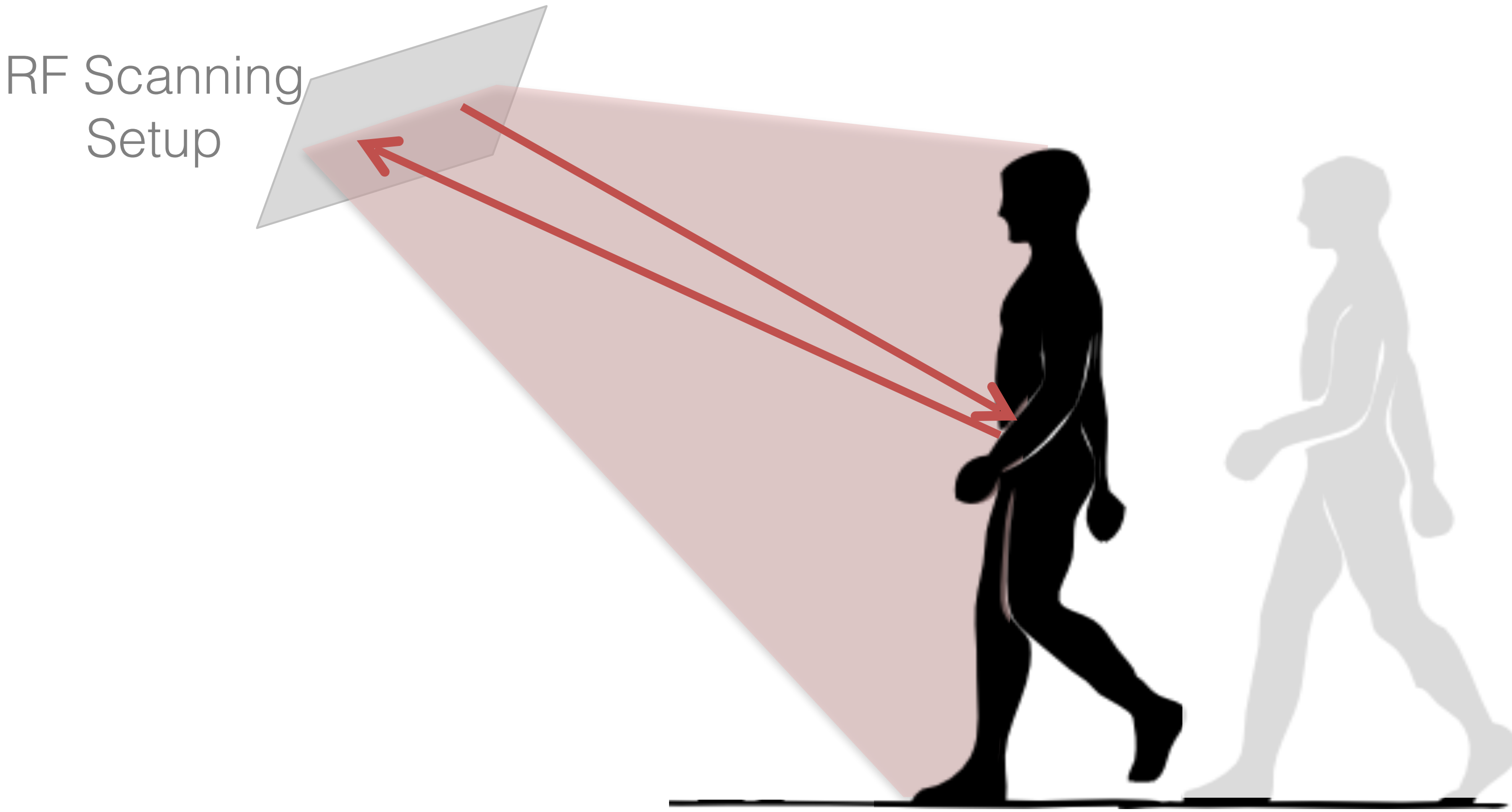

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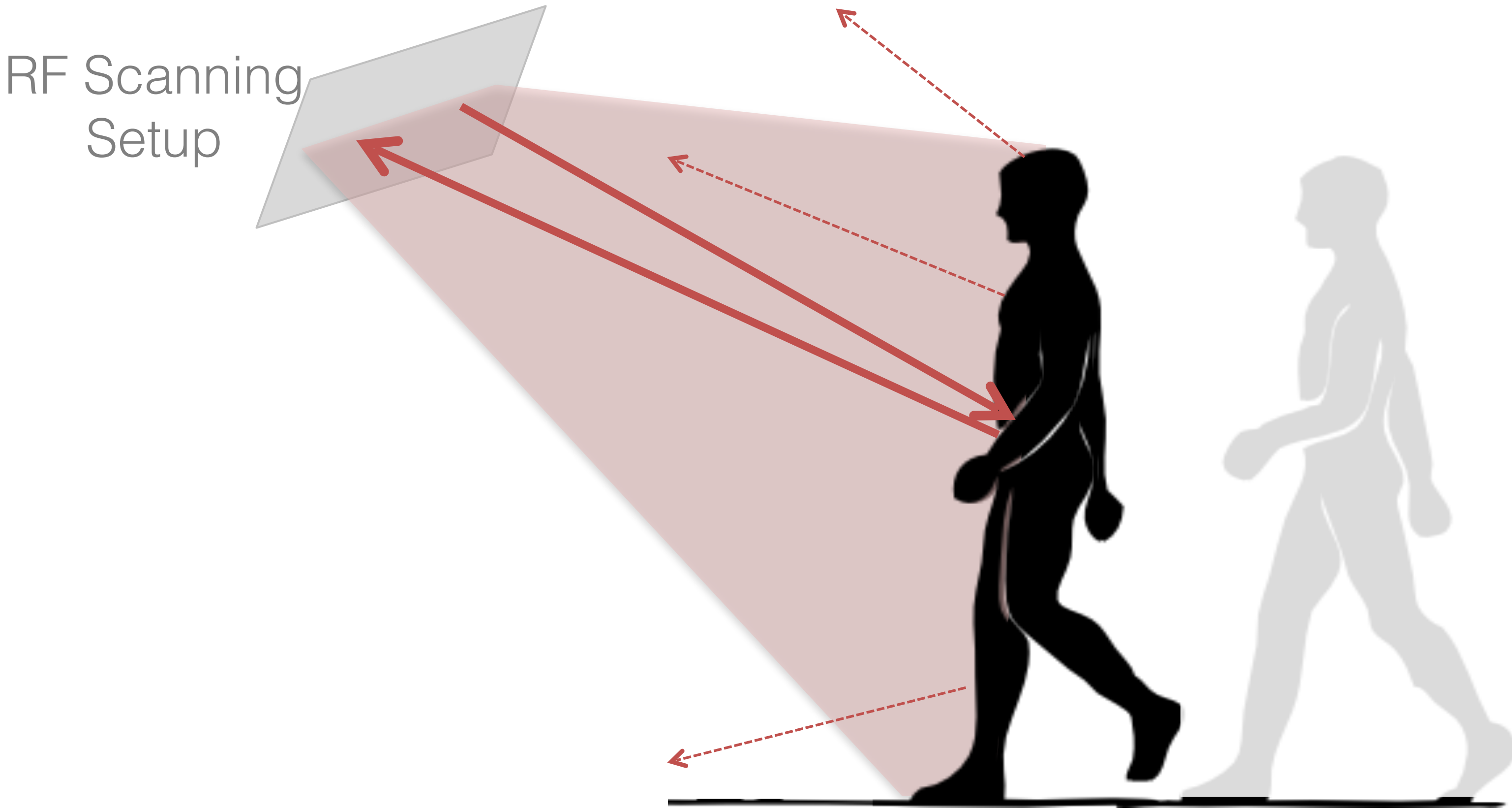

