Mobile Health

Lecture 11
Contactless Radio and Health

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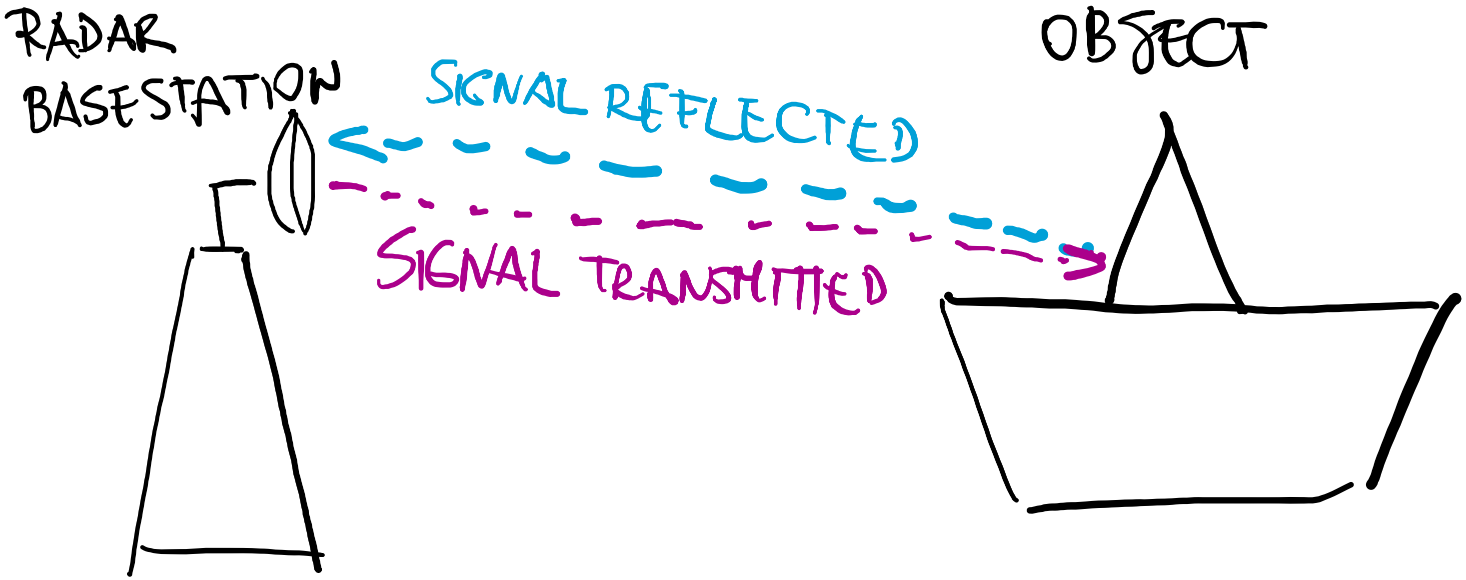
Radar and Sonar Properties

- The ability of radio signal to bounce off objects with different speed and intensity can be exploited to understand:
  - Position of objects and individuals
  - Physiological markers

Radio Reflection: not a new concept!



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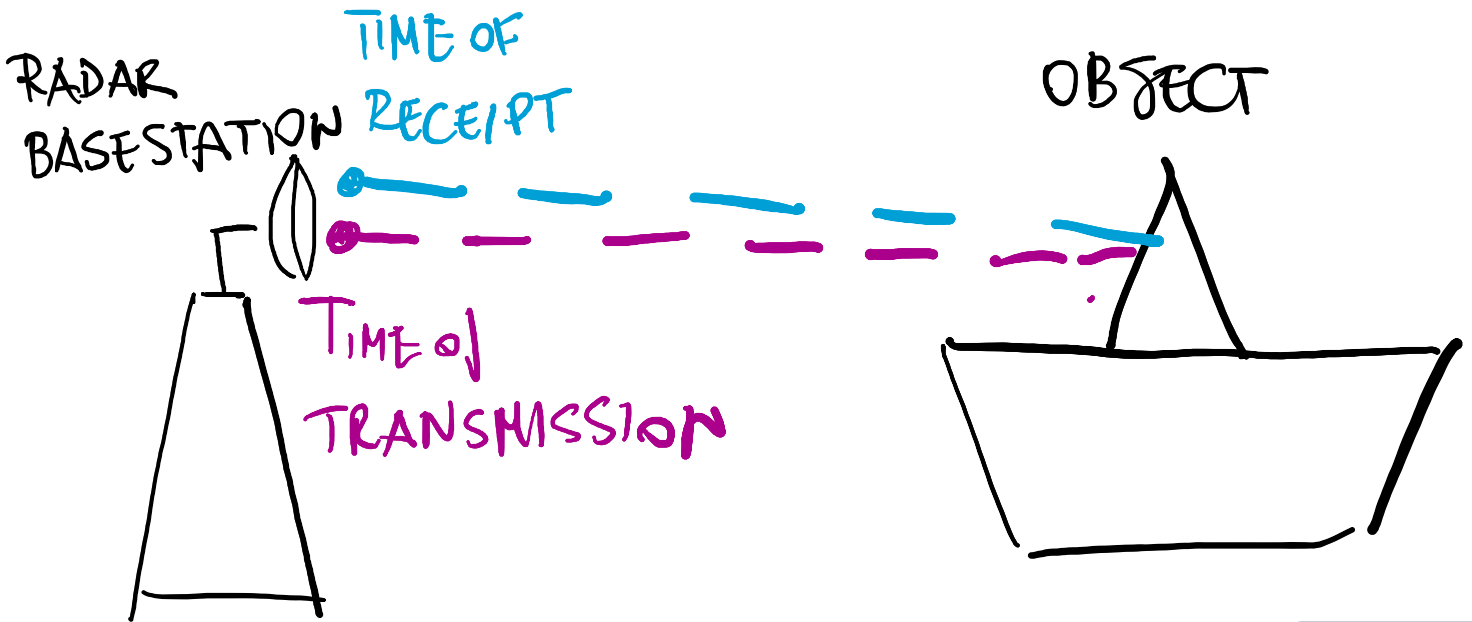
How do we use it for health

- Commodity (or small) devices (possibly low power).
- Acceptable radio frequencies.
- Can it detect meaningful aspects of our health?

- See through walls? (infrared/imaging cannot).
- Multiple users?

How can we detect an object and its distance?



