Wireless Sensing Methods

Applications in Health Monitoring, Localization, and Identification

Nicholas Saizan & Mark Prettyman

Key Concepts

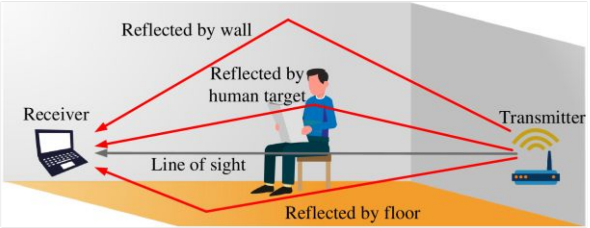
Wireless signals interact with the environment in various ways:

- Reflection
- Scattering
- Absorption

These interactions can be observed to extract knowledge about an environment.

Multipath effects can introduce both challenges and opportunities.

Existing WiFi AP's gather CSI, which can be used to learn about the environment.



Current Technology - Limitations

Most current activity/well-being monitoring systems are wearables

- “Body contact” devices

Past research in wireless sensing focuses on localization and detection of breathing/heart rate

- This is not the same as estimation.
- Some require line of sight to their subjects and for the user to face the sensor.

Past technologies often fail to account for scenarios with moving objects or multiple subjects.

- This is not suitable for the real world!
- Not working with multiple subjects means it’s expensive to scale.

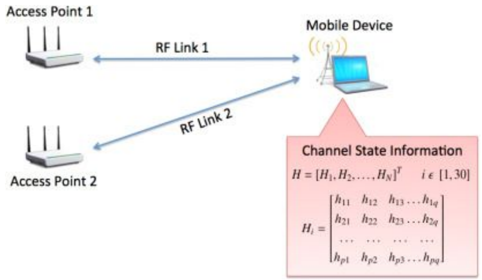
Wireless Sensing Methods - The Motivations

Using WiFi or similar signals as your sensing method means you **don't need LOS or "body contact"**

- A single device can cover more than one room
- Track more than one person

Most buildings are **already equipped with WiFi APs** that have good coverage

- Much of the information contained within CSI already gathered by APs is not used.



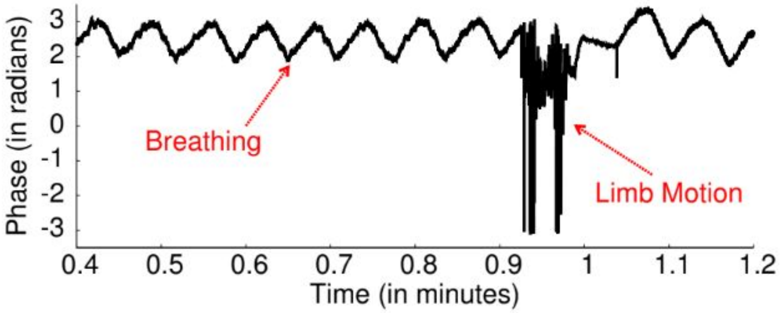
Can provide monitoring of elderly or children who won't reliably use a monitoring device themselves.

Wireless Sensing Methods - The Challenges

These technologies are targeted at fine-grained information that is easily masked by environmental factors

- Walking and moving limbs can obscure vital signs
- Nearby objects must be filtered away from targets
- How do you track heart rate of adjacent participants?