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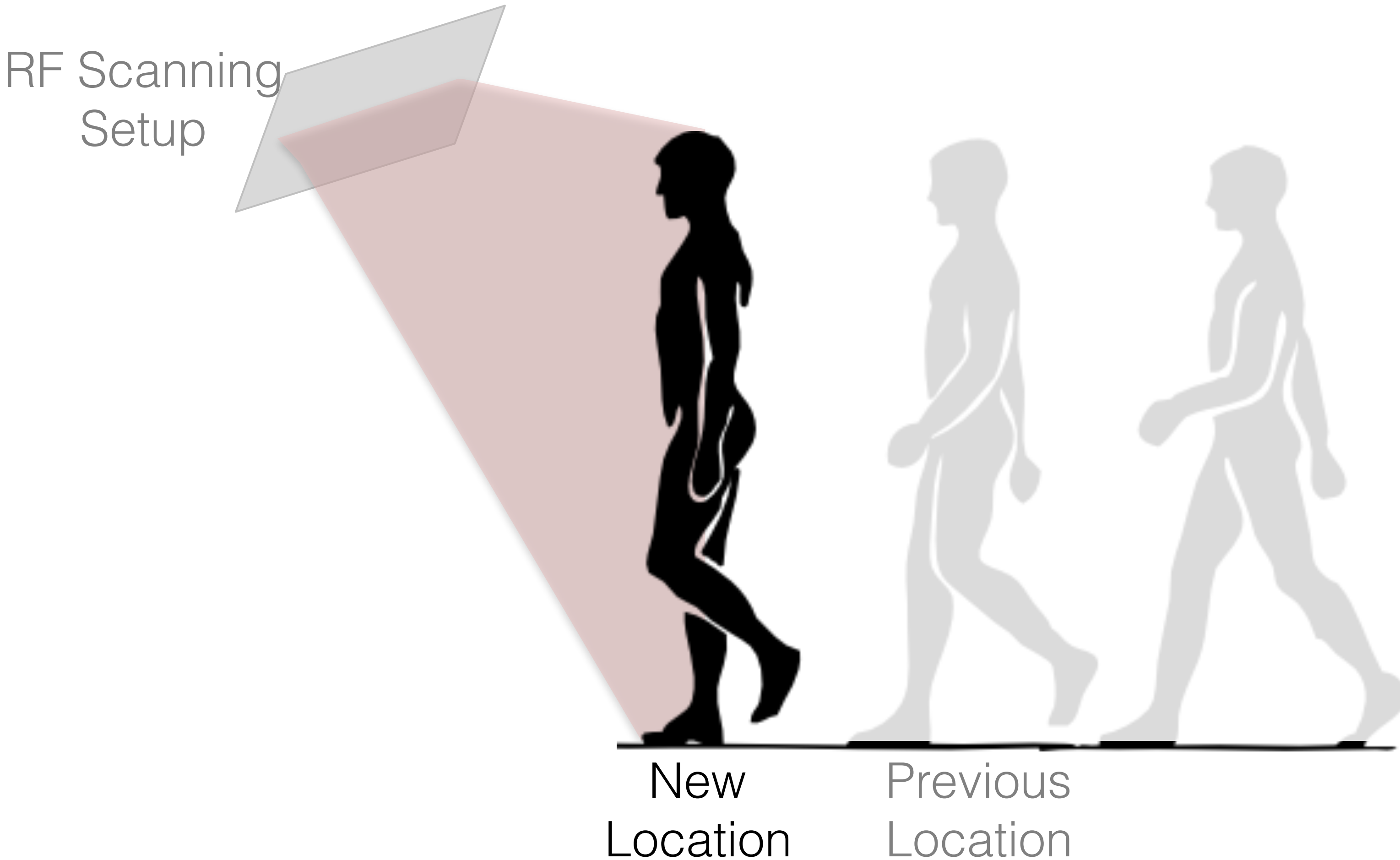

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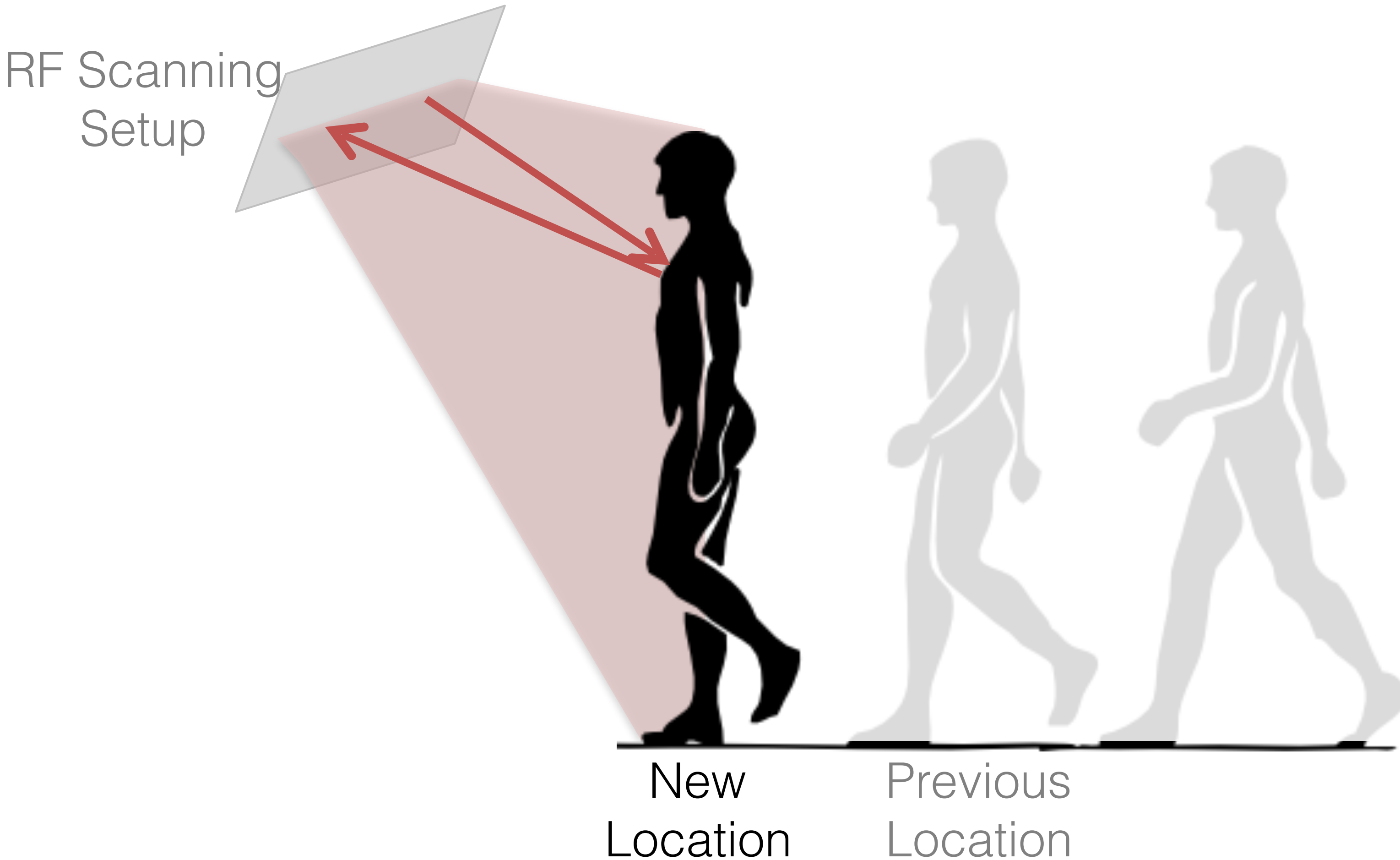

