Indoor Localization Without Infrastructure Using the Acoustic Background Spectrum

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http://empathicsystems.org

Video demonstration of Batphone app

Current acoustic fingerprint

Location estimate

Definition: indoor localization without infrastructure

Given:

- ✓ A smartphone
- ✓ A building composed of many rooms
- ✓ At least one prior visit to each room for training

Without:

- × Specialized hardware
- × Anything installed in the environment
- × Cooperation from the building owner

Goal:

- Determine which room the smartphone is currently located in

Summary

Motivation:

- Indoor localization is important
- Wi-Fi is imperfect and not always available
- Improved accuracy is desired

Distinctive elements of our method:

- Listen to background sounds
- Look at frequency domain
- Rank-order filter for noise

Results:

- 69% accuracy for 33 rooms using sound alone
- Publicly-available app
- Effectively combined Wi-Fi and sound

Related Work: mobile acoustic sensing

M. Azizyan, I. Constandache, and R.R. Choudhury. *SurroundSense:* mobile phone localization via ambience fingerprinting. MobiCom'09.

- Characterized rooms by loudness distribution
- Did not use sound exclusively

H. Lu, W. Pan, N.D. Lane, T. Choudhury, and A.T. Campbell. *SoundSense:* scalable sound sensing for people-centric applications on mobile phones. MobiSys'09.

- Focused on transient sounds
- Activity detection, not localization

Acoustic Background Spectrum (ABS)

A location fingerprint should be:

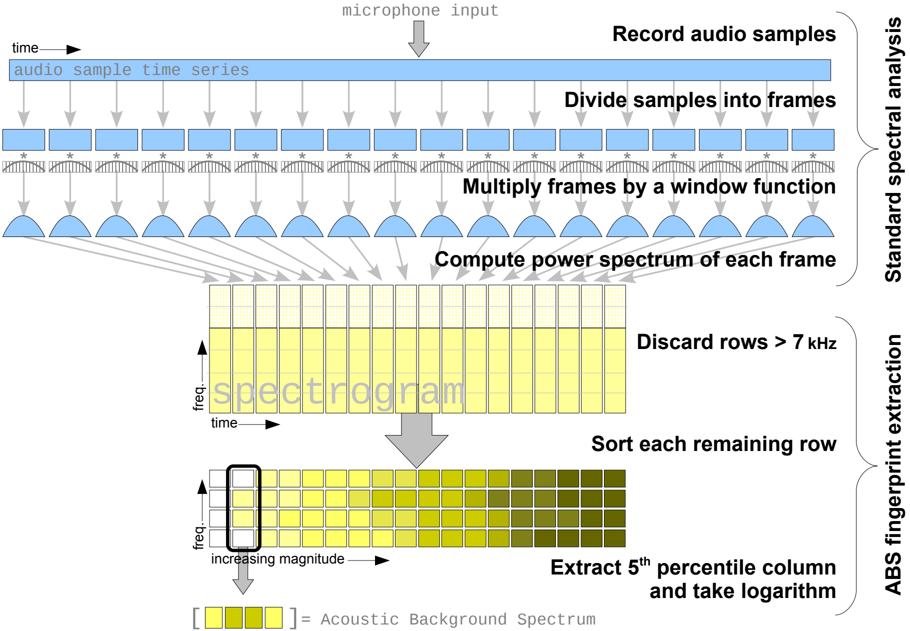
- **D**istinctive
- r**E**sponsive
- **C**ompact
- **E**fficiently-computable
- **N**oise-robust
- **T**ime-invariant

Acoustic Background Spectrum (ABS)

A location fingerprint should be:

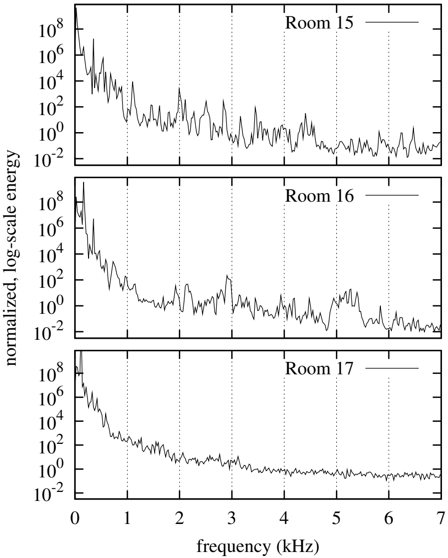
▶ **D**istinctive	✓ 69% matching accuracy
▶ r**E**sponsive	✓ 4–30 second sample
▶ **C**ompact	✓ $\sim$1 kB per fingerprint
▶ **E**fficiently-computable	✓ $\sim$12% mobile CPU usage
▶ **N**oise-robust	$\sim$ sometimes can adapt
▶ **T**ime-invariant	✓ tested on different days

Signal Processing

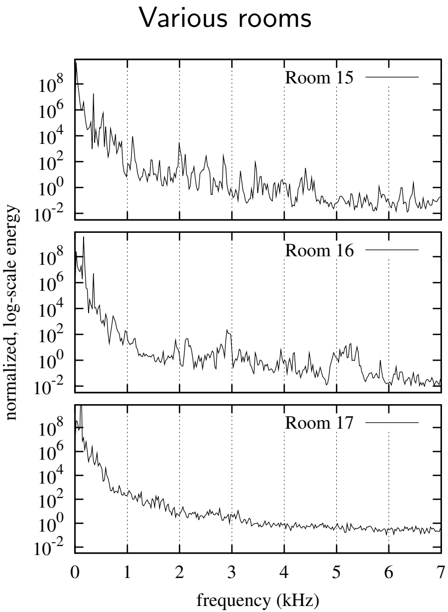


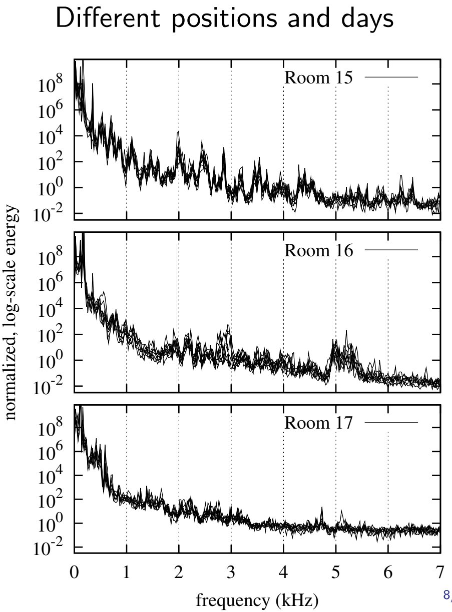
ABS Fingerprints

Various rooms



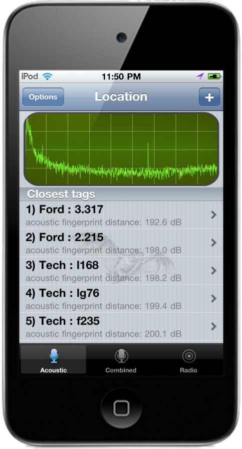
ABS Fingerprints





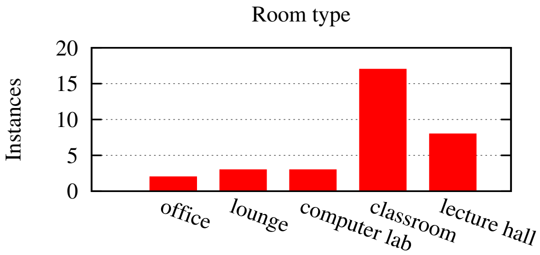
Experimental Platforms

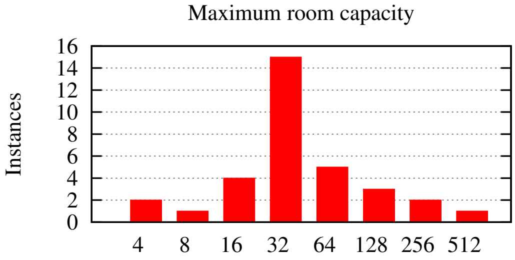
(a) Zoom H4n



(b) Apple iPod Touch

Experimental Rooms





Fingerprint-based localization

Supervised learning with two phases:

- Training – gather labeled fingerprints
- Testing/operation – observe new, unlabeled fingerprints
- Experiments use leave-one-out simulation

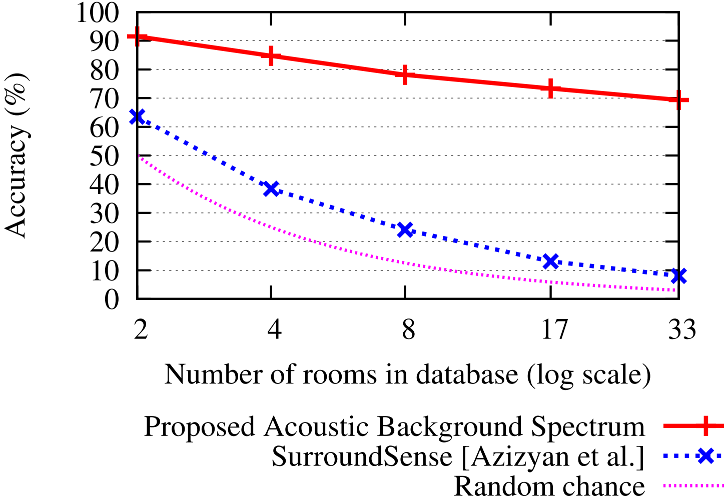
Our classifier:

- Euclidean distance metric for comparing fingerprints (equivalent to RMS error)
- Nearest-neighbor classification

In summary

To guess the current location find the “closest” fingerprint in a database of labeled fingerprints.

Accuracy Scaling



- SurroundSense is used in a way not intended by the authors: using the microphone alone

ABS Parameters

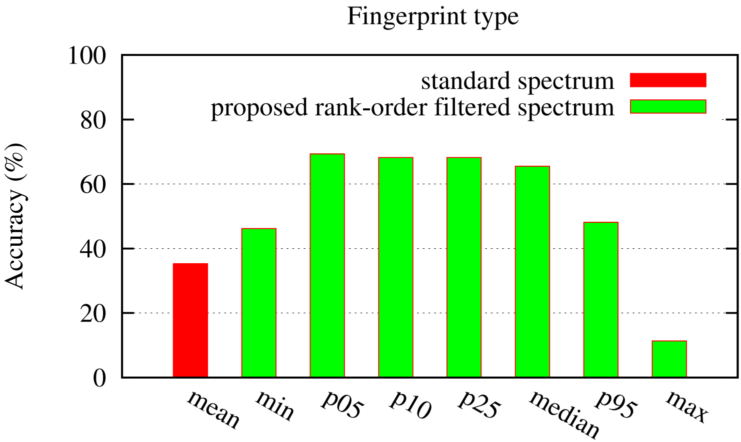
Presented now:

- Filter rank
- Listening time
- Fingerprint size/resolution

In paper:

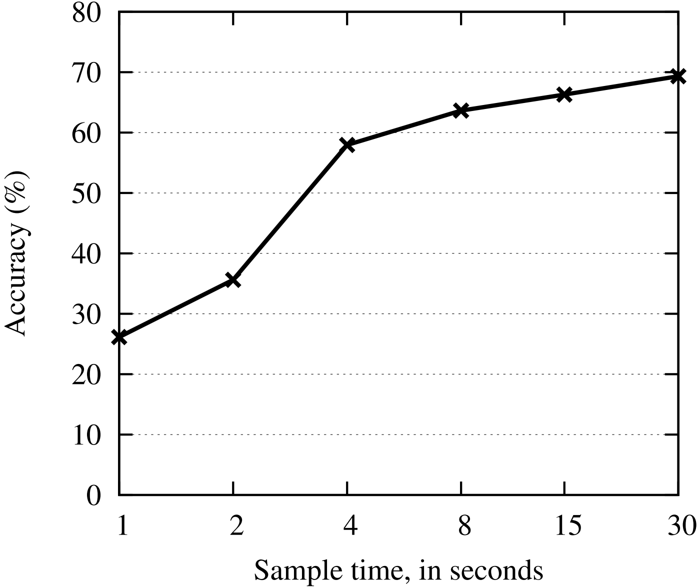
- Frequency band
- Distance metric
- Spectrogram window