Clever filtering and localization techniques are required



Wireless Sensing - Types of Approaches

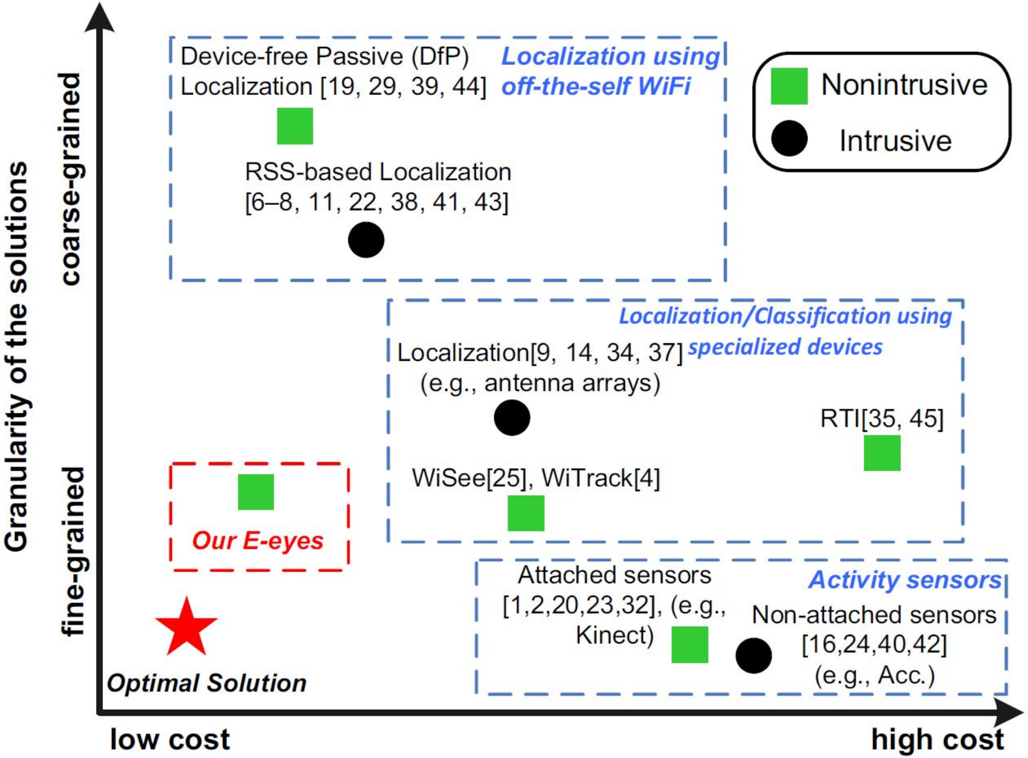
Without Specialty Hardware

- Mitigates the infrastructure requirements
- Requires use of existing devices to create mesh of wireless links (typically WiFi enabled devices)

With Specialty Hardware

- Allows for more customization in terms of signals generated and processed
- Potential for greater BW and thus greater accuracy

Wireless Sensing - A Trade Off

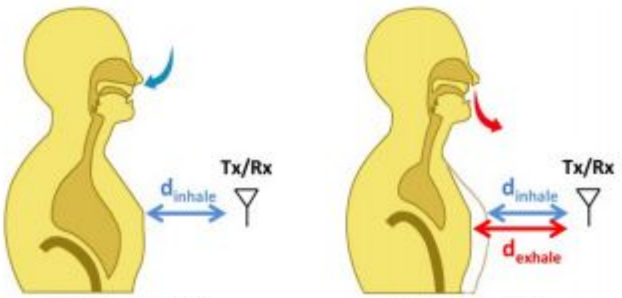


State of the Art Sensing Technology

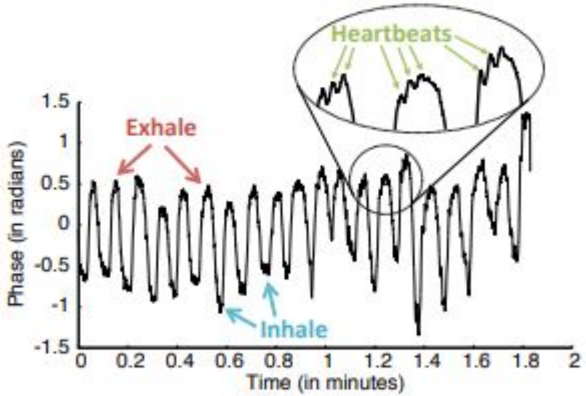
1) NLOS Vital Sign Detection (Vital Radio)
    a) Wireless heart-rate and breath-rate detection
    b) Multiple User Support
2) Fine-grained Activity Identification (E-eyes)
    a) Use existing WiFi APs to track activities through CSI
    b) Multiple Room Support
3) Material Sensing & Localization (IntuWition)
    a) Analyzes material reflection/scattering properties to differentiate between material types
    b) Uses existing WiFi hardware

Vital-Radio: The Idea

- Uses a single wireless base station to sense the breathing and heart-rate of multiple users.
- Non-intrusive, non-body-contact
- Small undulations in signal path distance indicate the presence of a body.
    - The base station will send out a low power signal and measure the reflection time.

