Context and Activity Recognition (aka "Sensors + Inference")

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CMSC 818G

Three Papers

1) Zhou, et al. IODetector: A Generic Service for Indoor Outdoor Detection

2) Miluzzo, et al. Sensing Meets Mobile Social Networks: The Design, Implementation and Evaluation of the CenceMe Application

3) Lu, et al. The Jigsaw Continuous Sensing Engine for Mobile Phone Applications


IODetector : A Generic Service for
Indoor Outdoor Detection

Uses of an Indoor Outdoor Detector ?

Uses of an Indoor Outdoor Detector

- Indoor/Outdoor localization - GPS or WiFi ?
    - GPS poor inside. WiFi poor outside.
- To vet the performance of GPS

- Tag locations/annotate smartphone photos automatically [1]
- Activity and context recognition [2]

[1]C.Qin, et al. Tagsense: a smartphone-based approach to automatic image tagging, MobiSys 11

[2]M. Keally, et al. Pbn: towards practical activity recognition using smartphone-based body sensor networks.

What sensors onboard a smartphone would you use to build an IO detector ?

What sensors onboard a smartphone would you use to build an IO detector ?

- Light Detector
  - Intrinsic differences between natural (outdoor) and man-made (indoor) light
- Cellular Module
  - Cellular Signal strength varies between indoor and outdoor (dividing walls)
- Magnetism Sensor
  - Intensity of Magnetic Field varies due to presence of electrical appliances.

Also, proximity sensor, system clock and accelerometer. (Why ?)

Most but not all Android smartphones are equipped with all five sensors.

Sensors

- Three sensors - each sensor isn’t perfect by itself. Then, aggregation
- Problems with light sensors
    - Light intensity changes with time, season, pose of phone, etc
- Problems with cellular tower
    - Varies significantly with location
- Problems with magnetism detector
    - Not accurate unless calibrated carefully

Some Requirements

- High Accuracy
    - duh!
- Prompt Response
    - no latency
- Shouldn’t drain the battery
- Universal applicability
    - sensors must be present on all devices

Three Indoor Outdoor Classes

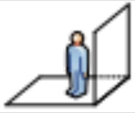
Environment	Outdoor	Semi-outdoor	Indoor
Definition	Outside a building	Near a building	Inside a building
Example			
Scene			

Figure 1. Three indoor/outdoor environment types and the representative scenes.

Why bring in semi-outdoor ?

System Overview

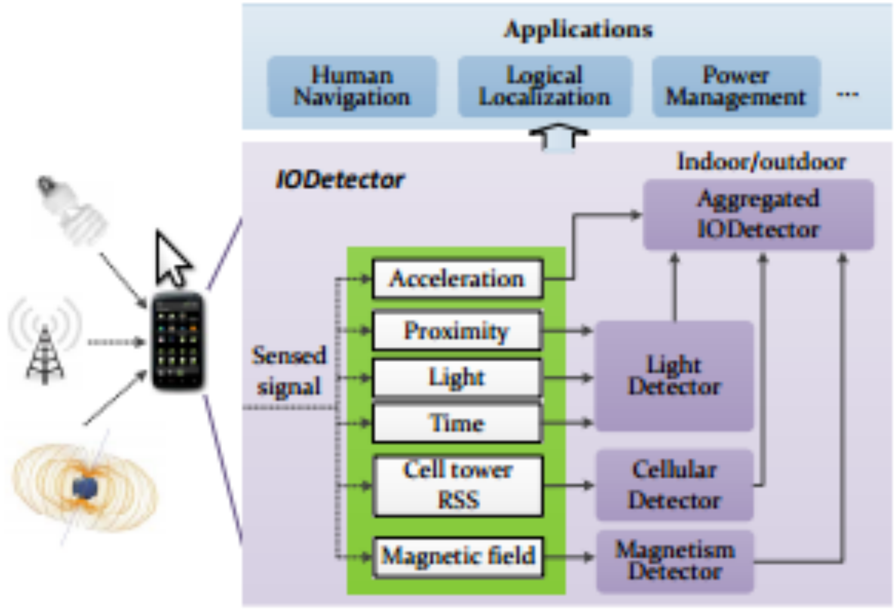


Figure 2. System architecture of IODetector.

Light Detector

- During the day, irrespective of weather,

$$\text{Intensity}_{indoor} << \text{Intensity}_{outdoor}$$

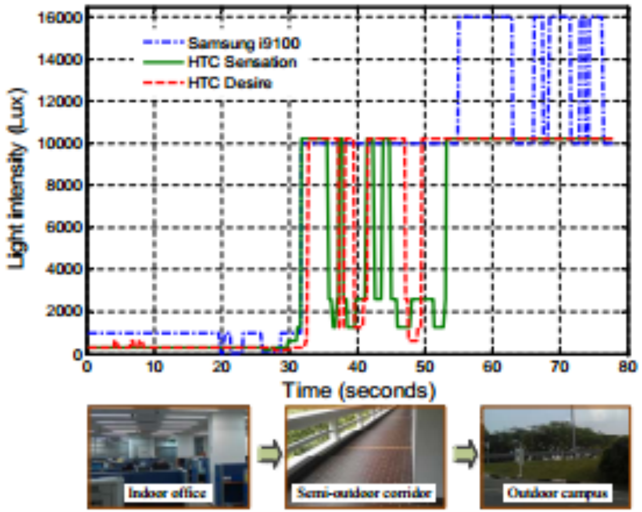


Figure 3. Mobile phone light sensor readings in different scenes.