Rank-order Filtering

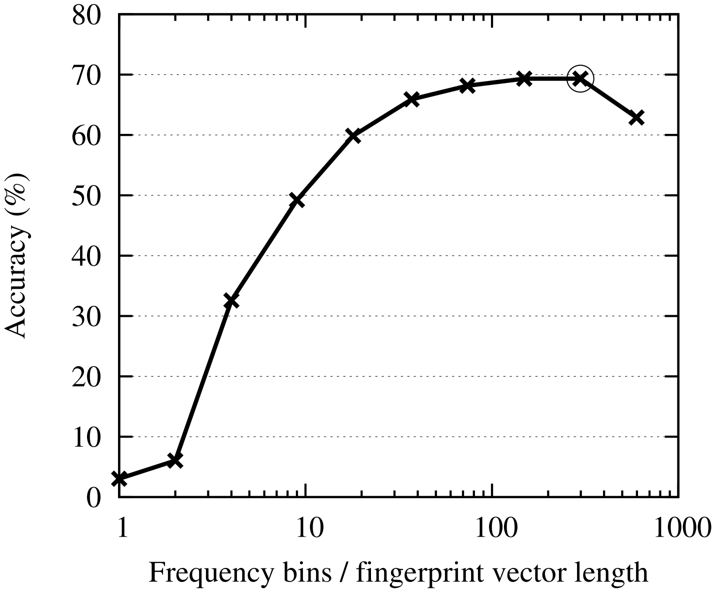


- 33 rooms in database
- Rank-order filters outperforms simple mean
  $\Rightarrow$ our transient noise filtering technique is effective

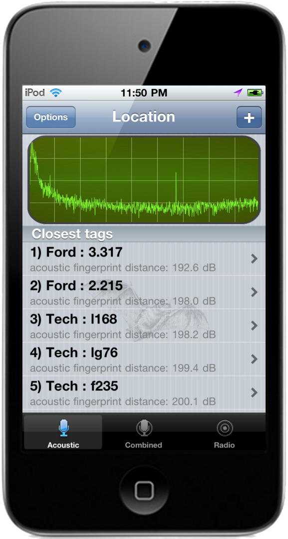
Listening time



Frequency resolution

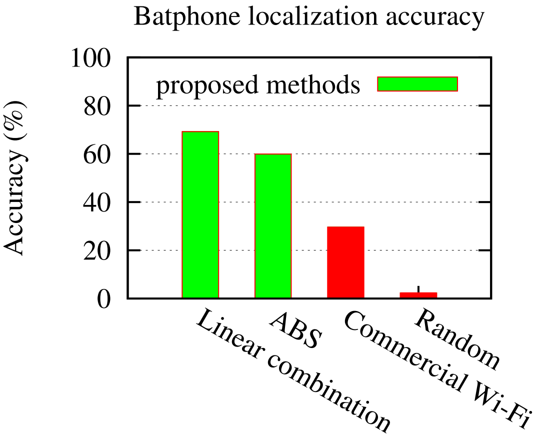


Batphone app in iTunes store



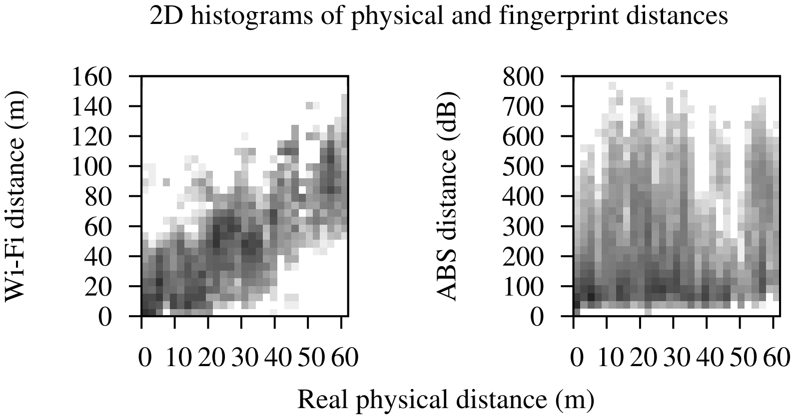
- Uses a 10 second sliding window
- Streaming signal processing
- Combines Wi-Fi with acoustic fingerprint