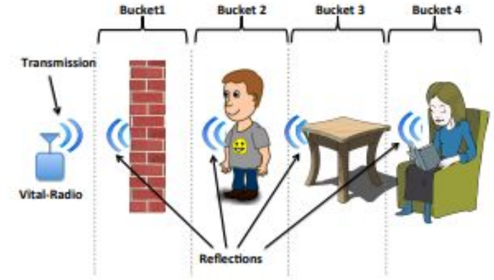


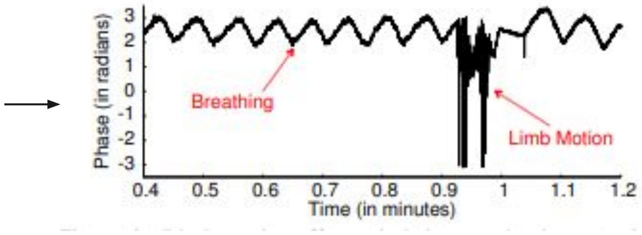
(a) Inhale Motion (b) Exhale Motion

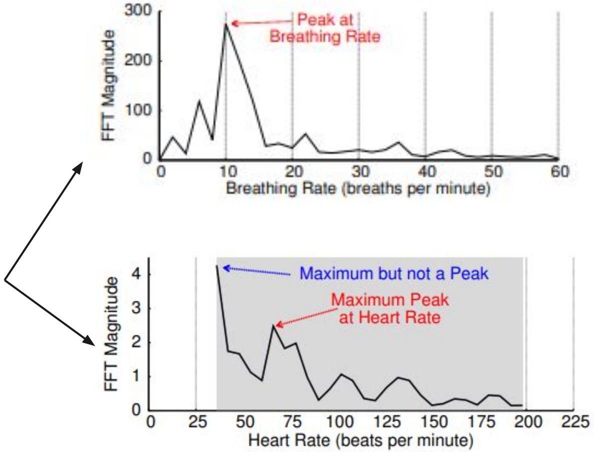


Vital-Radio: The Implementation

1) Isolate the humans from other objects using FMCW (Frequency Modulated Carrier Waves)
    a) Key Idea: different reflection times get put in different buckets.
2) Identify vital signs by looking for periodicity in time windows
    a) If periodicity is below a threshold, the time window is discarded
3) Extract heart-rate and breath-rate from frequency domain
    a) Additional filtering is implemented for more accuracy

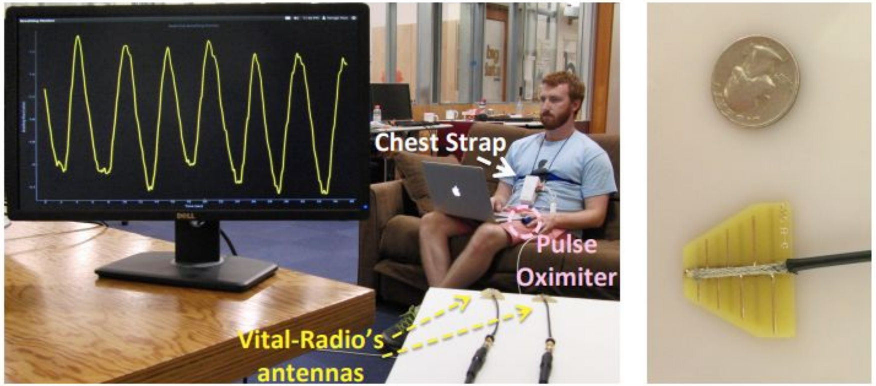




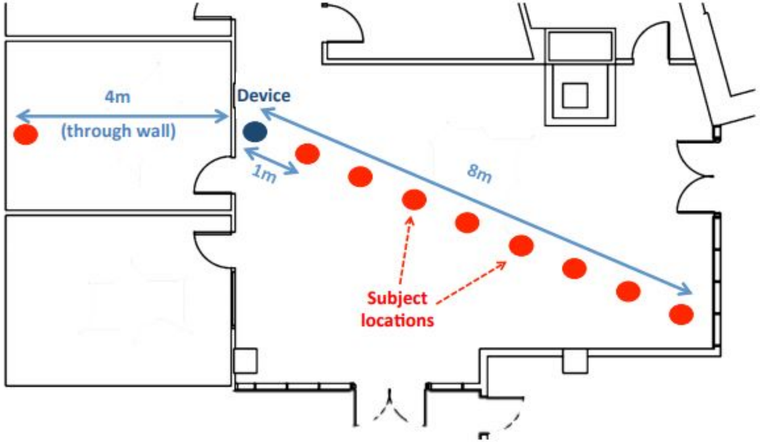


Vital-Radio: The Results

- Alice PDx chest strap for ground truth
- Breathing Rate Accuracy
  - 99.3% @ 1m
  - 98.7% @ 8m
- Heart Rate Accuracy
  - 98.5% @ 1m
  - 98.3% @ 8m
- Users at varying orientations
  - accuracy drop of up to 3%
  - **You don't need to face the device!**
- Through-wall
  - 99.2% and 90.1% for BR and HR
- Multiple Users
  - BR - 98% for 3 users @ 2m ,6m, 8m
- Moving Users
  - >98% someone walks >1.5m from user
  - 75% someone walks within <1m of user