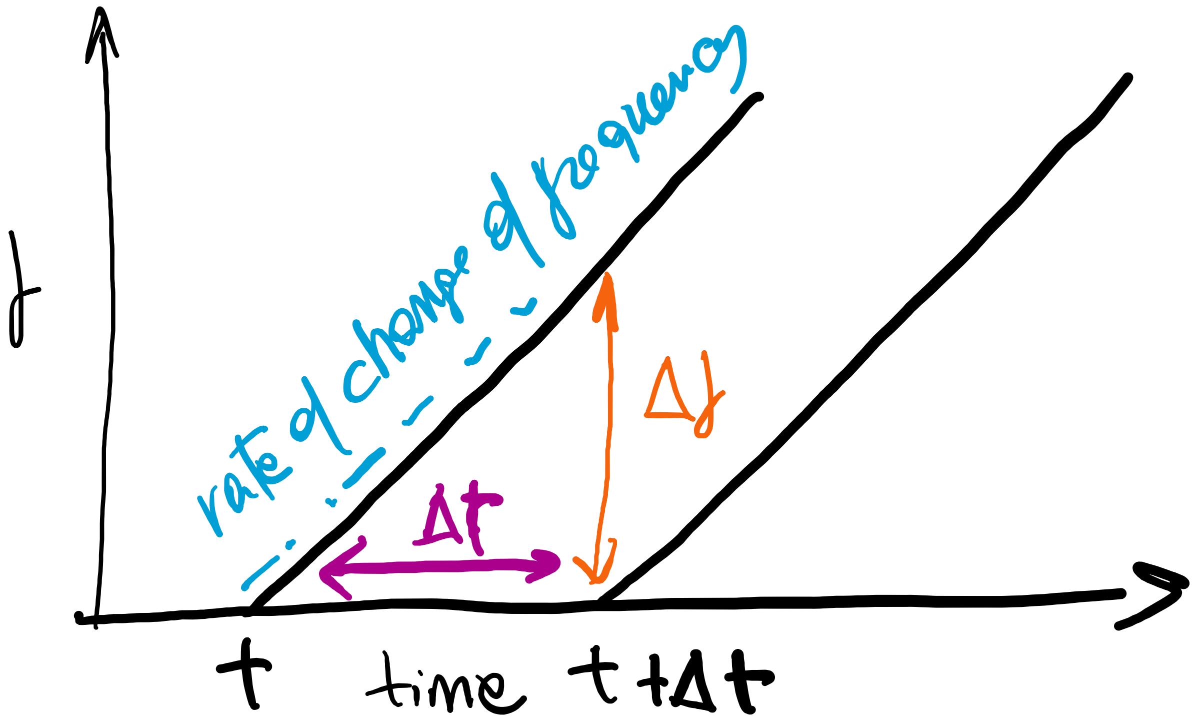
Distance= reflection time * speed of light

However our distances are small and light is fast!

The idea measuring reflection time using frequency changes!

Δ t= Δ f/slope

Δ f calculated by multiplying the wave with a simple function and looking at the DFT (this computation can happen on device)



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The signal changes frequency linearly…

https://www.mit.edu/~fadel/papers/Fadel_PhD.pdf

How do we measure Δf?

- We have f at sending time and ff at receiving time.
- We multiply the two frequencies.
- By trigonometry this is equivalent to:

*cos (f*ff) ~ cos (f+ff) + cos (f-ff)*

Very high value: can be filtered leaving the difference

- DFT can be used to determine this difference

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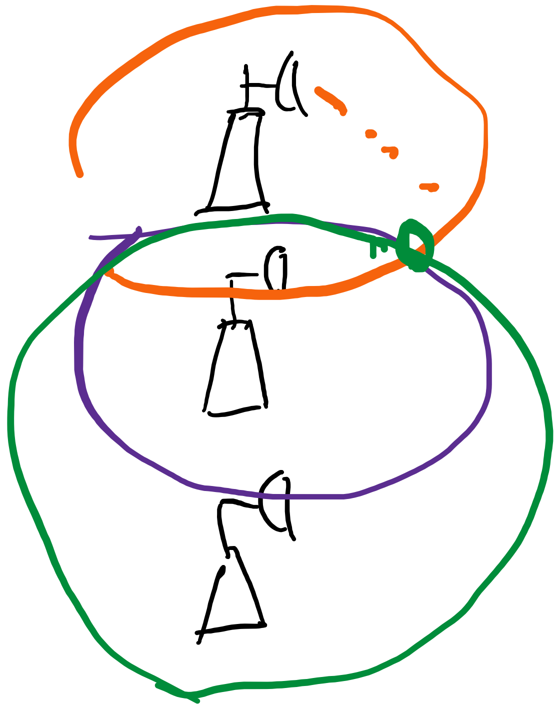
Distance vs Position

- With one antenna I can find out the object distance but not position.

- How do I find position?
  - Triangulation using multiple basestations



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Problems that needed solving

- Static multipath from objects (exclude)
- Dynamic multipath from movement of people
- Multiple people

Big Bang Theory S10E14

How to go from Radio Signal to Emotions?