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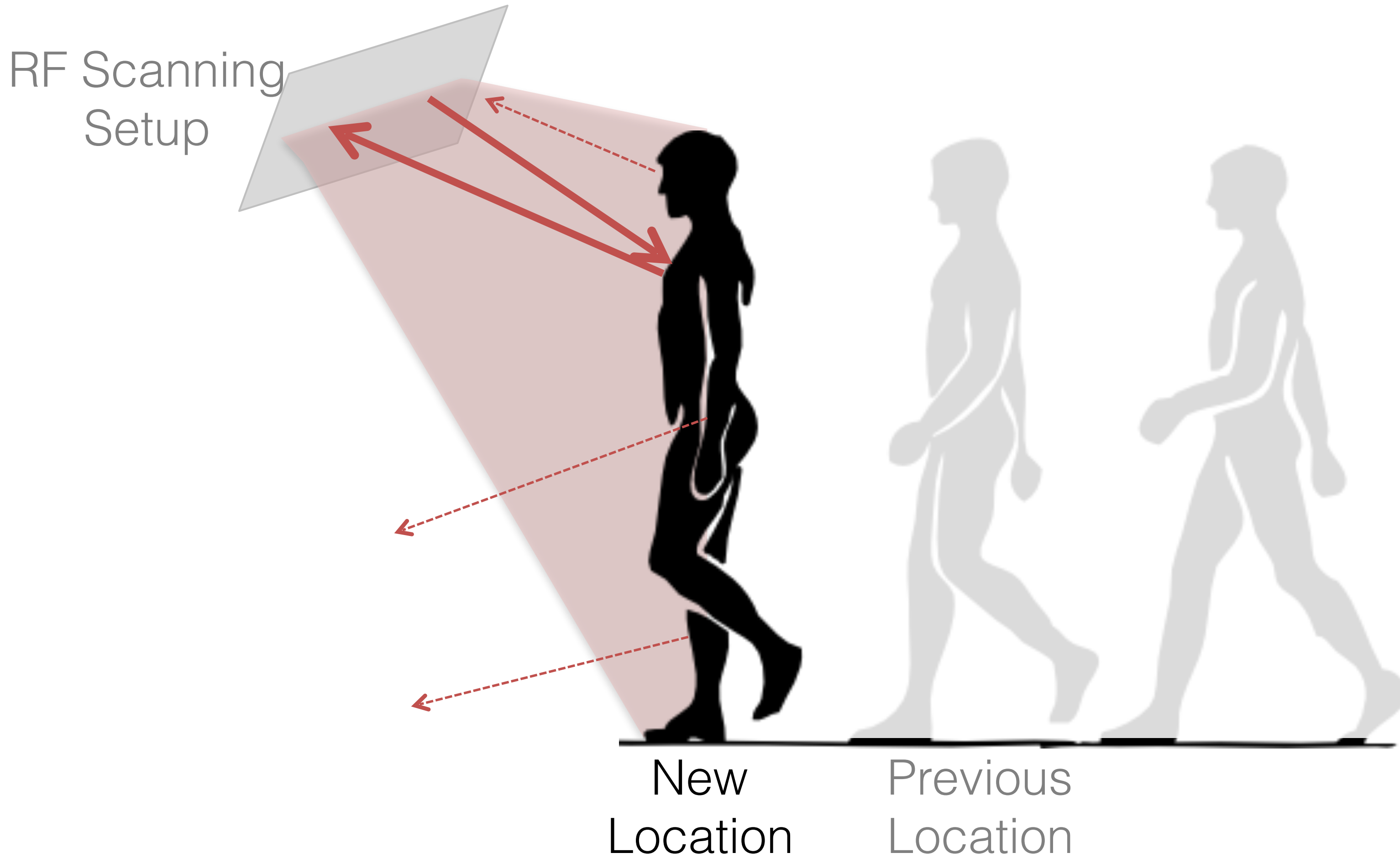

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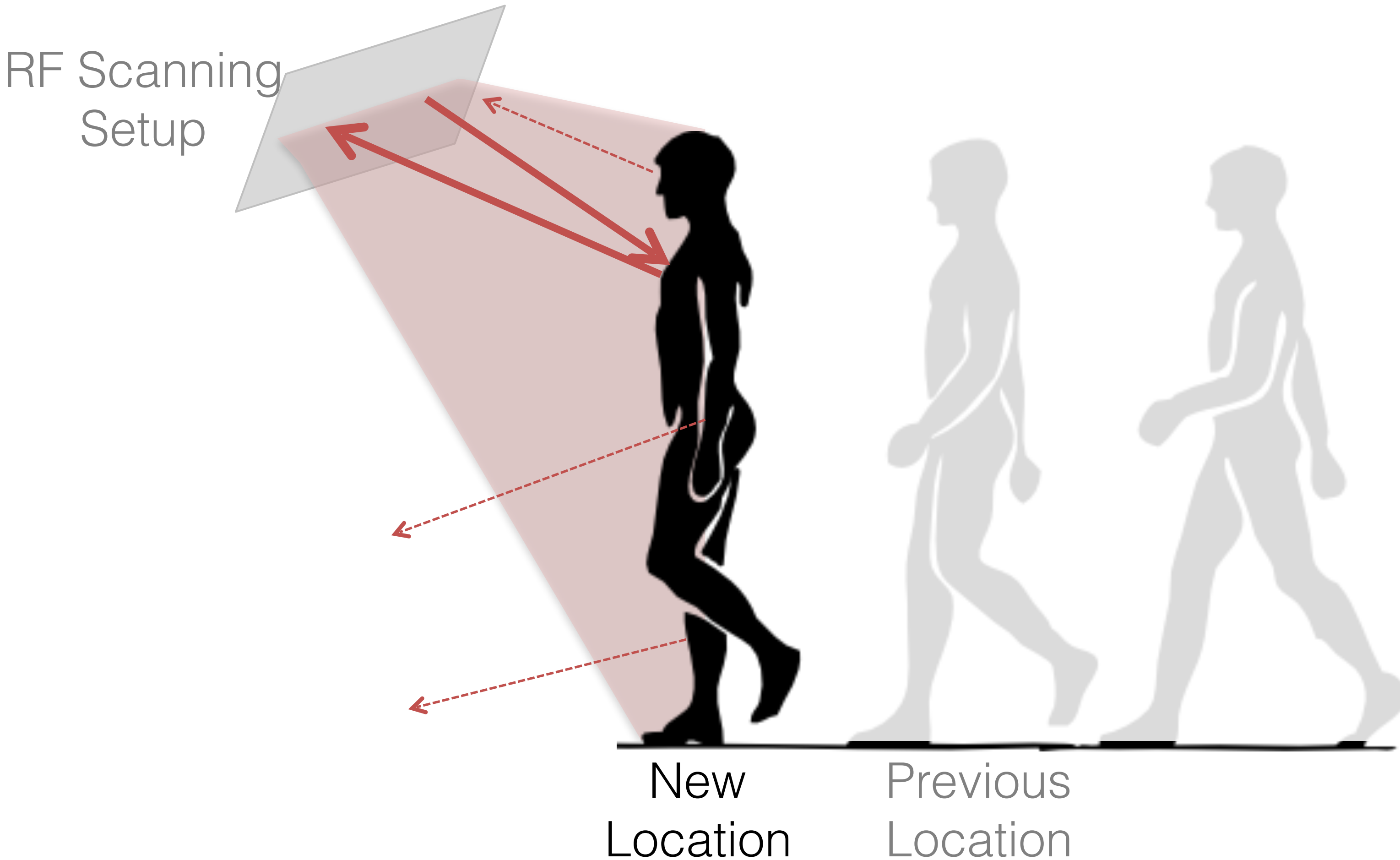