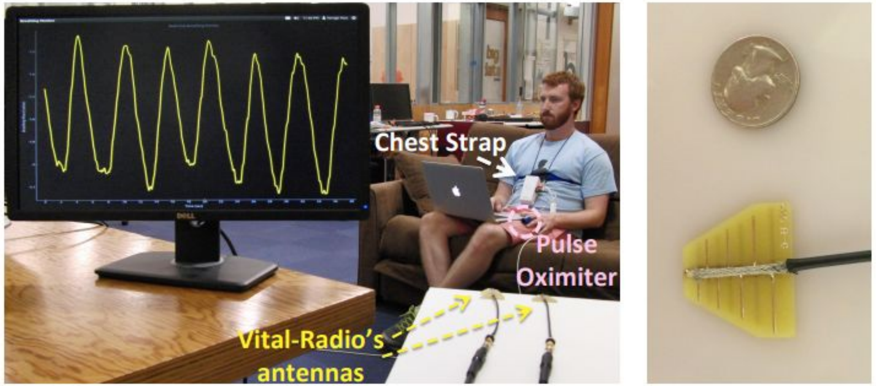


(a) **Setup.** (b) **Antennas.**

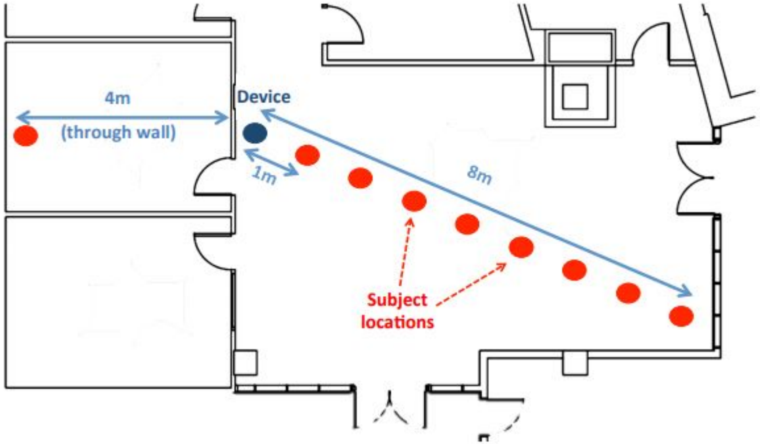


Vital-Radio: Limitations

- Accuracy drops of steeply outside the +- 75 degree viewing angle of antenna
- Multiple users sitting next to each other could end up in the same bucket
- Only produces valid reading for users doing static tasks (typing, reading, watching tv)
- State of the art FMCW radio is used to



(a) **Setup.** (b) **Antennas.**



E-eyes: The Idea

- Low cost, fine-grained, activity identification.
- Uses existing WiFI APs and devices.
- 802.11n provides amplitude and phase information from each of the 52 orthogonal OFDM subcarriers
    - This contains information about the environment
- Use that information to identify both in-place activities and walking movements