Batphone results



- 43 rooms in database
- Similar ABS accuracy for iPod and audio recorder
- Linear combination of Wi-Fi and ABS works well
- Didn't compare to state-of-the-art Wi-Fi localization

Orthogonality of Wi-Fi and Acoustics



- Wi-Fi fingerprints from distant rooms are always different
- ABS fingerprints from nearby rooms can be quite different

http://stevetarzia.com/listen

Can you identify this room?

0:00 0:08

The candidates, click to guess

0:00 0:08

0:00 0:08

0:00 0:08

0:00 0:08

Show Answer | Reload to try again

Conclusion

ABS fingerprint can be used for indoor localization
and it requires no infrastructure

See the paper for:

- Full parameter study
- Noise robustness experiment
- More Wi-Fi combination results
- Battery-drain measurements

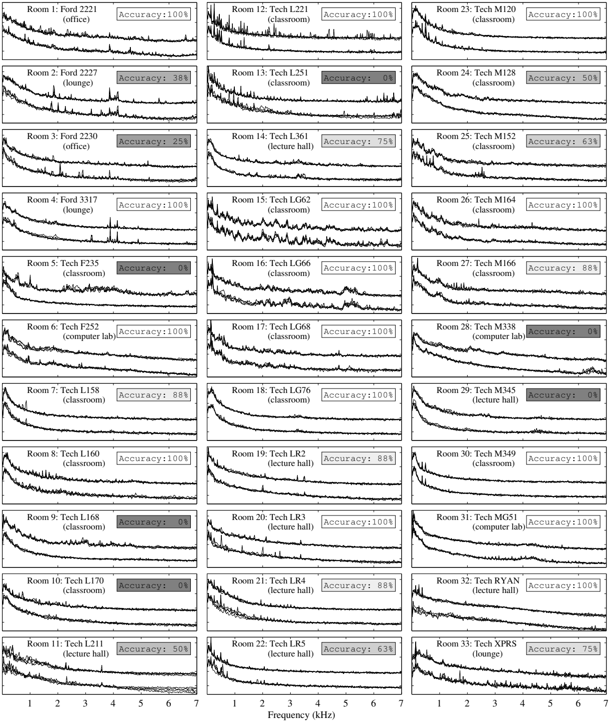
Future work

- Improved noise robustness
  - Train the various noise states
  - Adaptively chose fingerprint frequency band
- Use floorplan and history: Markov movement model
- Isolate factors that contribute to the ABS
- Add other sensors, as in SurroundSense
- In-pocket detection

Thanks!

For your enjoyment:

- App on the iTunes store:
  search for `Batphone`
- Listening demo at
  `http://stevetarzia.com/listen`
- Data and Matlab scripts at
  `http://stevetarzia.com`
- See our other projects at
  `http://empathicsystems.org`