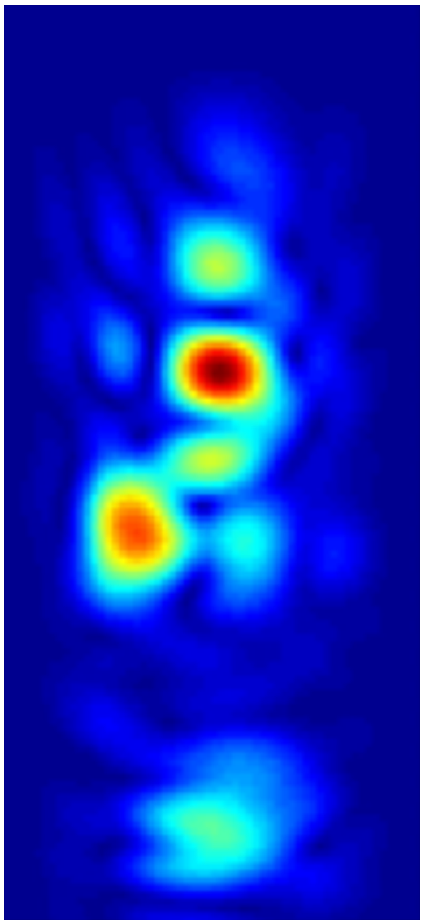
Combine the various snapshots

Human Walks toward Sensor

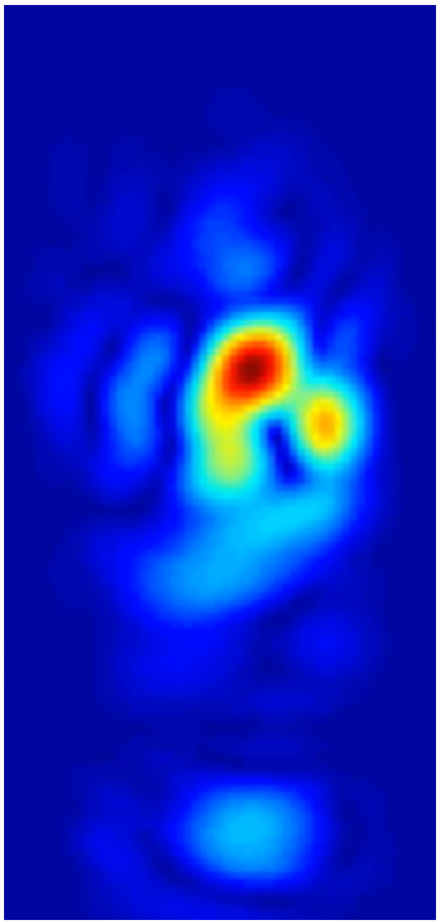
3m	2.5m	2m

Human Walks toward Sensor

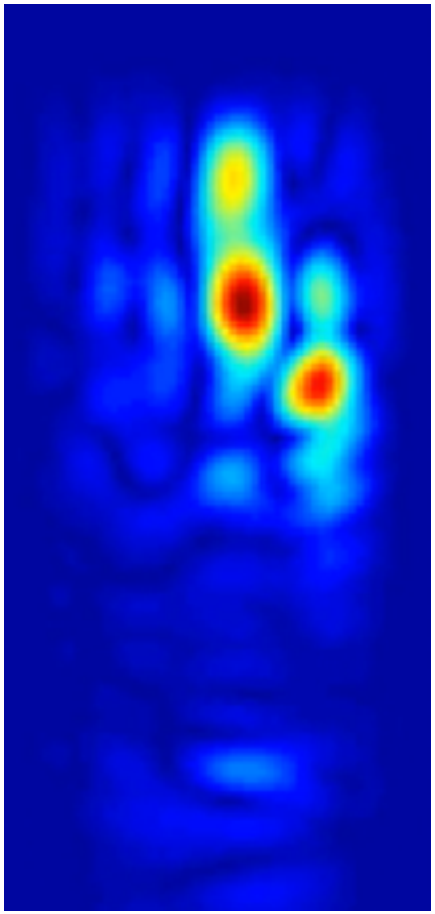
3m



2.5m



2m



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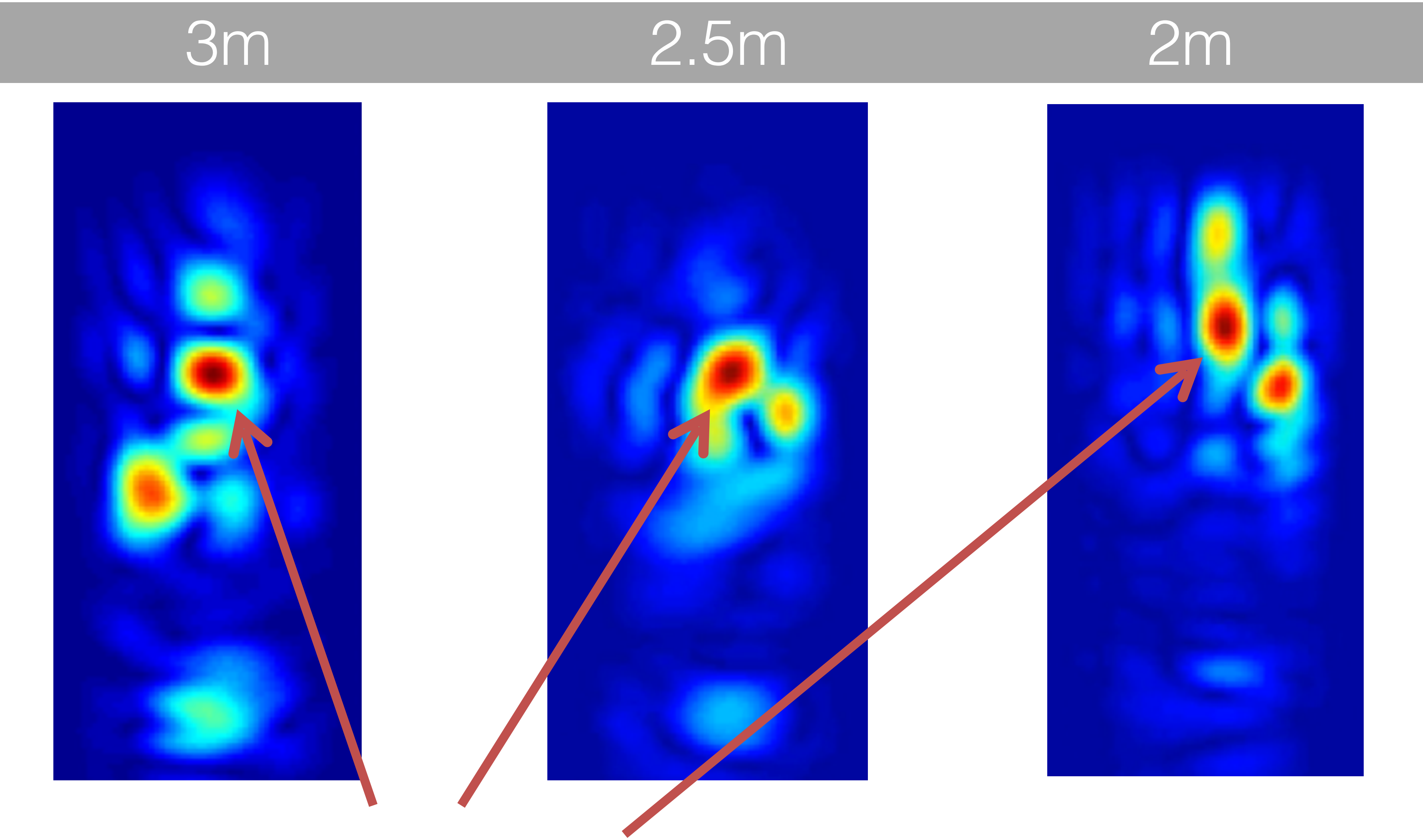