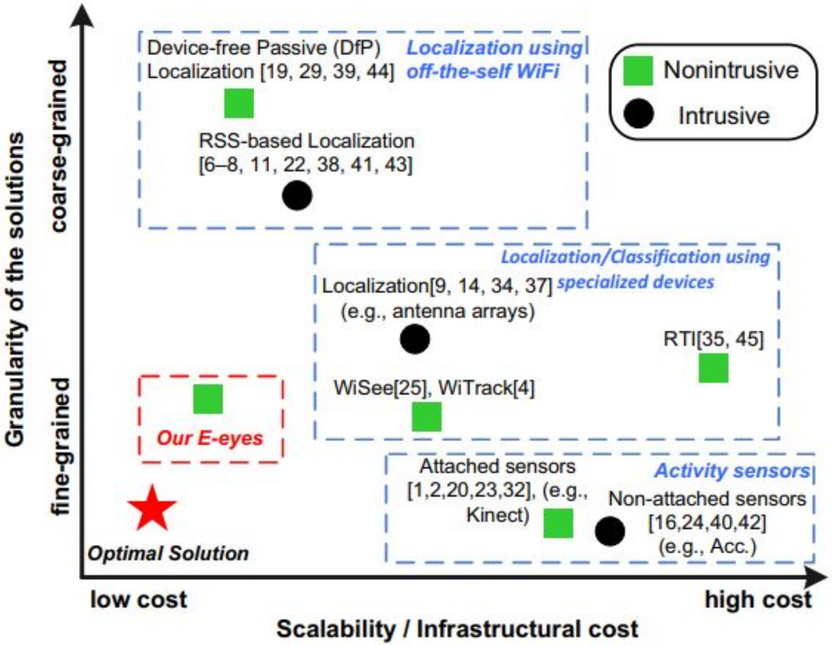
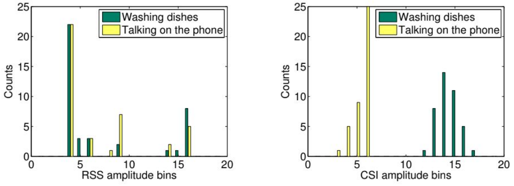


Figure 1: Design Space: comparing to related work.



(a) RSS distribution (b) CSI distribution

Figure 3: Histograms of RSS amplitude and CSI amplitude of a particular subcarrier for two different in-place activities at the same position: washing dishes and talking on the phone nearby the sink.

E-eyes: The Implementation

1) Activity Identification
   a) Compare CSI patterns against profiles to determine activity
   b) Walking activities produce change in CSI over time
   c) In-Place activities produce small repetitive changes in CSI
2) Profile Construction and Updating
   a) Monitor the environment and group similar instances of activity
   b) User can label those activities or update existing profiles with them

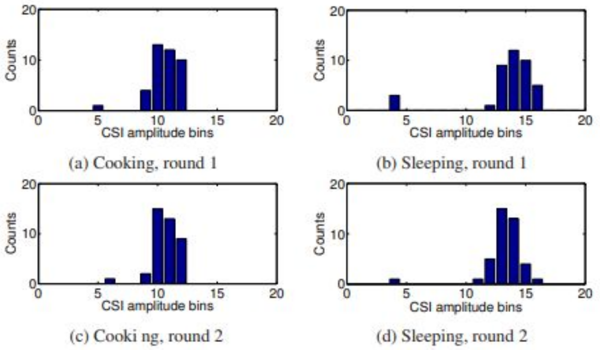


Figure 5: Histogram of CSI amplitudes on a particular subcarrier for cooking and sleeping.

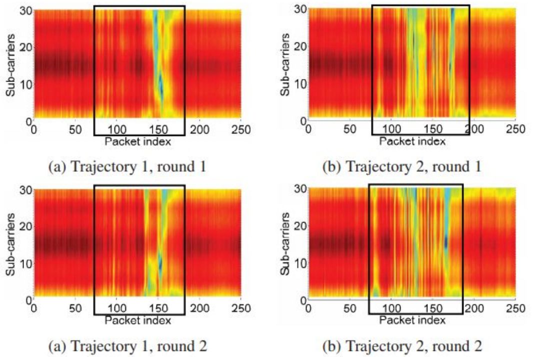


Figure 6: Similar CSI time series pattern for same walking trajectory.

E-eyes: The Implementation

1) Activity Identification
   a) Compare CSI patterns against profiles to determine activity
   b) Walking activities produce change in CSI over time
   c) In-Place activities produce small repetitive changes in CSI
2) Profile Construction and Updating
   a) Monitor the environment and group similar instances of activity
   b) User can label those activities or update existing profiles with them