Light Detector

- At night, $Intensity_{indoor} > Intensity_{outdoor}$

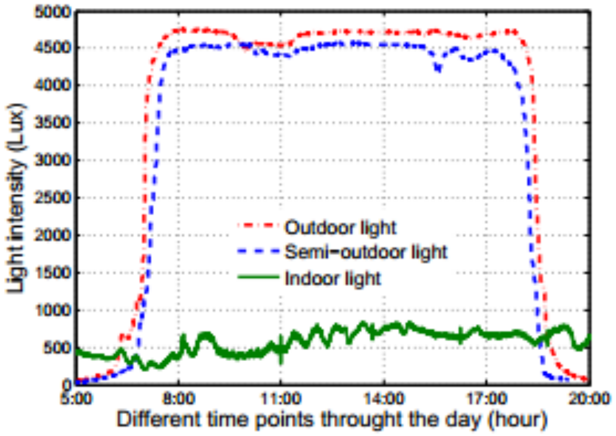


Figure 4. Outdoor and indoor light variation throughout the whole day.

Light Detector

Thresholds are 2000 Lux and 50 Lux.

Confidence is calculated in the simplest possible way.

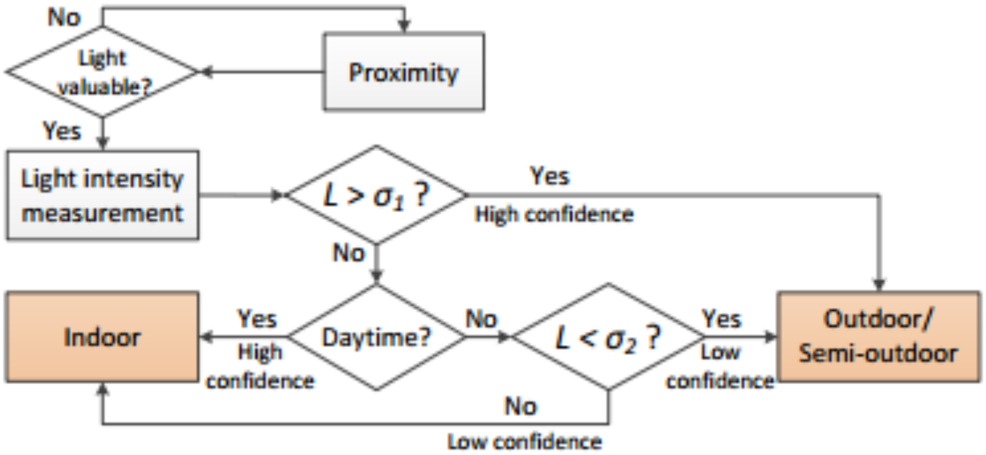


Figure 6. Detection flow of light detector.

Also, man-made light flickers with frequency of alternating current.

Therefore, Fourier Transforms.

System Overview

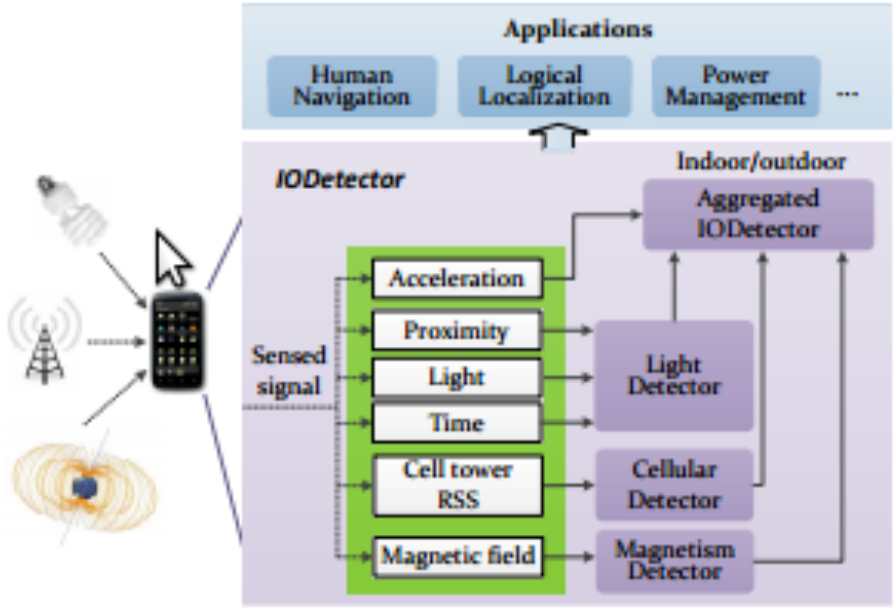
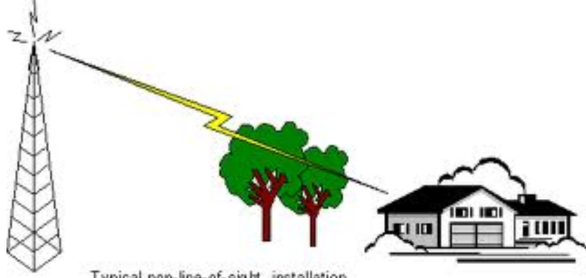


Figure 2. System architecture of IODetector.