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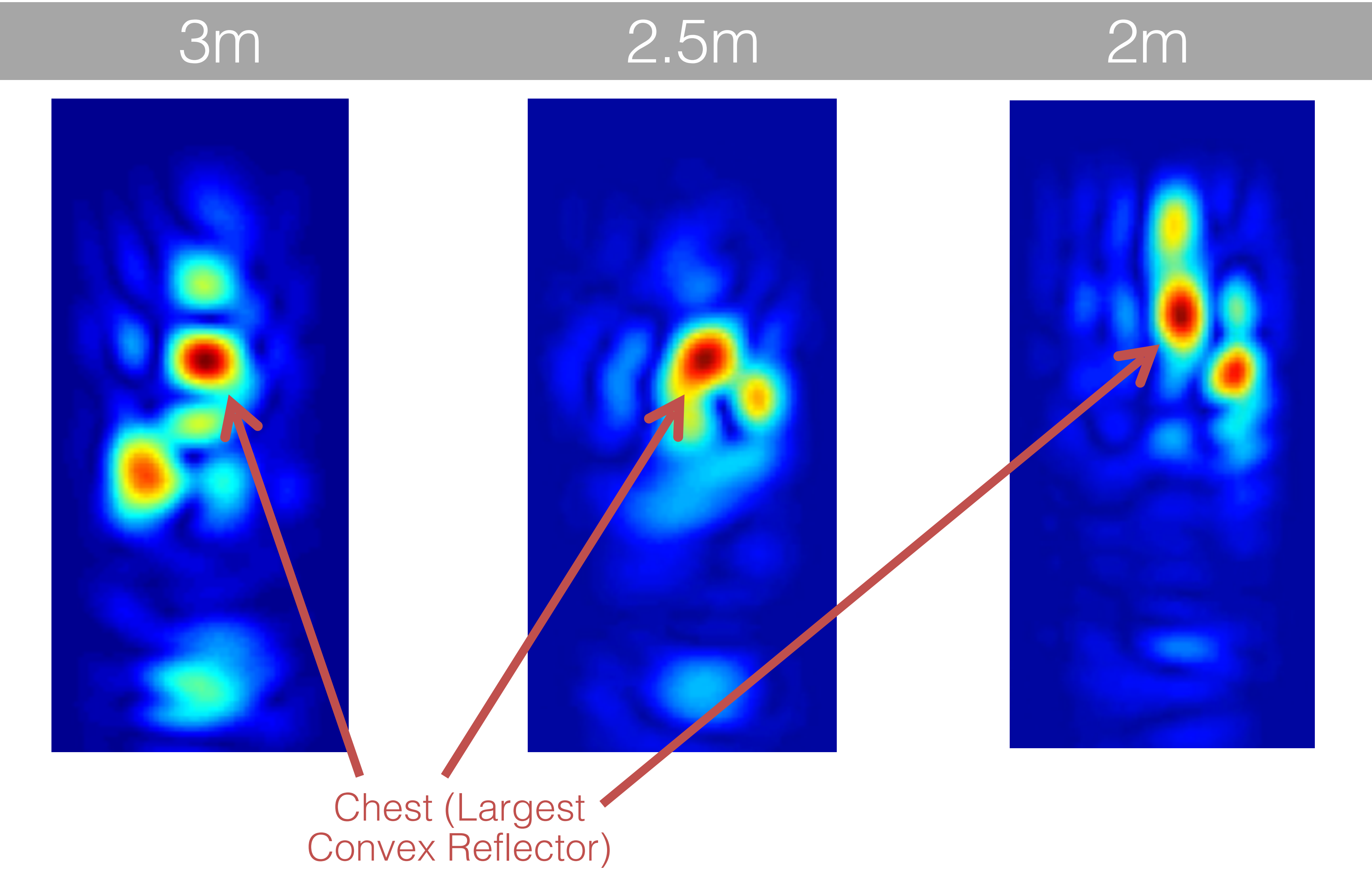
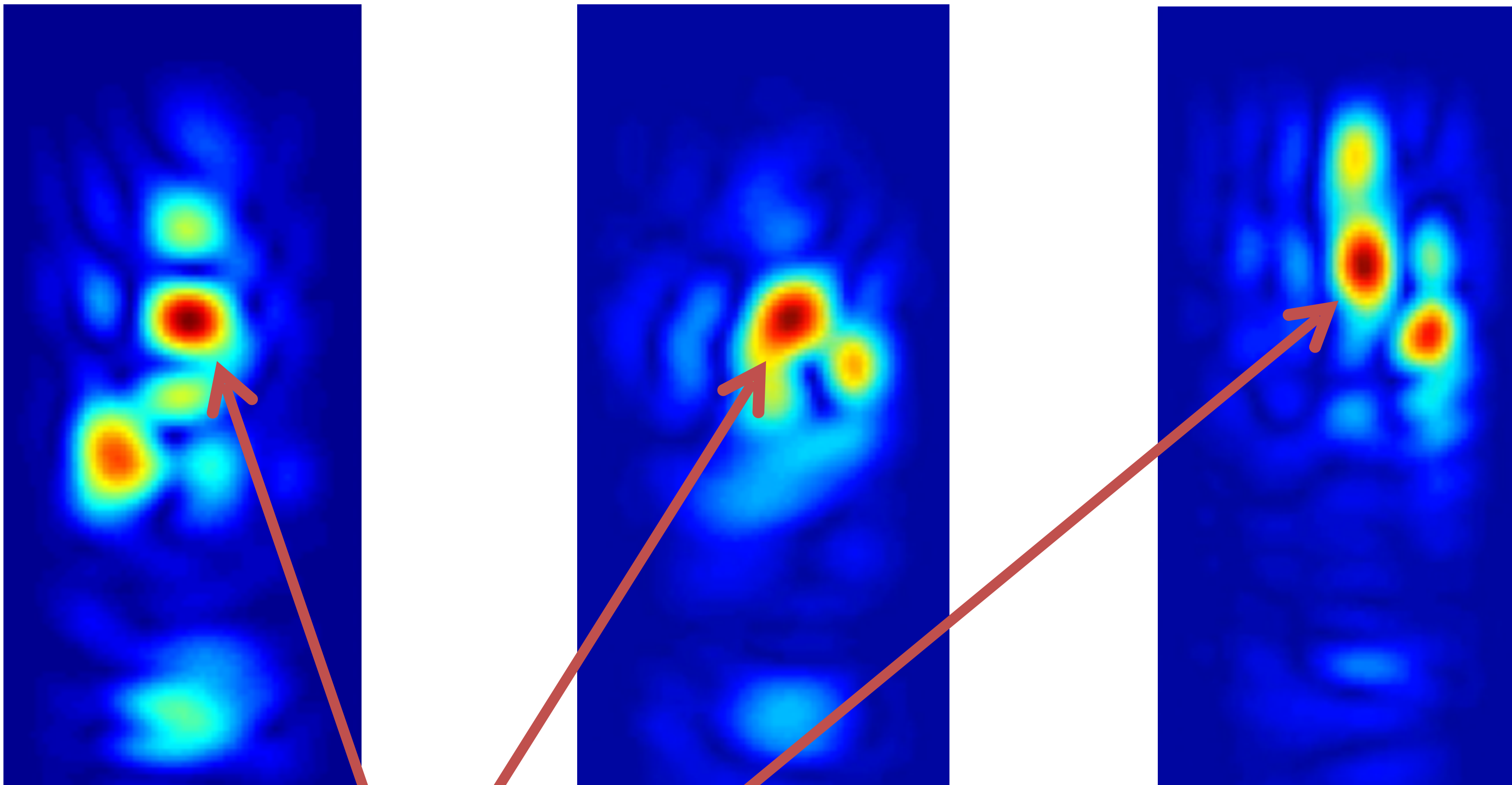


Human Walks toward Sensor

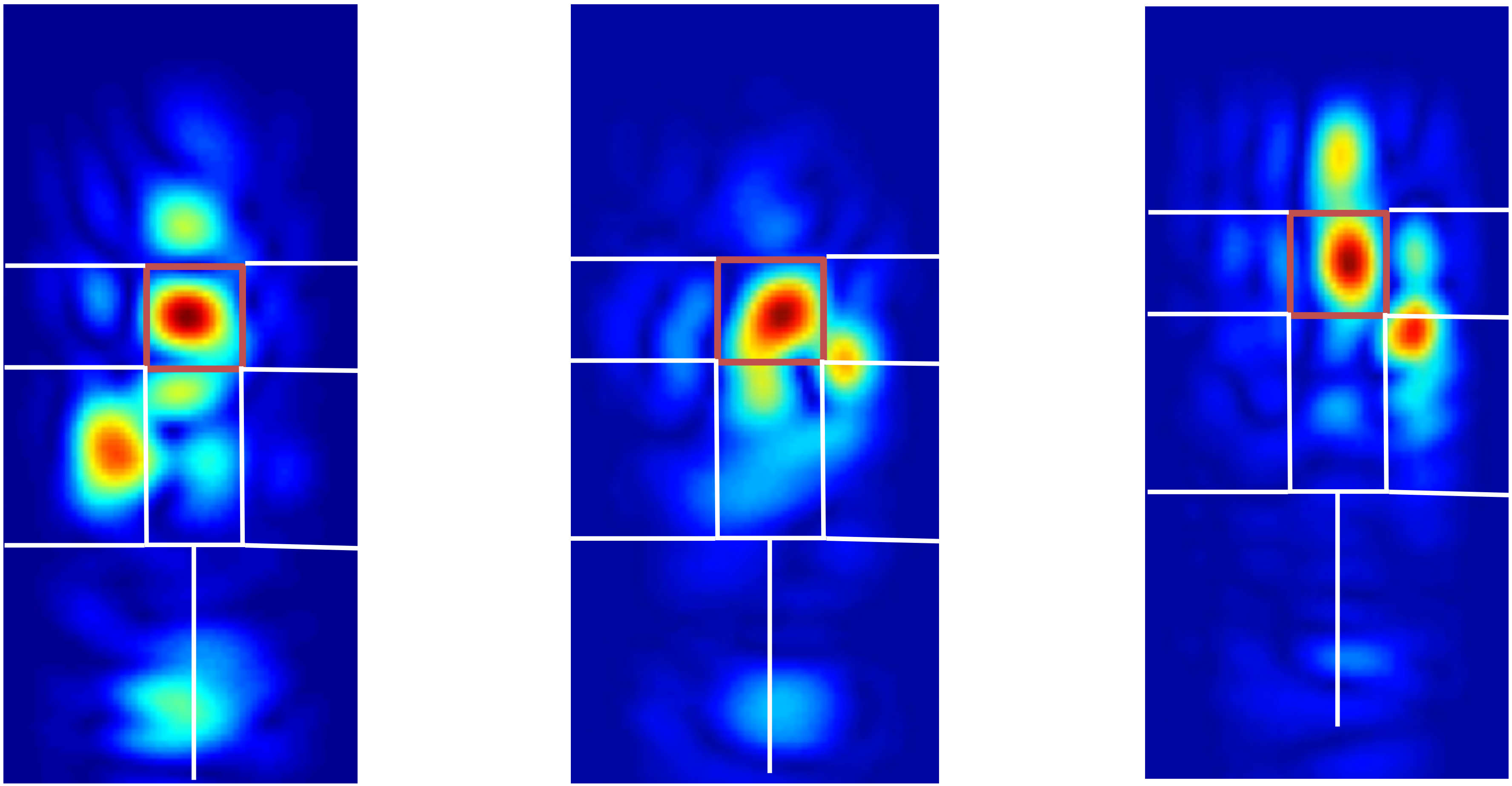
3m | 2.5m | 2m



Chest (Largest Convex Reflector) → Use it as a pivot: for motion compensation and segmentation