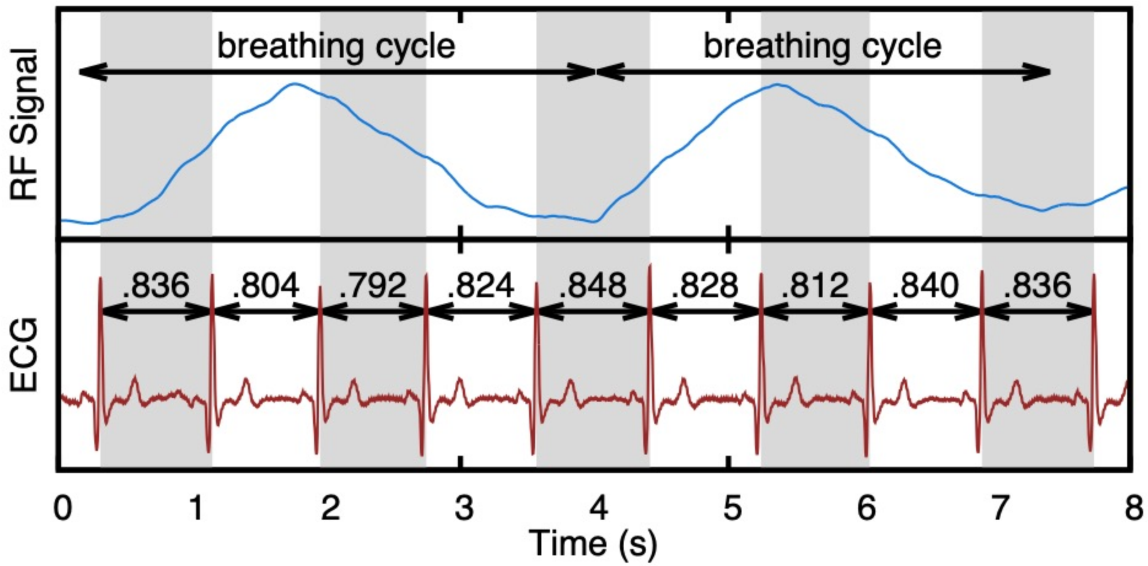
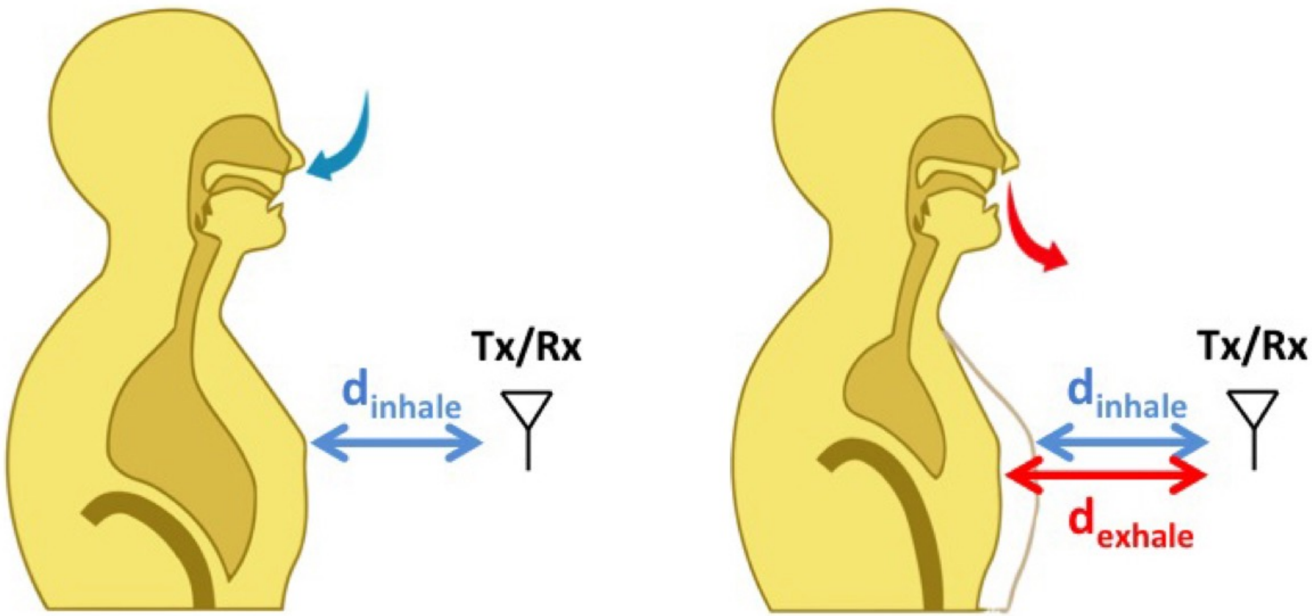


Figure from Emotion Recognition using Wireless Signals, Mingmin Zhao, Fadel Adib, Dina Katabi. International Conference on Mobile Computing and Networking (Mobicom'16).

Monitoring Respiration



(a) Inhale Motion (b) Exhale Motion

From Emotion Recognition using Wireless Signals, Mingmin Zhao, Fadel Adib, Dina Katabi. International Conference on Mobile Computing and Networking (Mobicom'16).

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Detecting Respiration and Inter Beat Intervals