Cellular Detector



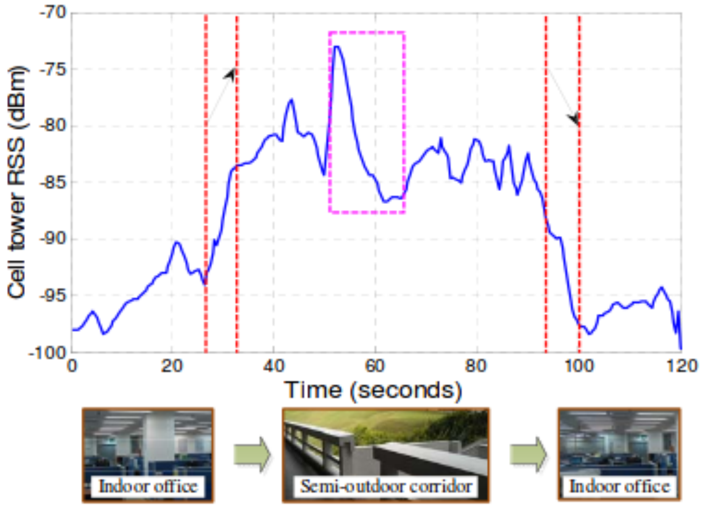
- Cellular Received Signal Strength (RSS)
- Dividing walls block signals
- When the user walks indoors from outdoors, RSS drops significantly.

- Why not WiFi RSS ?

Cellular Detector

- Usually connect to one tower (with strongest RSS), but like [3], uses all visible cell towers.

- Issues
    - Handovers
    - Corner Effect

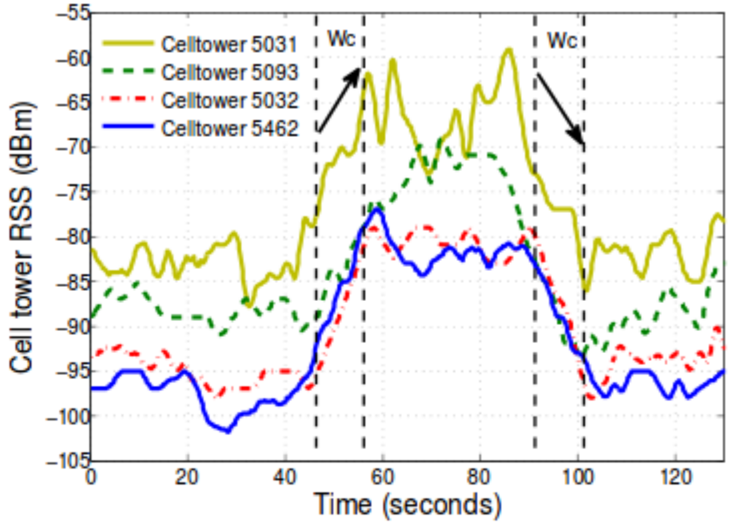


(a) Single cell tower's RSS variation in environmental change.

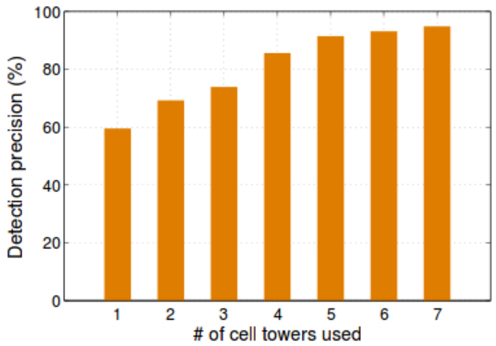
[3]P. Zhou, et al. How long to wait? : predicting bus arrival timing with mobile phone based participatory sensing

Cellular Detector

- Over multiple cell towers.
- Idea : If aggregate RSS drops - outdoor -> indoor , and vice versa.



(b) Multiple cell towers' RSS variation in environmental change.



(c) Detection accuracy with the varied number of cell towers.

System Overview

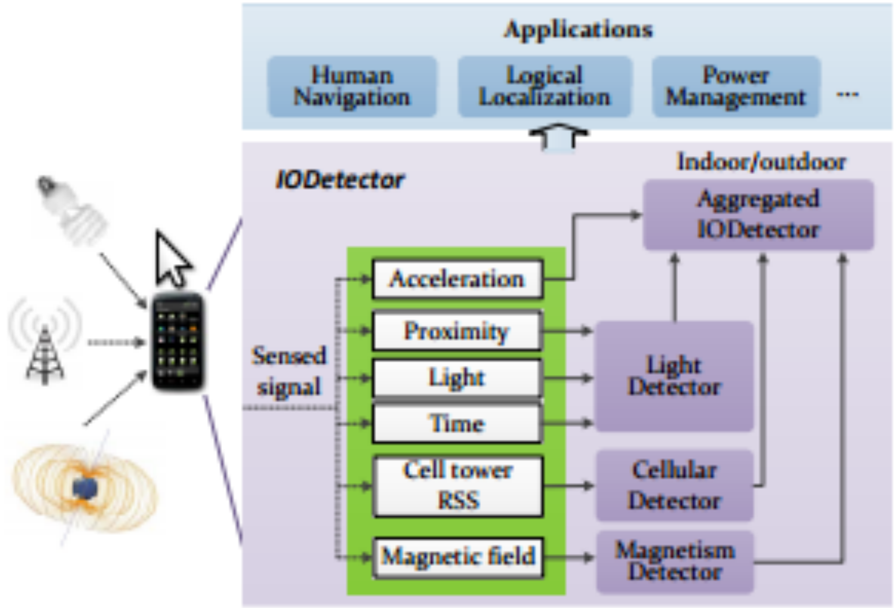


Figure 2. System architecture of IODetector.

Magnetism Detector

- Earth’s magnetic field is distorted due to electrical and steel appliances.
    - Eg : At equator - 0.25Gauss, At poles - 0.65Gauss
    - Fridge magnet - 100Gauss

- Magnetic Field shows greater variance when user is indoors (due to appliances), than outdoors, except when ______________ .