Human Walks toward Sensor

3m	2.5m	2m



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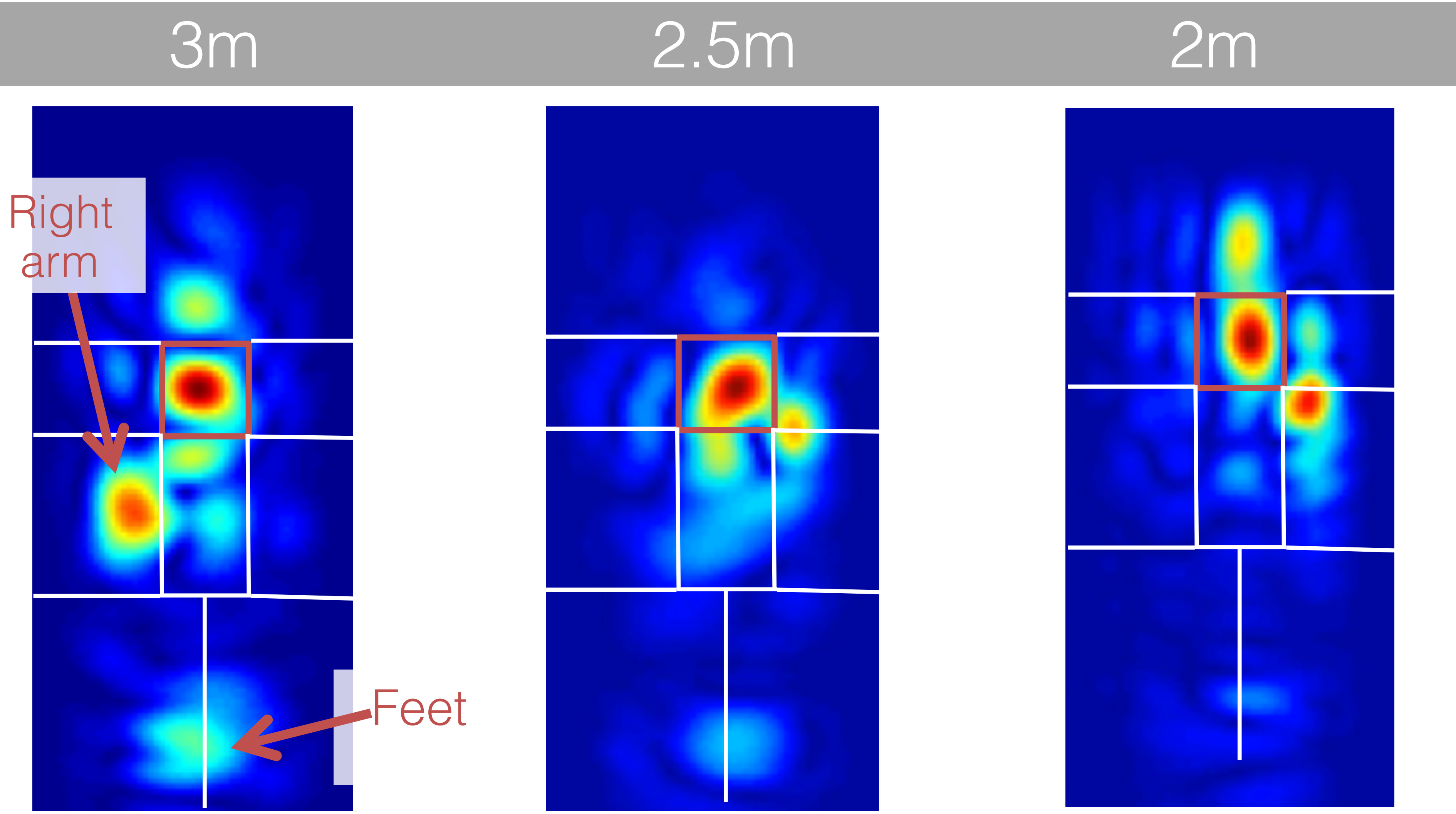
Human Walks toward Sensor



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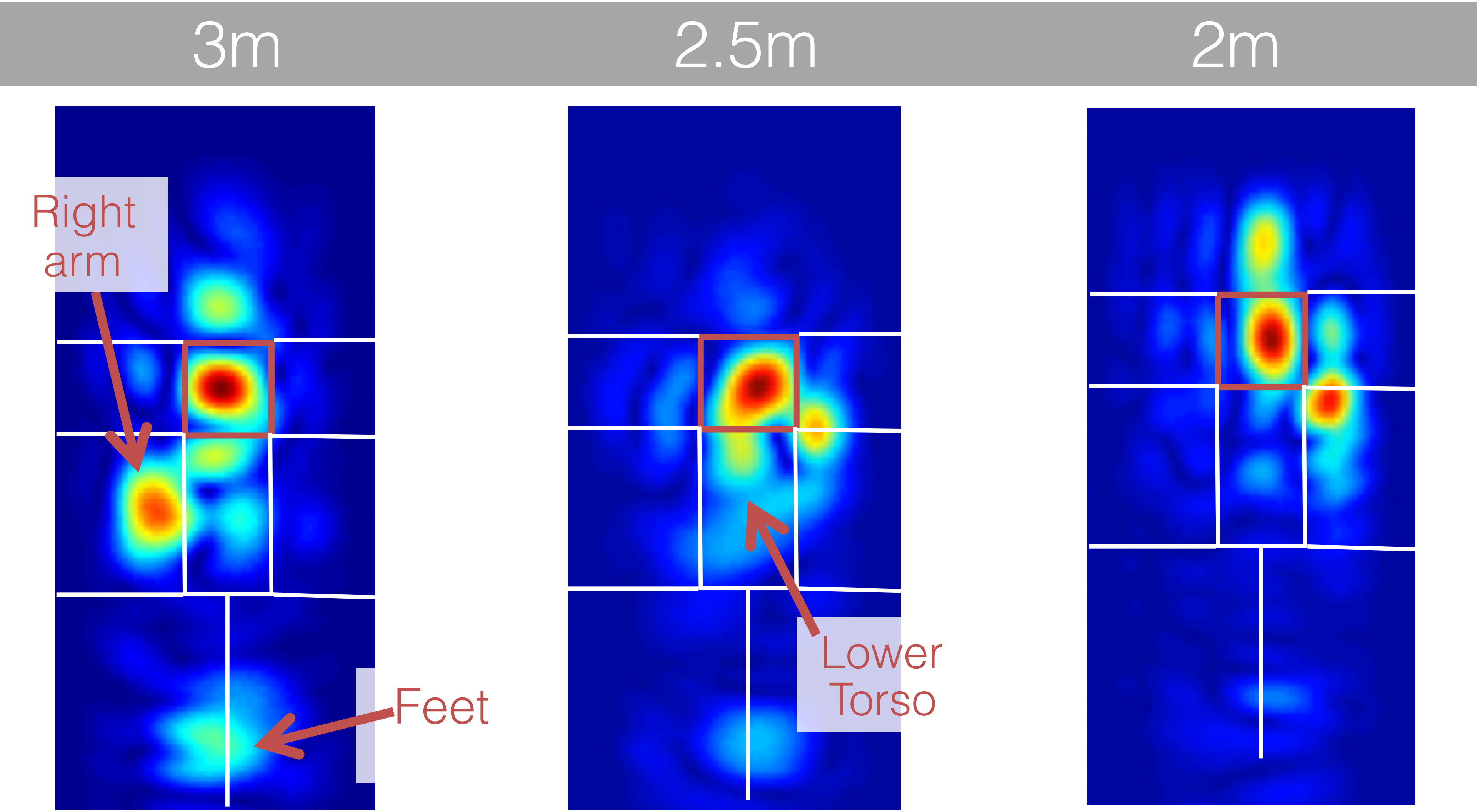
Human Walks toward Sensor