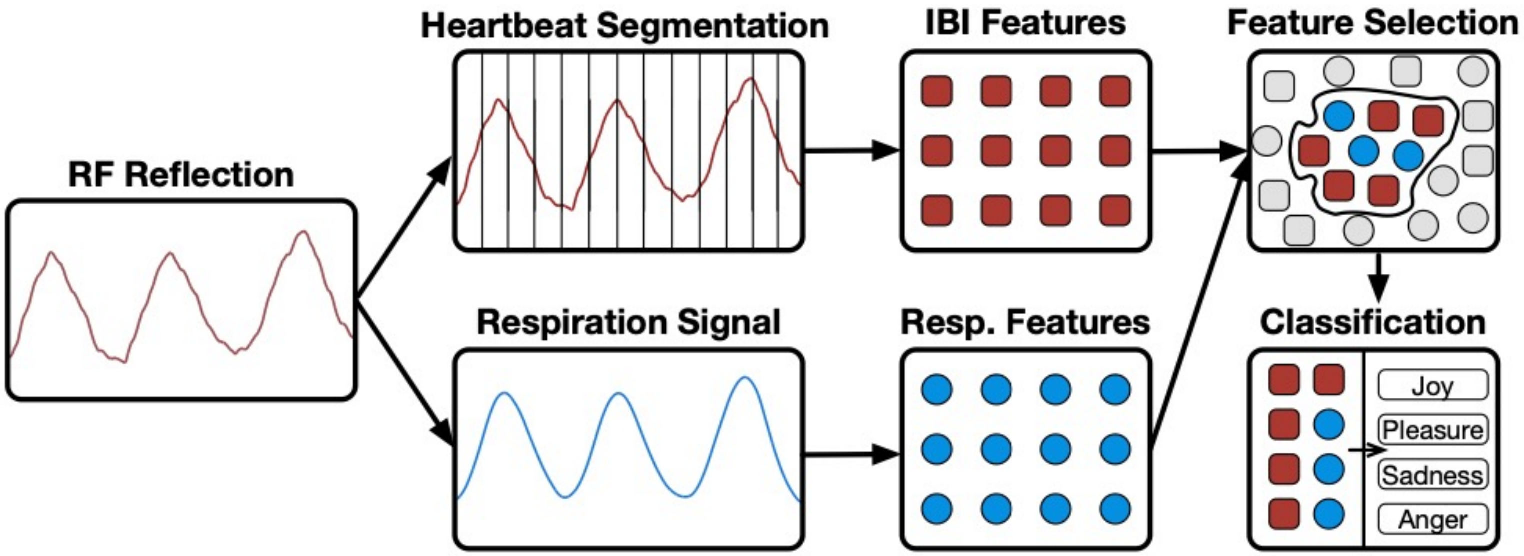

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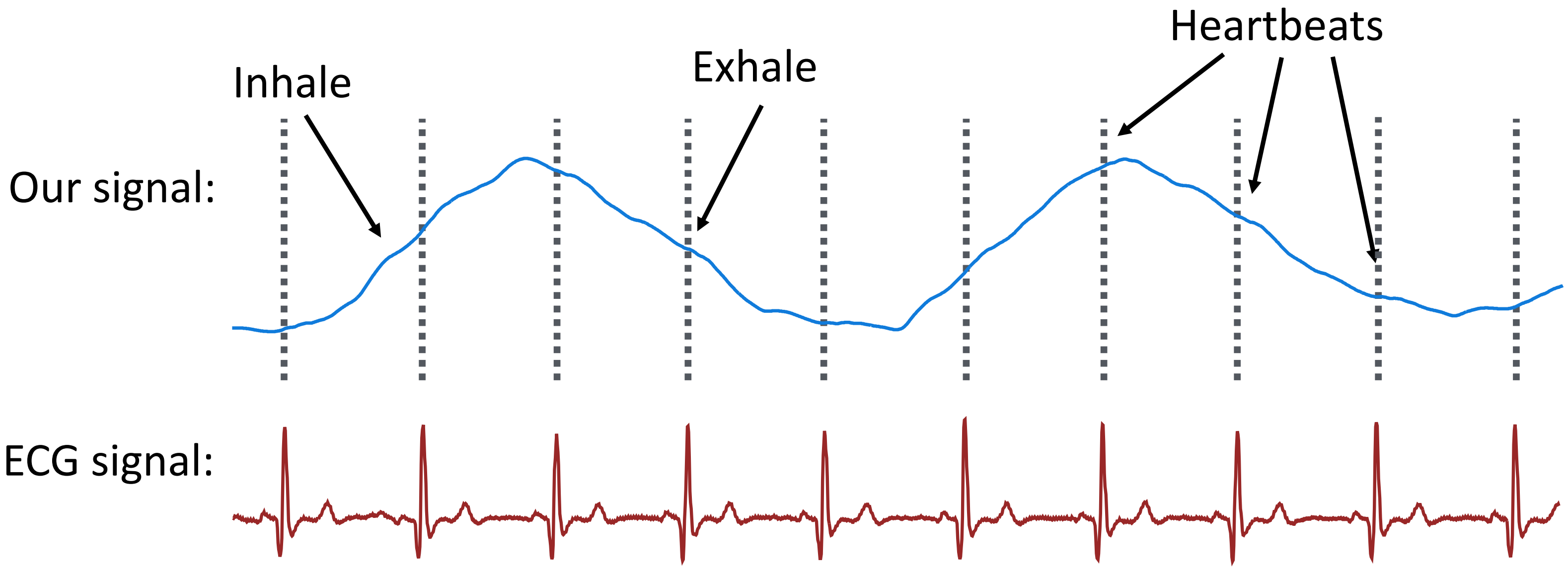
Figure from Emotion Recognition using Wireless Signals, Mingmin Zhao, Fadel Adib, Dina Katabi. International Conference on Mobile Computing and Networking (Mobicom'16).

Input signal



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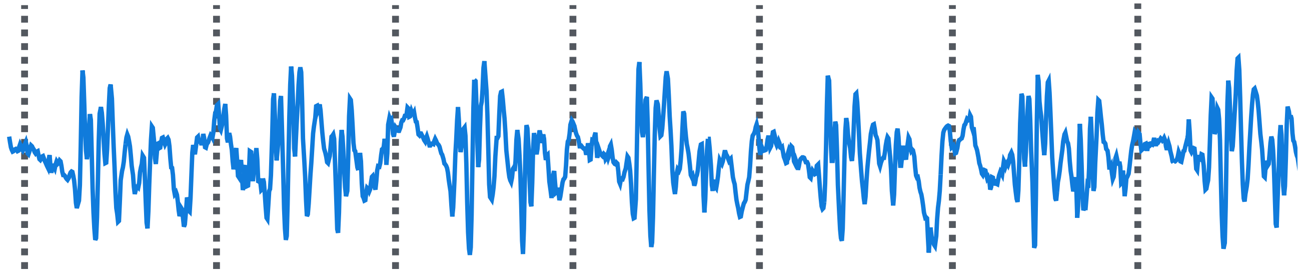
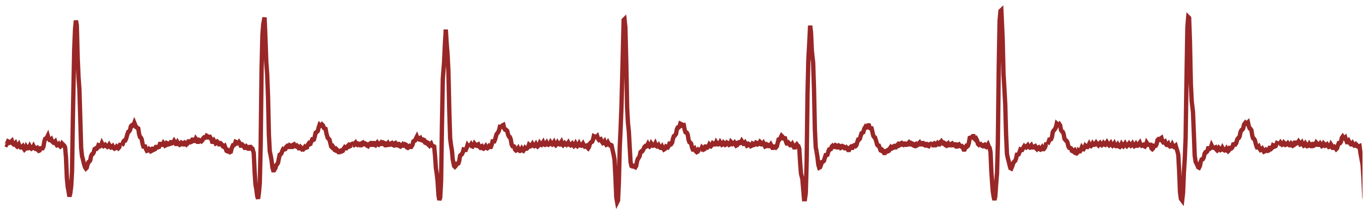
Spotlight on heart beat

- Signal second derivative



- ECG signal



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Physiological Features for Emotion Recognition

- 37 Features similar to PPG methods
  - Variability of IBI
  - Irregularity of breathing

Domain	Name
Time	Mean, Median, SDNN,**pNN50**, RMSSD, SDNNi, meanRate, *sdRate*, HRVTi, *TINN*.
Frequency	Welch PSD: **LF/HF**, peakLF, peakHF. Burg PSD: **LF/HF**, peakLF, peakHF. Lomb-Scargle PSD: **LF/HF**, peakLF, peakHF.
Poincaré	SD_1, $\mathbf{SD_2}$, $\mathbf{SD_2/SD_1}$.
Nonlinear	$\mathbf{SampEn_1}$, $\mathbf{SampEn_2}$, $\mathbf{DFA}_{all}$, DFA_1, DFA_2.

selected IBI features in **bold**;
selected respiration features in *italic*.