Magnetism Detector

- Limitation ?
  - What other sensor would help ?

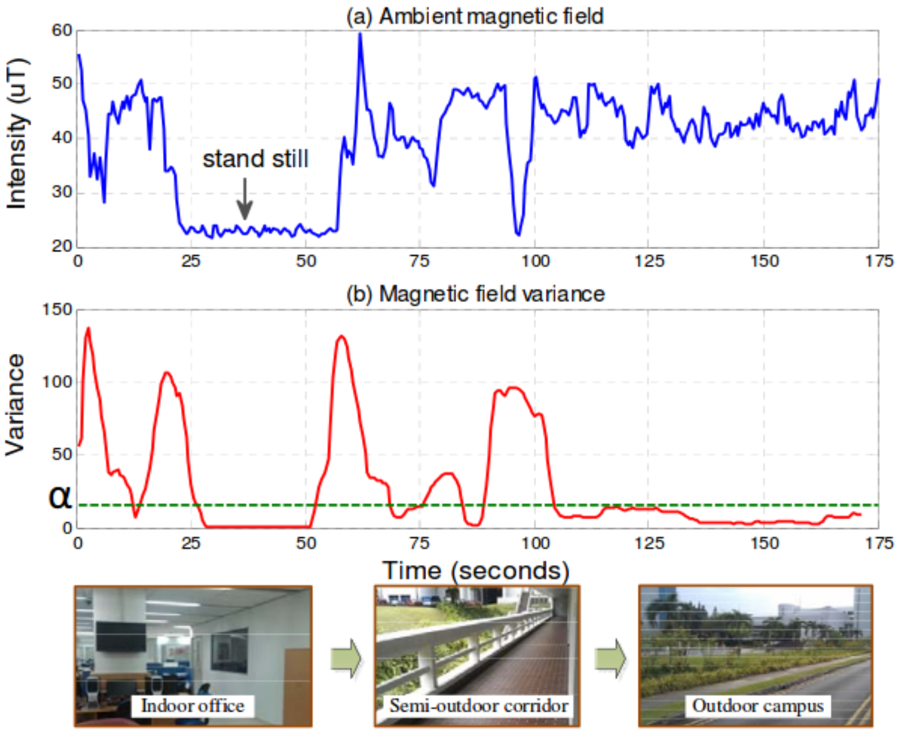


Figure 8. The variation of magnetic field intensity.

Advantages/Disadvantages

Sensor	Advantage	Disadvantage
Light	Rapid	Doesn’t work if phone is in pocket or bag.
Cellular	Natural function of phone, no battery drain	Slow, Requires sufficient cell tower coverage
Magnetism	It can distinguish between semi-outdoor and outdoor	Only works when user moves, not reliable.

- Aggregate them.
    - Sum up individual confidences (stateless)
    - HMMs (stateful)

Results

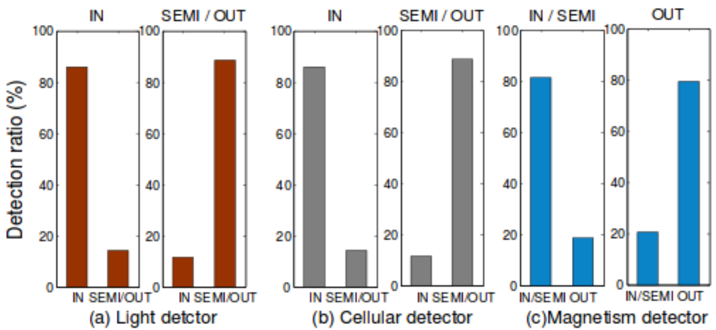


Figure 11. Detection performance of three sub-detectors.

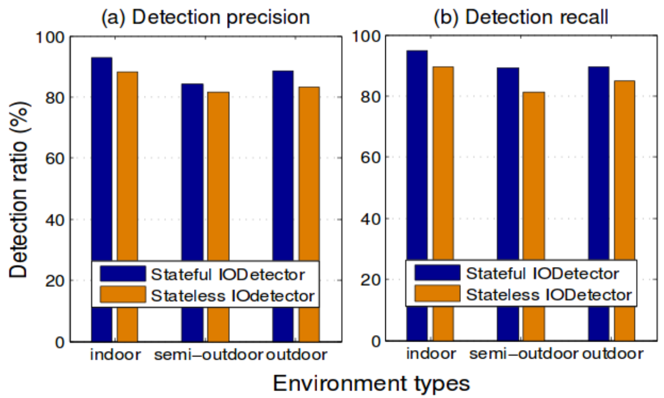


Figure 12. Detection precision and recall of stateless IODetector and stateful IODetector.