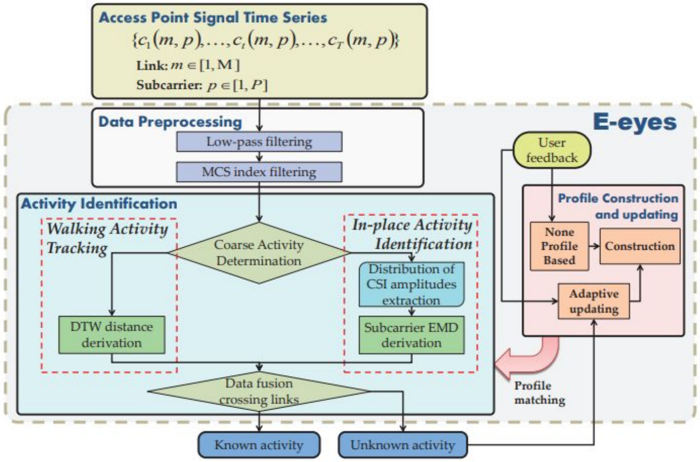
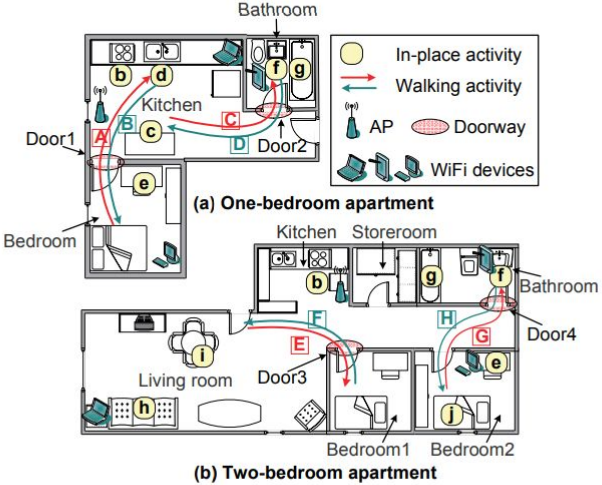


Figure 4: System flow of activity recognition using CSI.

E-eyes: The Results

- 50 rounds of each activity performed
- 100 rounds of unknown activity performed
- In-Place Activities Identification
  - 97% in 1 BR apartment
  - 97.38% in 2 BR apartment



Actual Activity Performed

1-bedroom apt.	a	b	c	d	e	f	g	unknown
a: empty	1	0	0	0	0	0	0	0
b: cooking	0	1	0	0	0	0	0	0
c: eating	0	0	1	0	0	0	0	0
d: washing dishes	0	0	0.16	0.84	0	0	0	0
e: studying	0	0	0	0	1	0	0	0
f: brushing	0	0	0.06	0	0	0.94	0	0
g: bathing	0	0	0.02	0	0	0	0.98	0
o: others	0	0	0	0	0	0	0	1

Identified In-place Activity

(a) 1-bedroom apartment

Actual Activity Performed

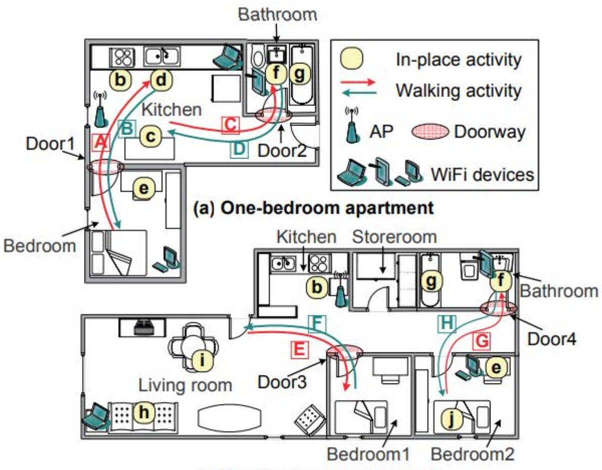
2-bedroom apt.	a	b	f	g	h	i	j	unknown
a: empty	1	0	0	0	0	0	0	0
b: cooking	0	1	0	0	0	0	0	0
f: brushing	0	0	1	0	0	0	0	0
g: bathing	0	0	0	0.96	0	0	0	0.04
h: watching TV	0	0	0	0	1	0	0	0
i: gaming	0	0	0	0	0	1	0	0
j: sleeping	0	0	0	0	0	0	0.88	0.12
o: others	0	0	0	0	0	0	0.05	0.95

Identified In-place Activity

(b) 2-bedroom apartment

E-eyes: The Results (cont’d)

- 50 rounds of each activity performed
- 100 rounds of unknown activity performed
- Walking Activities Identification
  - 97% in 1 BR apartment
  - 94% in 2 BR apartment
- Doorway Passing Identification
  - 99.17% in 1 BR apartment
  - 95.83% in 2 BR apartment



(a) One-bedroom apartment

(b) Two-bedroom apartment

Actual Activity Performed

1-bedroom apt.	A	B	C	D	unknown	Door	Door1	Door2	None
A	1	0	0	0	0	Door1	1	0	0
B	0	1	0	0	0				
C	0	0	0.95	0.05	0	Door2	0	0.975	0.025
D	0	0	0	1	0				
O	0	0	0.1	0	0.9	None	0	0	1

Identified Walking Activity & Doorway

(a) 1-bedroom apartment

Actual Activity Performed

2-bedroom apt.	E	F	G	H	unknown	Door	Door3	Door4	None
E	1	0	0	0	0	Door3	1	0	0
F	0.15	0.85	0	0	0				
G	0	0	0.9	0.1	0	Door4	0	0.875	0.125
H	0	0	0	1	0				
O	0.05	0	0	0	0.95	None	0	0	1

Identified Walking Activity & Doorway

(b) 2-bedroom apartment

E-eyes: Limitations

Tracking multiple users at once requires large number of profiles.