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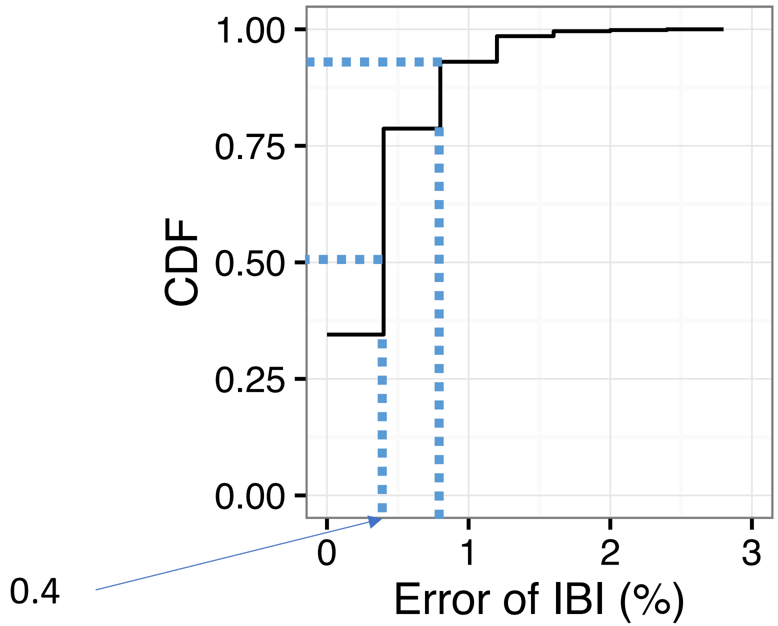
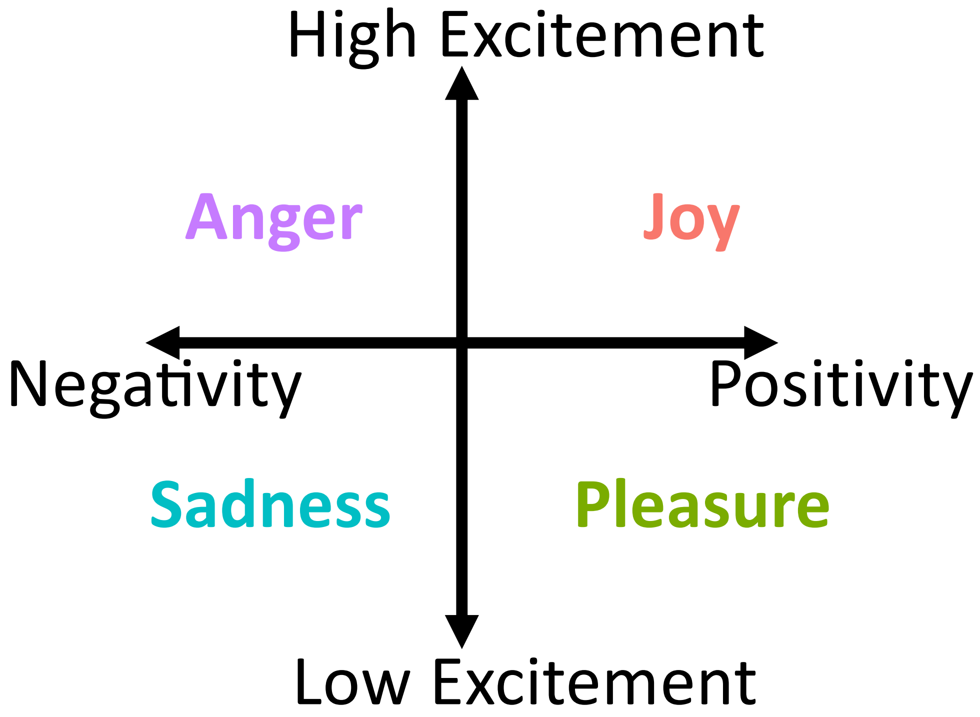
Is IBI Detection Accurate?

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



Emotion Model

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

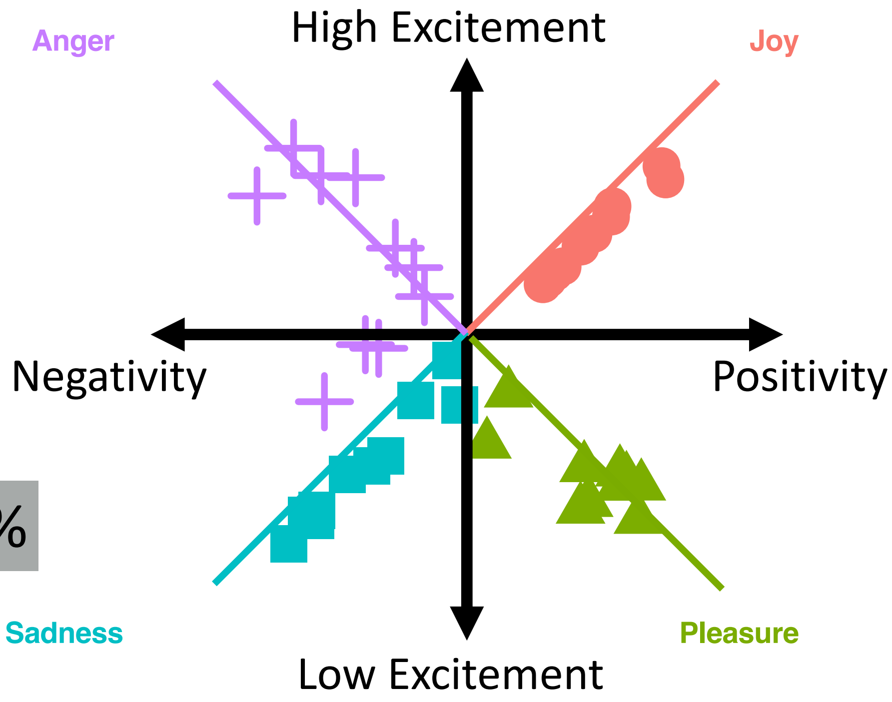


Does EQ-Radio detect emotion accurately?

- 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.