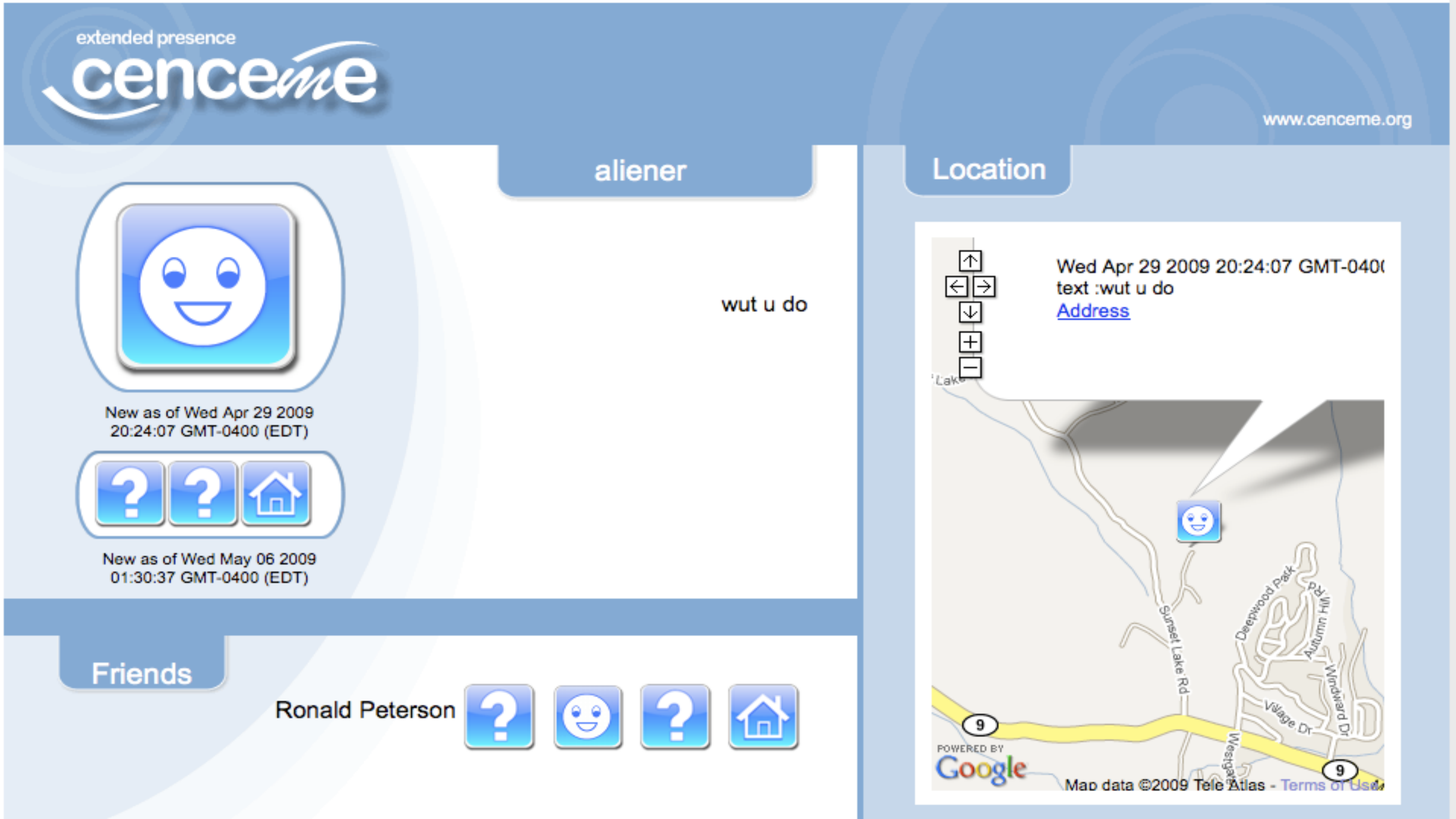
- Case study : GPS performs poorly indoors, but performs well outdoors.
  - Use IO-Detector to vet GPS performance. If indoors, use alternative means for localization.

Conclusion

- IODetector uses 3 sensors - light, cellular RSS and magnetism.
- Aggregates results of three.
- Tested on Android phones.

- Cast study to infer GPS availability.

Questions ?


extended presence
cenceme
www.cenceme.org
aliener
Location
wut u do
New as of Wed Apr 29 2009
20:24:07 GMT-0400 (EDT)
New as of Wed May 06 2009
01:30:37 GMT-0400 (EDT)
Wed Apr 29 2009 20:24:07 GMT-040
text :wut u do
Address
Sunset Lake Rd
Deepwood Park
Autumn Hill Rd
Windward Dr
Village Dr
9
POWERED BY
Google
Map data ©2009 Tele Atlas - Terms of Use
Friends
Ronald Peterson

Introduction

Introduction

- Automated answers to “where r u?” or “what r u doing?”

- Nokia N95, Symbian, Java Micro Edition

- sensing, classification + sharing on a social network

Some issues

- Continuous Sensing / Always on softwares drain battery

- Cannot disrupt normal functioning like phone calls

customizable tags
resiliency to WiFi dropouts
Lesser data to push (cheaper)
Raw sensor data stays on the phone (privacy)
Preserves battery life of phone

Split Level Classification

- Do “some” processing/classification on client, push it to server. Data to “Primitives”.
- Do “higher level” processing/classification on server. “Primitives” to “Facts”.