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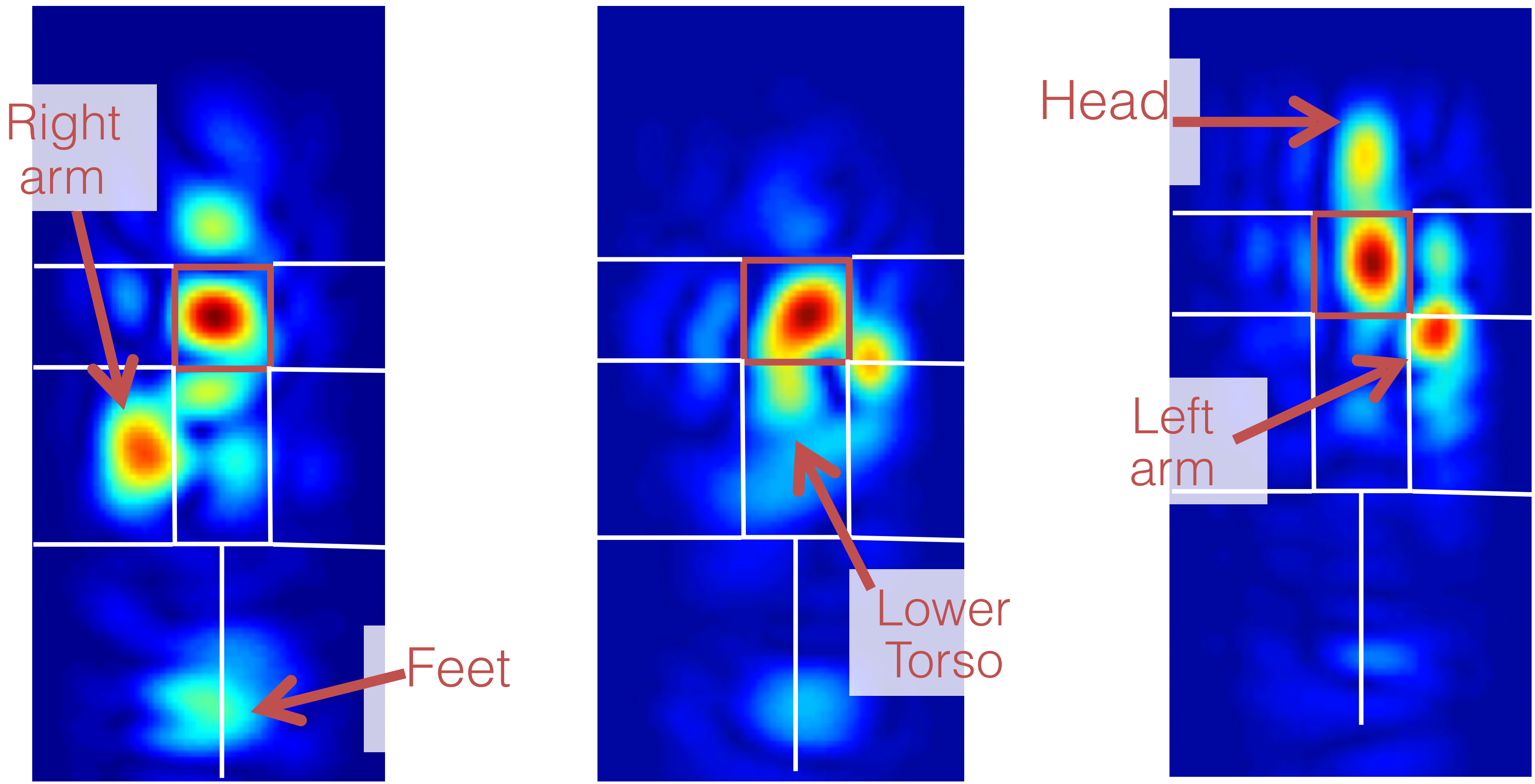

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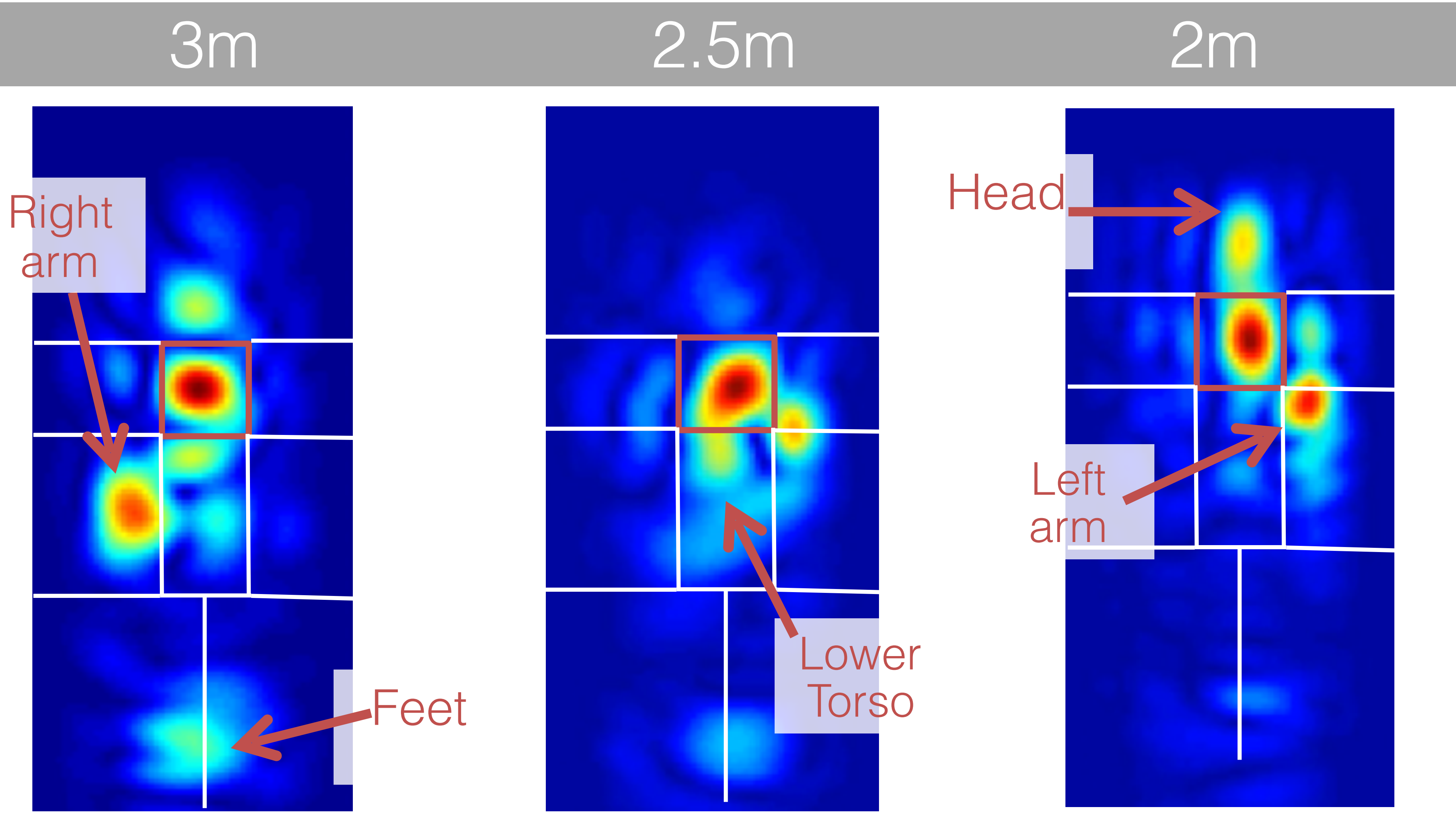