Person-dependent Classification

- Train and test on the same person



Accuracy: 92.5%

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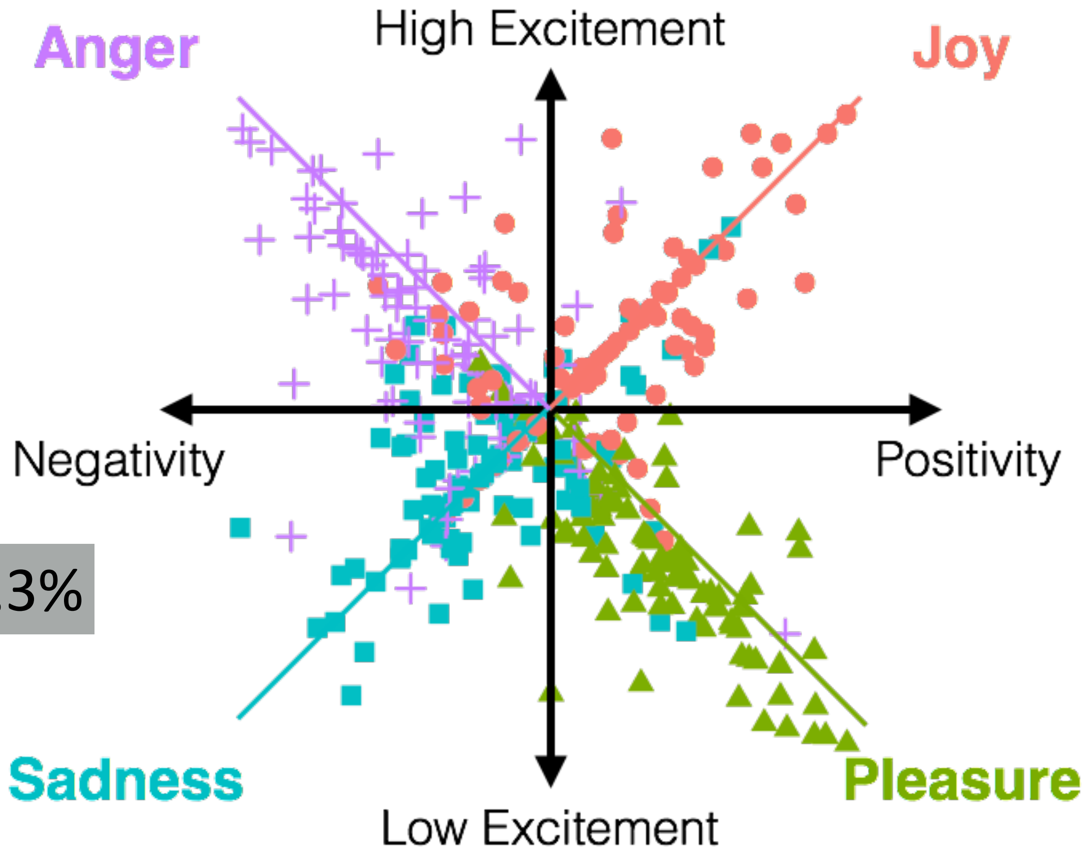
Person-independent Classification

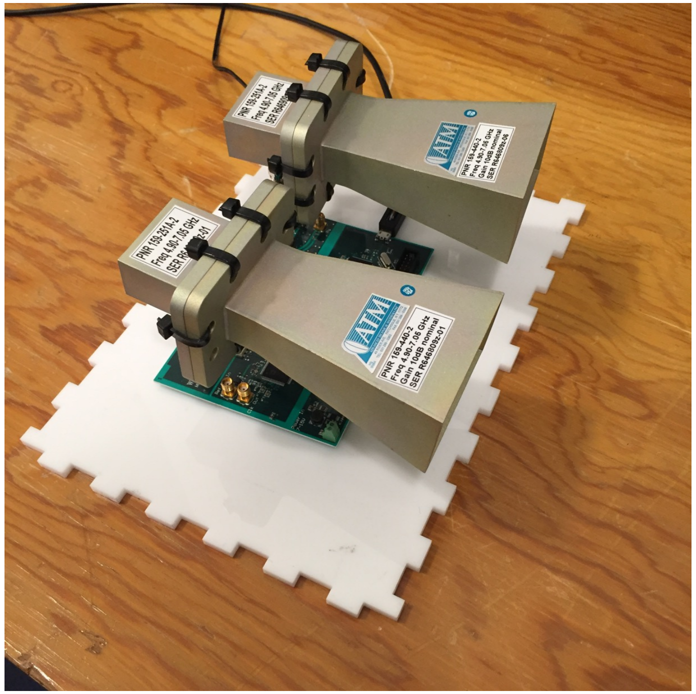
- Train and test on the different person



Accuracy: 72.3%

Hardware

- 5.5 GHz to 7.2 GHz
- sub-mW power



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Sleep Posture Monitoring: Why

- Avoiding bedsores after surgery,
- Reducing sleep apnoea events,
- Progression of Parkinson’s disease,
- Alerting epilepsy patients to potentially fatal sleep postures.

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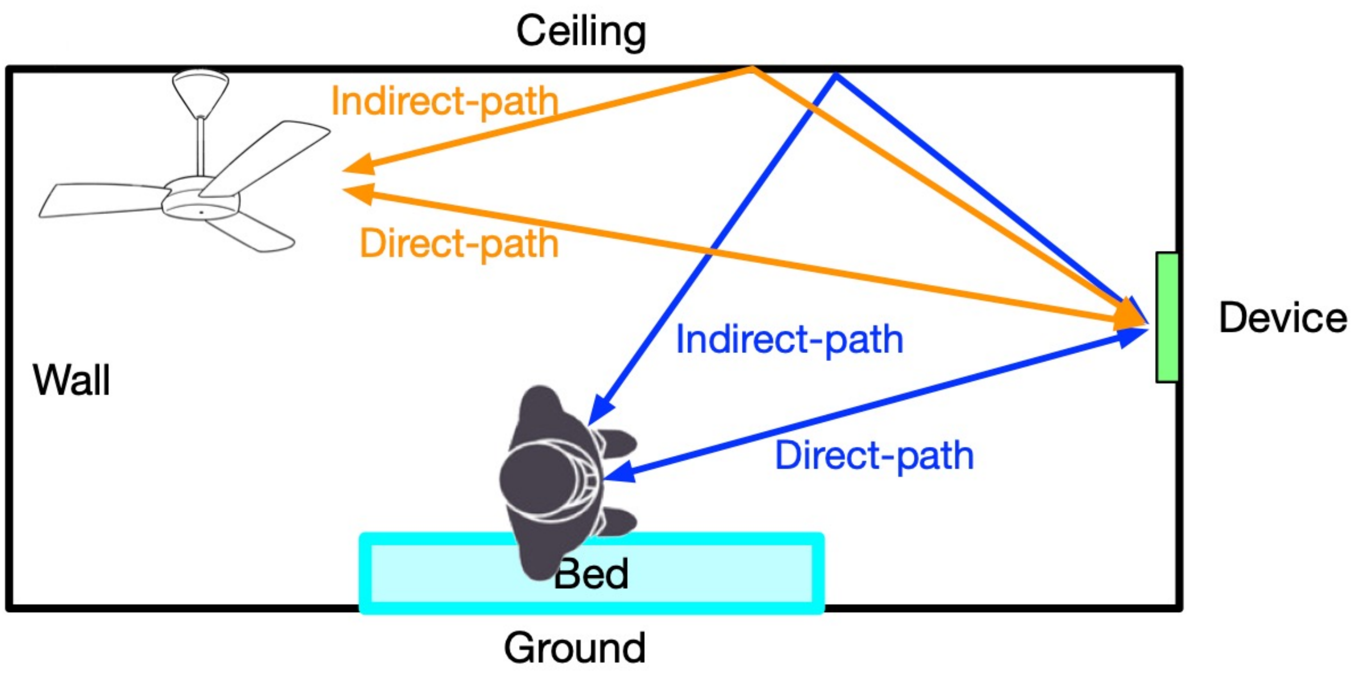
BodyCompass: Monitoring Sleep Posture with Wireless Signals. S. Yue, Y. Yang, H. Wang, H. Rahul, D. Katabi ACM (Ubicomp 2020)