microphone accelerometer

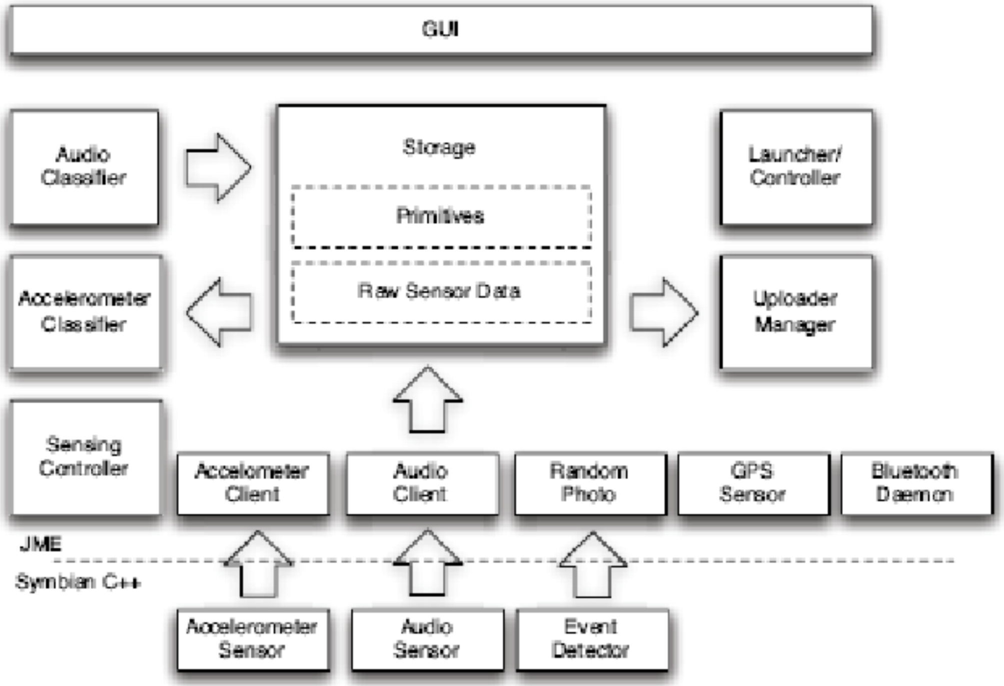
eg : Primitives - talking, loud noise, running. Fact - “party”

Primitives are :

1) Sound classification
2) Accelerometer classification
3) Nearby Bluetooth Mac Addresses
4) GPS readings
5) Random photos

Phone Software Architecture

- Run as a daemon



ClickStatus

- ClickStatus is the “front end”

Figure 2: ClickStatus on the Nokia N95.

Backend Architecture

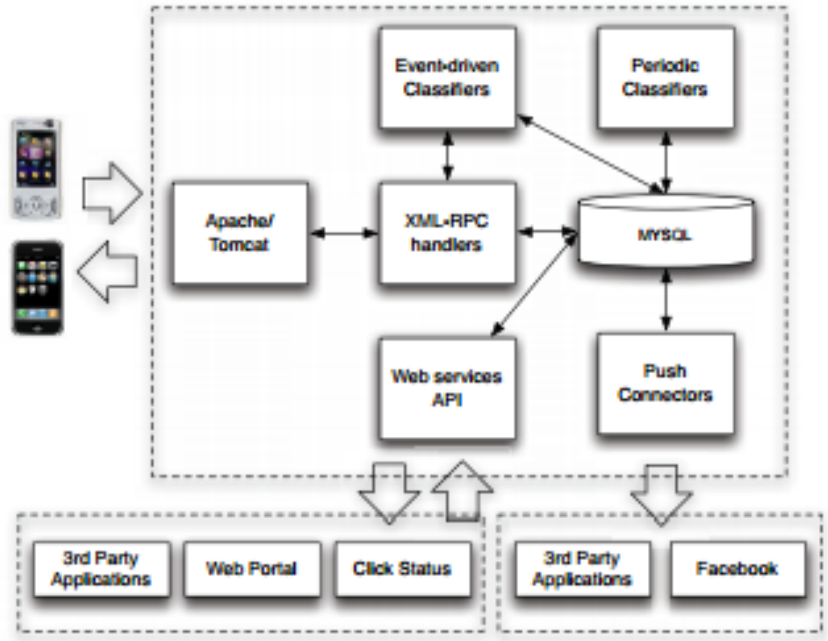


Figure 3: Software architecture of the CenceMe backend.

Front-end Classification

- Data to Primitives

Sound Classification

- Features - Mean and Std. deviation of DFT
- Classes - talking or no-talking

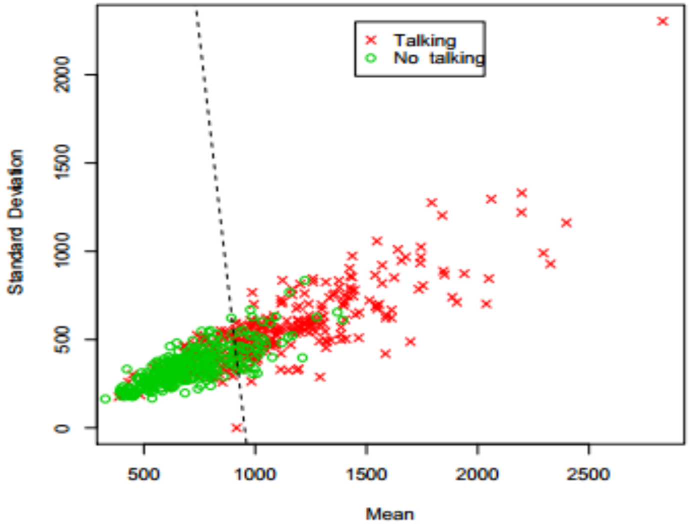
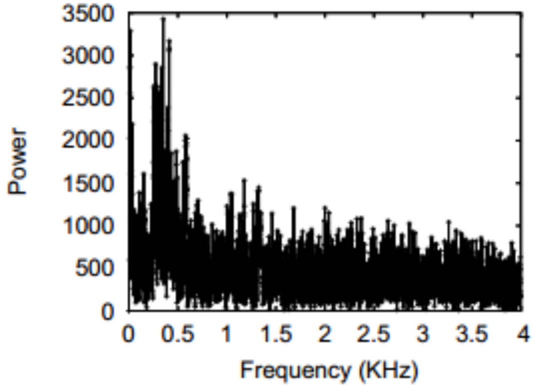
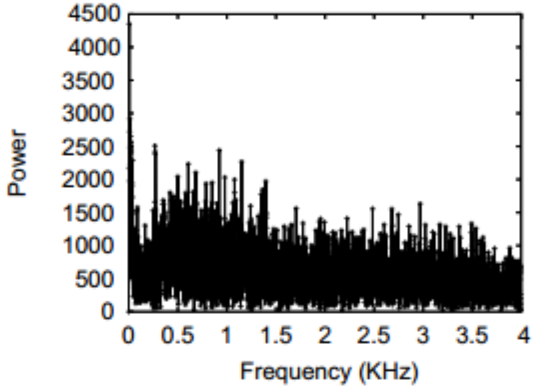


Figure 5: Discriminant analysis clustering. The dashed line is determined by the discriminant analysis algorithm and represents the threshold between talking and not talking.