Moving furniture means profile updates are required.

IntuWition: The Idea

- Other research has been shown to track the presence of people or objects, but they fail to identify the **type of object** or the **materials it's made of**.
- Polarized waves are reflected and scattered differently by different materials.
    - Use these properties to identify materials of objects
- Identifying difference of materials allows us to tag and track multiple entities in an environment.

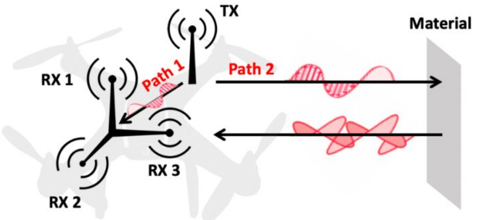


Figure 4: IntuWition transmits signals from a vertically polarized antenna to 3 mutually perpendicular receive antennas and processes polarization changes due to reflections from materials.

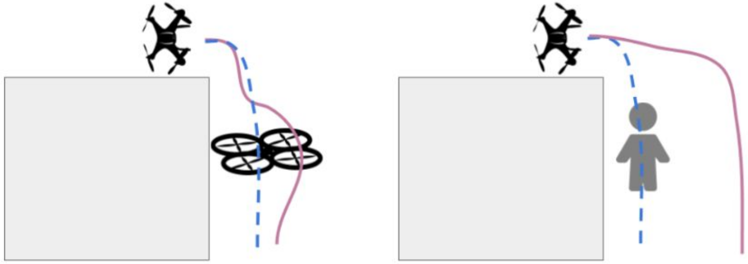
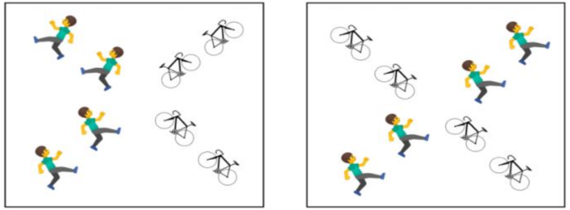


Figure 1: IntuWition helps detect the type of material of an object hidden from view. This could assist, say a drone's path planning algorithm, to change its planned path (blue) to a new path (purple). For example, it could swerve upwards to avoid another drone, but would give a human a wide berth.

IntuWition: The Implementation

- Uses existing hardware on WiFi-enabled devices.
- Uses Multi-Layer Perceptrons to classify data
  - Automatically learns from inputs
  - Takes in raw feature inputs and outputs material or object type
- Can use material information to tag objects and track them.



(a) Paths not crossing

(b) Paths crossing

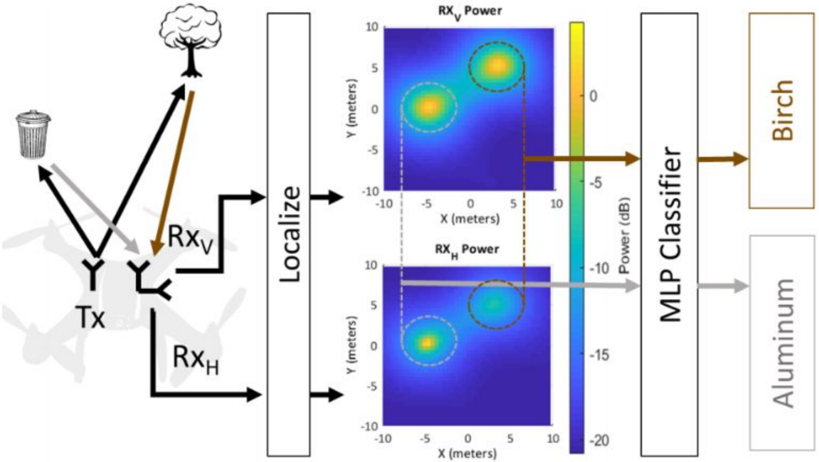


Figure 3: IntuWition Workflow: An example in 2-D (for simplicity) shows how IntuWition isolates locations of two objects and compares powers across horizontally and vertically polarized antennas to infer material type.