The idea

- Reflection from a body is modulated by breathing
- Reflection from other objects are not



BodyCompass: Monitoring Sleep Posture with Wireless Signals. S. Yue, Y. Yang, H. Wang, H. Rahul, D. Katabi. ACM (Ubicomp 2020)

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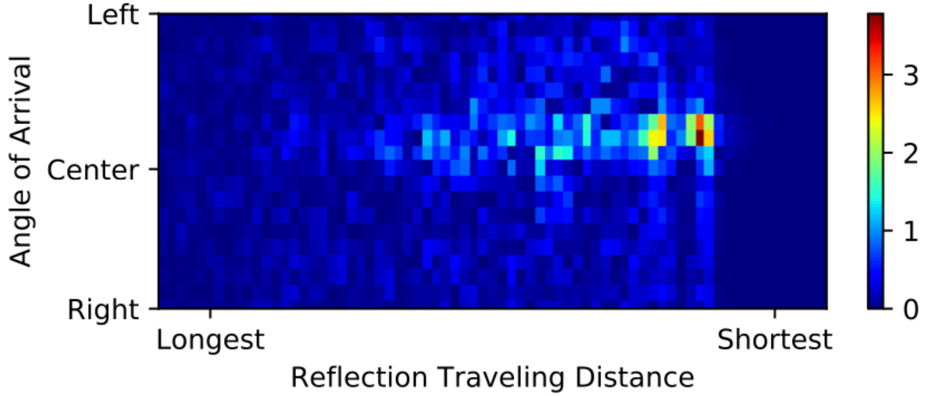
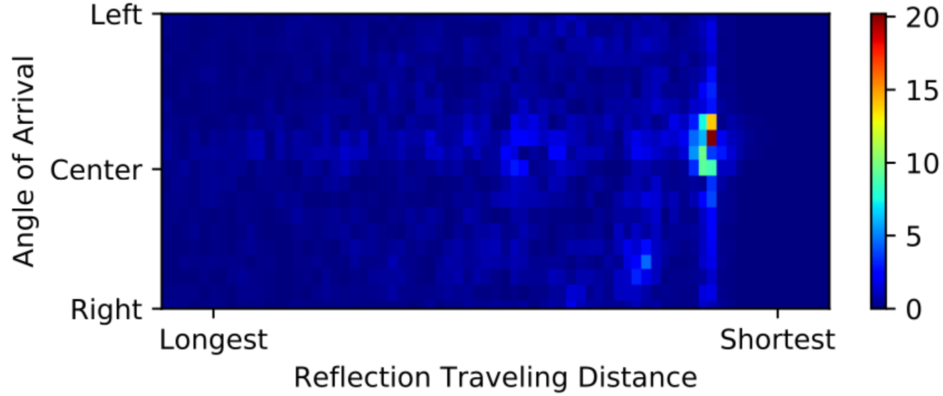
Heatmaps of different postures



User facing up: lots of indirect reflections



User facing towards the device

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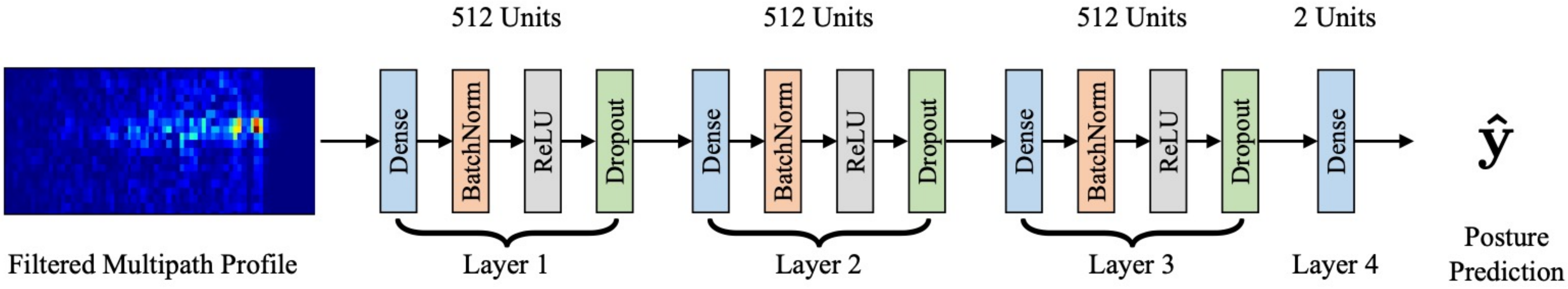
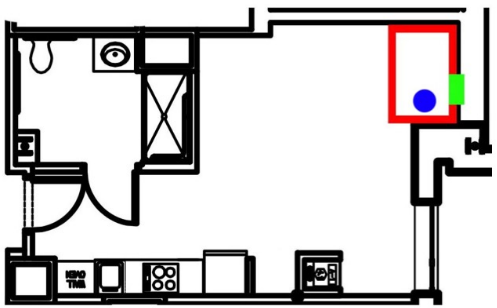
Deep Learning over multipath profiles