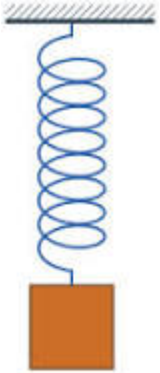
(a) DFT of a human voice sample registered by a Nokia N95 phone microphone.

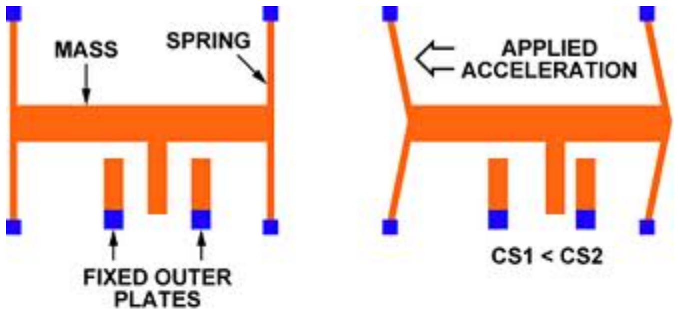


(b) DFT of an audio sample from a noisy environment registered by a Nokia N95 phone microphone.

Accelerometers

- Not particularly different from a spring mass system





Accelerometer Classification

- features - mean, std dev, number of peaks along three axes
- Decision tree classifier
- classes = {sitting, standing, walking, running}
- For training, phone in belt, bag, pocket

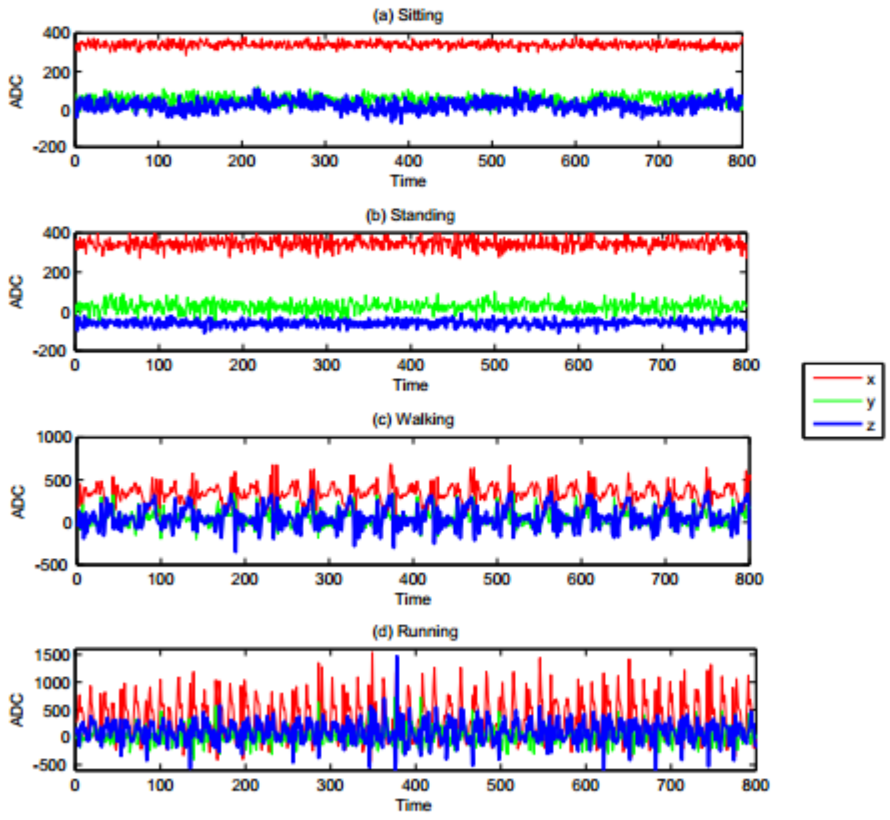


Figure 6: Accelerometer data collected by the N95 on board accelerometer when the person carrying the phone performs different activities: sitting, standing, walking, and running.

Backend Classification

conversation detector - If 2 out of 5 audio windows contain a conversation

- Primitives to Facts
- Eg. facts are : {Meeting, Partying, Dancing}, “do you go to the gym more”, “do you spend time in museums”, etc.
- Rules like “if you are in a conversation, and background noise is high” → party
- Party + “running” → dancing

Backend Classification

- Social Context - Scans bluetooth addresses to find nearby friends.

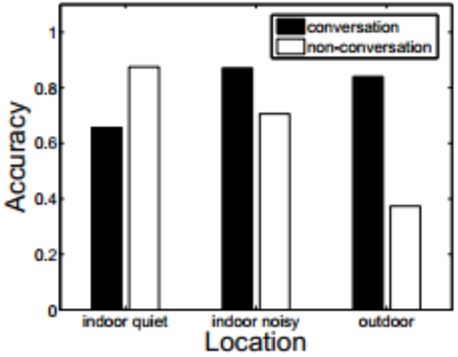
Eg : Are you alone, or are you with other "Cenceme buddies"

- Mobility (using accelerometer - vehicle or not)
- Location (using GPS)

Backend Classification - Am I Hot ?