Combine the various snapshots

Human Walks toward Sensor

Human Walks toward Sensor

Sample Captured Figures through Walls

Sample Captured Figures through Walls

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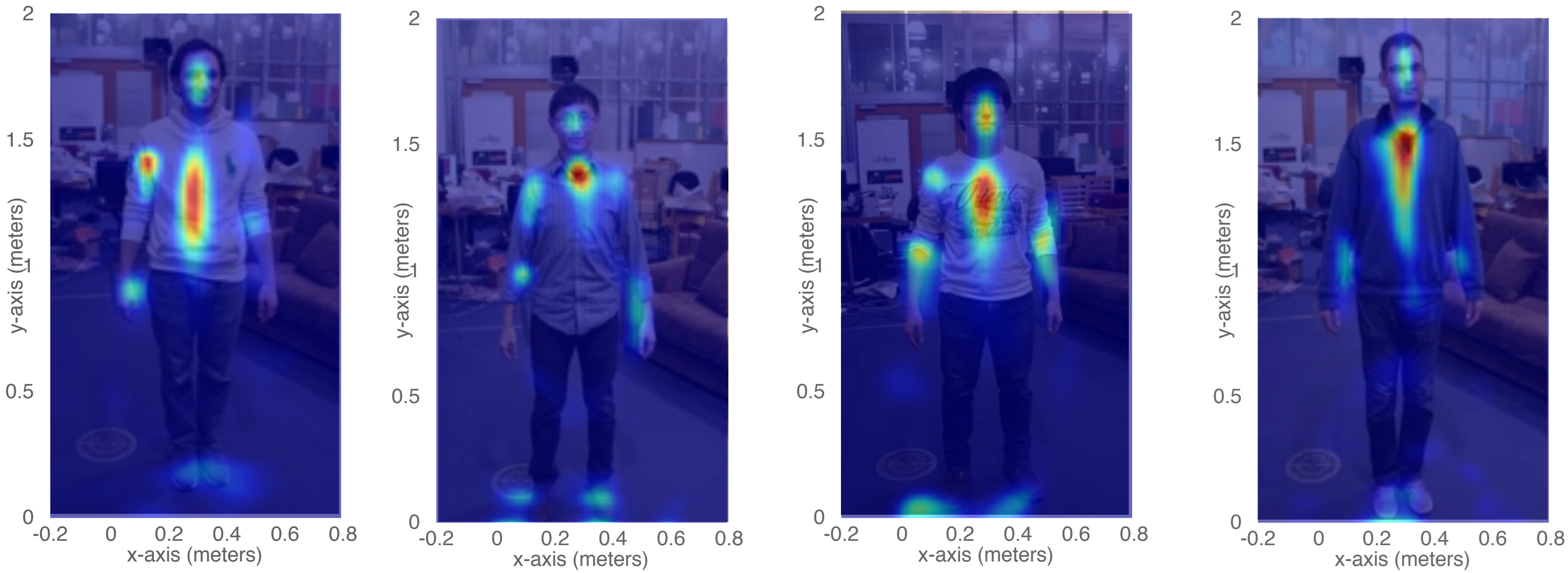
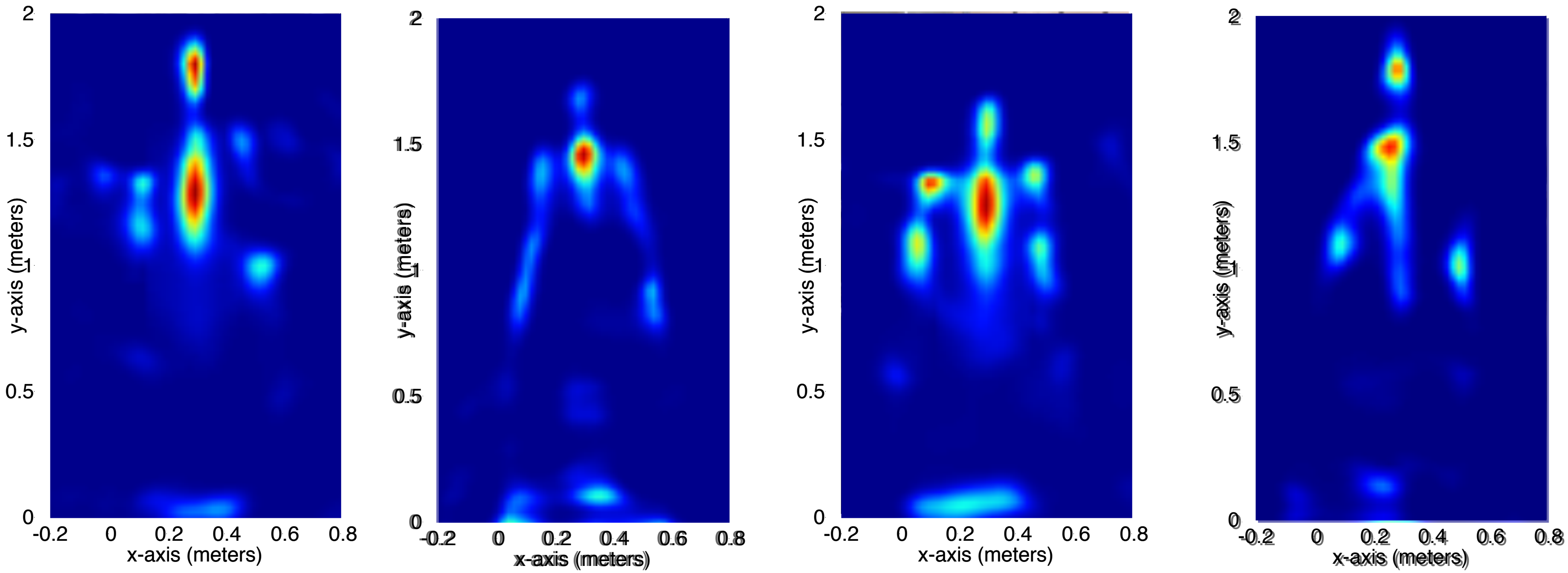
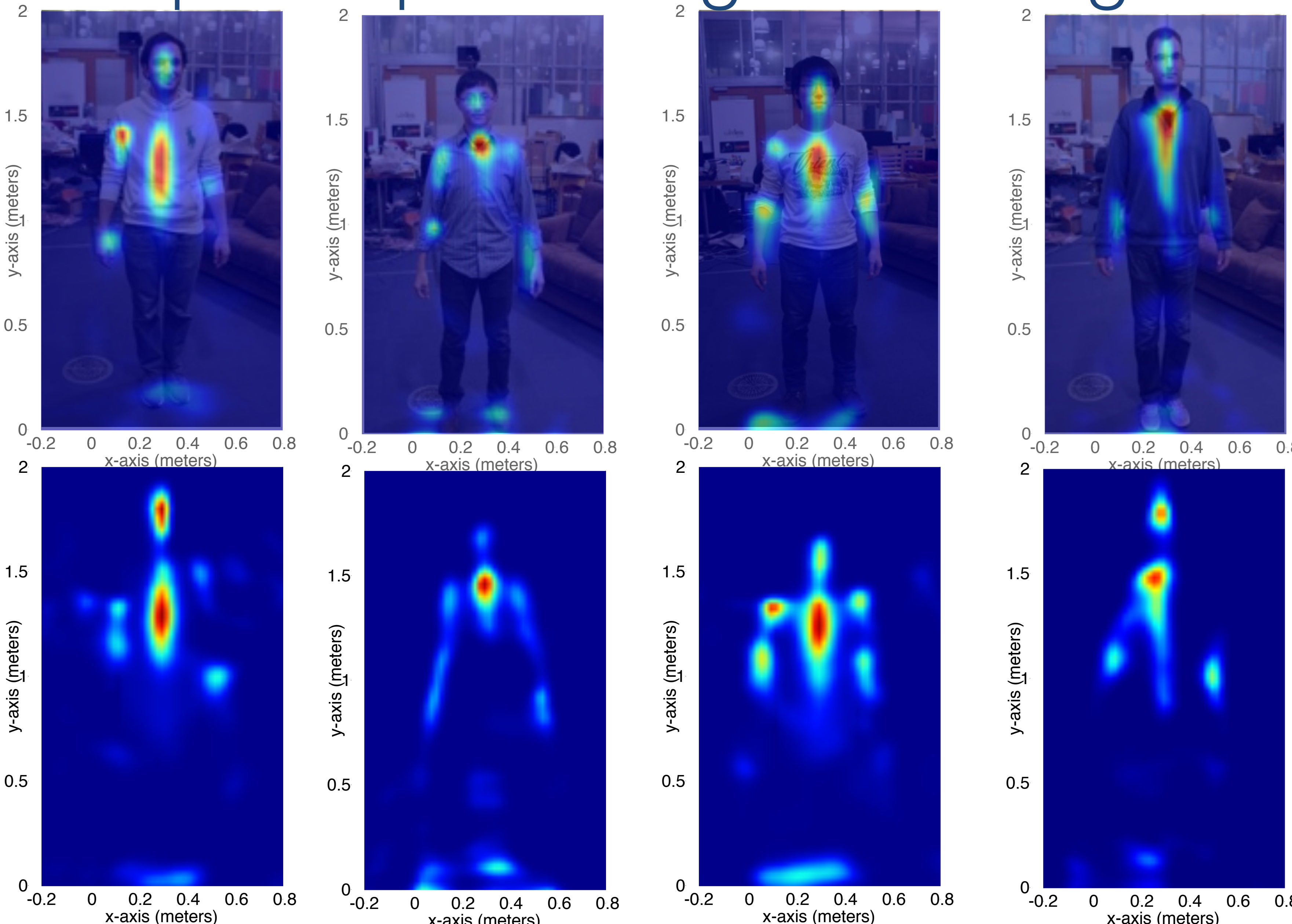


Sample Captured Figures through Walls



Sample Captured Figures through Walls



Through-wall classification accuracy of 90% among 13 users