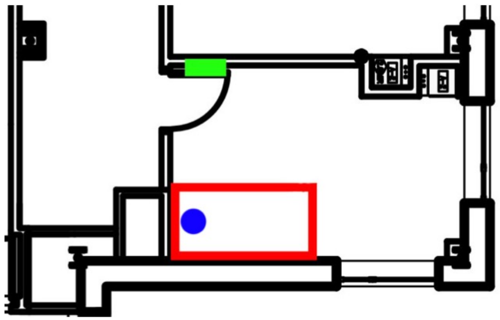


Data Scarcity and Room Diversity Issues

- Limited data from one user
- Training on all users and testing on target user yields bad results
  - There are differences in bed position and room layout which affect radio

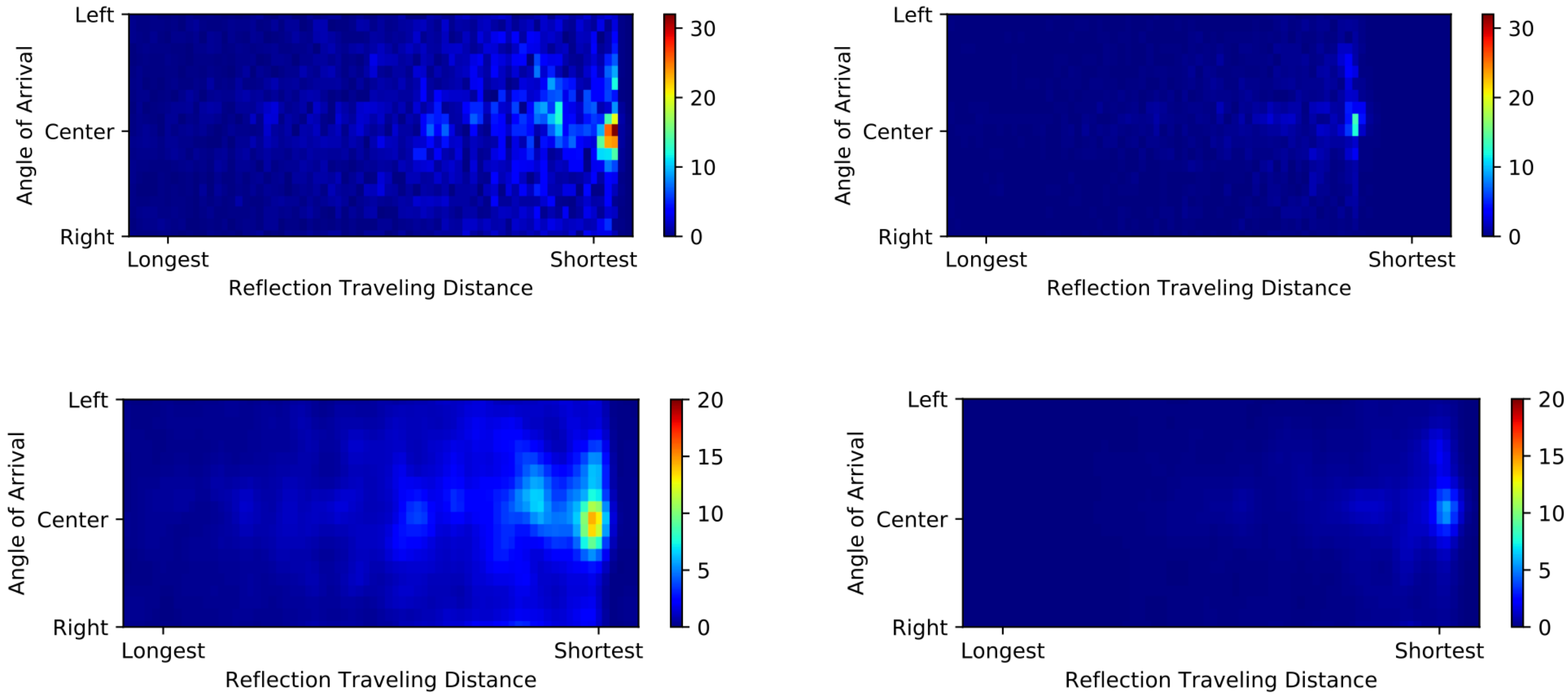


(a) User A's bedroom layout



(b) User B's bedroom layout

Bed Automatic Alignment



Transfer Learning

- Assume limited labelled data for a target user (and their house).
- Data from different (source) users (labelled) exist.
- Source users models corrected using augmented with data most similar to target user.
- Model is tried on target (scarce) labelled data. Some source models discarded (bad accuracy). Majority voting of prediction among other models is used as prediction.

Performance

	BodyCompass	k-NN (A)	k-NN (T)	RF (A)	RF (T)	XGB (A)	XGB (T)
Angle Error (1-week)	15.3° ± 4.4°	NA	31.3° ± 9.7°	NA	33.8° ± 13.0°	NA	33.8° ± 13.3°
Accuracy (1-week)	94.1% ± 4.3%	NA	77.7% ± 9.8%	NA	75.4% ± 12.0%	NA	75.5% ± 12.9%
Angle Error (1-night)	25.6° ± 6.7°	43.1° ± 11.0°	40.6° ± 11.0°	52.5° ± 17.0°	45.4° ± 15.1°	53.9° ± 16.2°	49.2° ± 13.1°
Accuracy (1-night)	86.7% ± 6.7%	65.2% ± 10.5%	67.8% ± 10.2%	54.8% ± 14.5%	62.2% ± 13.8%	53.5% ± 14.2%	59.9% ± 10.5%
Angle Error (16-min)	28.3° ± 8.7°	59.1° ± 19.0°	60.6° ± 19.0°	58.4° ± 20.2°	55.0° ± 18.9°	60.7° ± 20.1°	65.1° ± 13.1°
Accuracy (16-min)	83.7% ± 6.8%	50.3% ± 14.6%	46.4% ± 17.0%	51.0% ± 14.9%	52.2% ± 15.0%	48.7% ± 15.8%	42.8% ± 11.4%

Other things that can be monitored

- Stress
- Sleep stages
- Movement

Other signals (e.g. audio) can be used!

communications
biology

ARTICLE

Check for updates

https://doi.org/10.1038/s42003-021-01824-9 OPEN

Using smart speakers to contactlessly monitor heart rhythms

Anran Wang[1✉], Dan Nguyen[2], Arun R. Sridhar[2✉] & Shyamnath Gollakota[1✉]

Questions