Room 1: Ford 2221 (office)
Accuracy:100%
Room 2: Ford 2227 (lounge)
Accuracy: 38%
Room 3: Ford 2230 (office)
Accuracy: 25%
Room 4: Ford 3317 (lounge)
Accuracy:100%
Room 5: Tech F235 (classroom)
Accuracy: 0%
Room 6: Tech F252 (computer lab)
Accuracy:100%
Room 7: Tech L158 (classroom)
Accuracy: 88%
Room 8: Tech L160 (classroom)
Accuracy:100%
Room 9: Tech L168 (classroom)
Accuracy: 0%
Room 10: Tech L170 (classroom)
Accuracy: 0%
Room 11: Tech L211 (lecture hall)
Accuracy: 50%
Room 12: Tech L221 (classroom)
Accuracy:100%
Room 13: Tech L251 (classroom)
Accuracy: 0%
Room 14: Tech L361 (lecture hall)
Accuracy: 75%
Room 15: Tech LG62 (classroom)
Accuracy:100%
Room 16: Tech LG66 (classroom)
Accuracy:100%
Room 17: Tech LG68 (classroom)
Accuracy:100%
Room 18: Tech LG76 (classroom)
Accuracy:100%
Room 19: Tech LR2 (lecture hall)
Accuracy: 88%
Room 20: Tech LR3 (lecture hall)
Accuracy:100%
Room 21: Tech LR4 (lecture hall)
Accuracy: 88%
Room 22: Tech LR5 (lecture hall)
Accuracy: 63%
Room 23: Tech M120 (classroom)
Accuracy:100%
Room 24: Tech M128 (classroom)
Accuracy: 50%
Room 25: Tech M152 (classroom)
Accuracy: 63%
Room 26: Tech M164 (classroom)
Accuracy:100%
Room 27: Tech M166 (classroom)
Accuracy: 88%
Room 28: Tech M338 (computer lab)
Accuracy: 0%
Room 29: Tech M345 (lecture hall)
Accuracy: 0%
Room 30: Tech M349 (classroom)
Accuracy:100%
Room 31: Tech MG51 (computer lab)
Accuracy:100%
Room 32: Tech RYAN (lecture hall)
Accuracy:100%
Room 33: Tech XPRS (lounge)
Accuracy: 75%
1 2 3 4 5 6 7
Frequency (kHz)

Parameter Study

(a)

Frequency band	Accuracy
full (0–48 kHz)	59.8%
audible (0–20 kHz)	64.8%
low (0–7 kHz)*	69.3%
very low (0–1 kHz)	61.0%
(0–600 Hz)	51.5%
(0–400 Hz)	44.3%
(0–300 Hz)	40.9%
(0–200 Hz)	30.7%
(0–100 Hz)	15.5%
high (7–20 kHz)	28.4%
ultrasonic (20–48 kHz)	25.0%

Parameter Study (cont.)

(b)

Distance metric	Accuracy
Euclidean*	69.3%
city block	66.7%

(c)

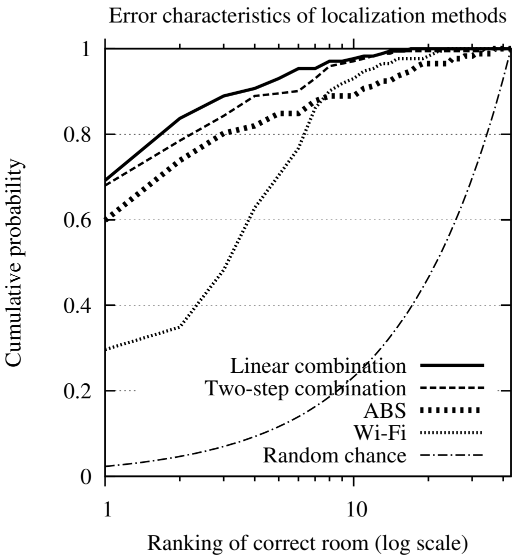
Spectrogram window	Accuracy
rectangular	65.2%
Hamming*	69.3%
Hann	68.2%
Blackman	67.4%

Optimal Parameters

symbol	meaning	optimal value	Batphone
R_s	sampling rate	96 kHz	44.1 kHz
n_{spec}	spectral resolution	2048 bins	1024 bins
n_{fp}	ABS size	299 bins	325 bins
t_{spec}	frame size	0.1 s	0.1 s
t_{samp}	sampling time	30 s	10 s
	frequency band	0–7 kHz	0–7 kHz
	window function	Hamming	rectangular

Dealing with Noise by changing Frequency band

	Occupancy Noise State		
Frequency band	Quiet	Conversation	Chatter
(a) Tech LR5 lecture hall			
low (0–7 kHz)	**89.2%**	2.5%	0.0%
(0–300 Hz)	75.7%	**63.4%**	0.0%
(b) Ford 3.317 lounge			
low (0–7 kHz)	**98.2%**	47.2%	—
(0–300 Hz)	87.7%	**79.2%**	—



- Batphone (ABS) beats Wi-Fi at fine granularity
- Wi-Fi beats Batphone (ABS) at coarse granularity.
- Combination is best overall