IntuWition: The Results

- Larger targets have less error. The metal and wood samples were larger targets than the humans

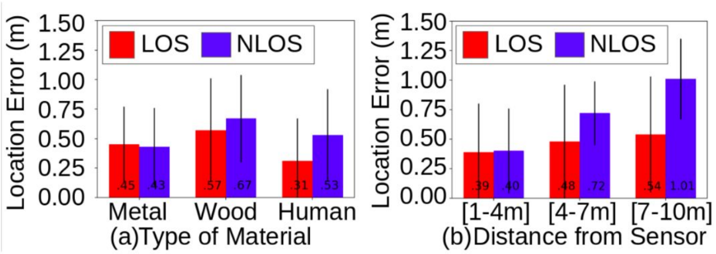


Figure 9: (a) Effect of Material Type on Localization Error: We observe our system localizes wood and metal best, which we expect is due to the larger surface areas of our material samples on average when compared to humans, for an overall mean error of 0.49m. (b) Effect of Round-trip Distance on Material Sensing: we see accuracy slightly increases with distance at the beginning, as the reflector becomes more distinguishable from the strong line-of-sight signal, and eventually falls with distance.

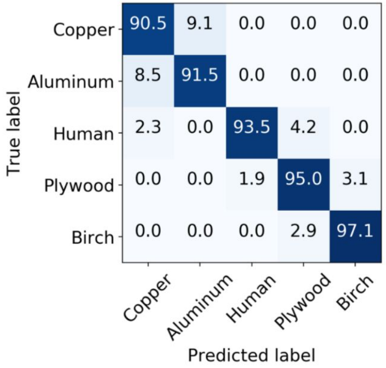


Figure 11: This confusion matrix shows our efficacy in classifying between five different materials using our Multi-layer Perceptron Classifier.

IntuWition: The Results

- Promising results for object identification

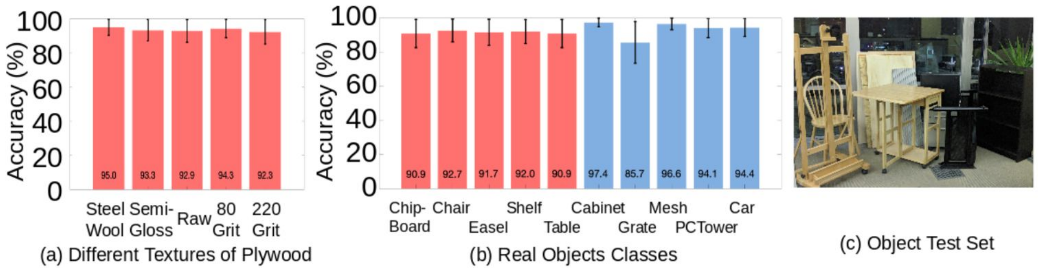


Figure 13: (a) We show our classification network accuracy dealing with different surface textures of the same material (wood). (b) We show our classification network accuracy dealing with real objects used in our daily life of different material (wood is showed as red, metal is showed as blue). (c) We show the boards, furniture, and objects used for these experiments.

IntuWition: The Limitations

- Performs poorly with weak reflectors
  - smaller objects
  - less dense materials
- Bandwidth of WiFi limits it’s localization resolution (0.4m)
- Object of similar materials are hard to differentiate

Summary

- Past sensing technologies often rely on:
    - LOS or body-contact sensors
    - They use specialty hardware
    - Fail to work in many real word scenarios (multiple users)
    - Do not provide fine-grained information on activities and object types
- We've seen that new research:
    - Can compete with previous vital sensing tech wirelessly and without LOS
    - Can utilize existing WiFi hardware that is widely available
    - Can work amongst multiple users without breaking down
    - Can give detailed insight into user behaviors or environmental materials
        - New opportunities for object/activity tracking

Sources

http://www.mit.edu/~fadel/papers/vitalradio-paper.pdf
https://www.groundai.com/project/farsense-pushing-the-range-limit-of-wifi-based-respiration-sensing-with-csi-ratio-of-two-antennas/1
http://www.swarunkumar.com/papers/intuwition-mobicom2019.pdf
https://dl.acm.org/doi/10.1145/2639108.2639143
http://www.winlab.rutgers.edu/~gruteser/papers/E_eyes_paper.pdf