- Nerdy
- Party Animal
- Cultured
- Healthy
- Greeny

Results



(a) Conversation classifier in different locations.

Table 3: Mobility mode classifier confusion matrix

	Vehicle	*No Vehicle*
Vehicle	0.6824	0.3176
No Vehicle	0.0327	0.9673

Table 1: Activity classifier confusion matrix

	Sitting	*Standing*	*Walking*	*Running*
Sitting	0.6818	0.2818	0.0364	0.0000
Standing	0.2096	0.7844	0.0060	0.0000
Walking	0.0025	0.0455	0.9444	0.0076
Running	0.0084	0.0700	0.1765	0.7451

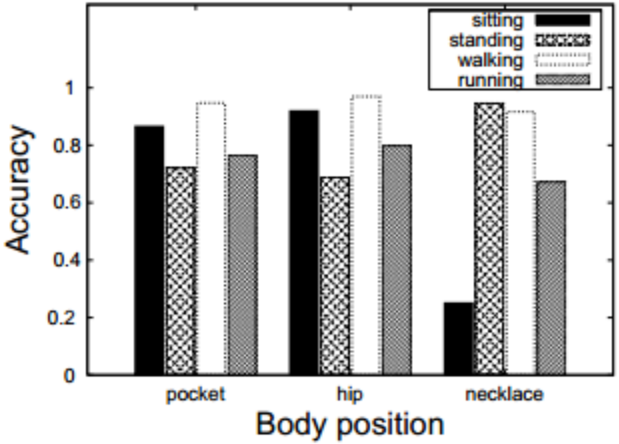


Figure 7: Activity classification vs. body position.

Table 2: Conversation classifier confusion matrix

	Conversation	*Non-Conversation*
Conversation	0.8382	0.1618
Non-Conversation	0.3678	0.6322

Mean battery life is 6.2 hours

Energy Consumption

- Battery Drainers
  - GPS
  - Bluetooth scan
  - DFT and classification
- Other factors
  - distance to cell tower
  - data to upload

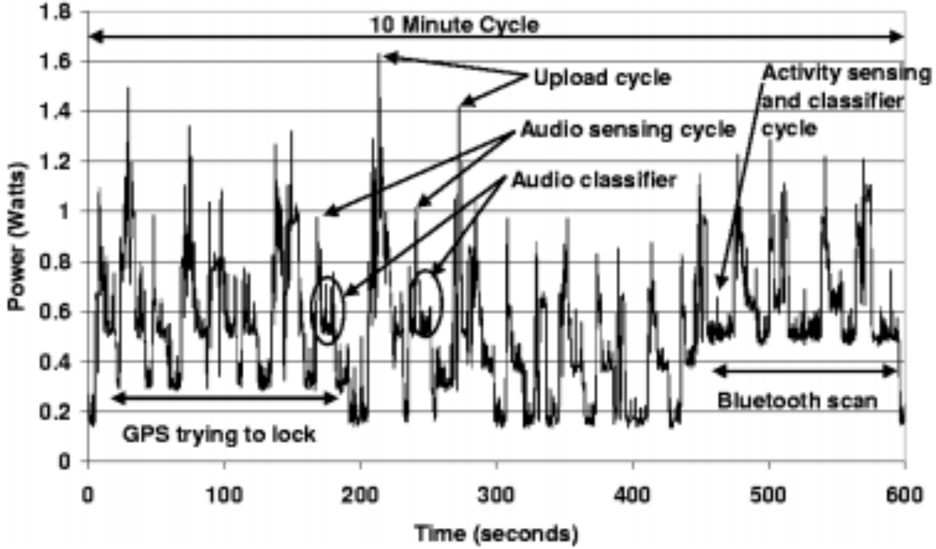


Figure 9: Details of the power consumption during a sampling/upload interval.

User Study

- 12 undergrads + 7 grad students
+ 1 Research assistant + 1 Professor + 1 staff

CenceMe makes the following claims
1) Almost everyone liked it - alrighty
2) Facebook users are more willing to share their personal information than others - okay
3) Privacy could be a concern, but there are settings
4) People want to know what others are doing - debatable
5) People can discover their own activity patterns and social status - cool

- Location feature most frequently used
- Some people turned off the "random photos" features

<u>Improvements :</u>

1) Better battery life
2) Better privacy settings
3) Shorter classification time

Questions ?

The Jigsaw Continuous Sensing Engine for Mobile Phone Applications

What is a Continuous Sensing Application ?

Continuous Sensing Applications

- Continuous Sensing Applications

    - typically always on, read from sensors, make accurate inferences

- But, must maintain battery life, and not overload CPU.

    - shouldn’t compromise the normal functioning of the phone (calls, messages, internet, email)

- How would you maintain battery life, but also make accurate inferences ?

Contributions

- Make accelerometer more resilient
    - body positions
- Reduce microphone sensing and computing costs
    - Don’t send silences to GMM classifier, etc
- Sample GPS judiciously
    - Sitting in an office vs Travelling on the highway

Accelerometer

- Accelerometer is cheap but good inference is difficult because of :

1) Body positions (Eg:hip pocket, bag)

2) Extraneous activities (Eg : messaging, calling)

3) Transition states (Eg : taking phone out, etc)

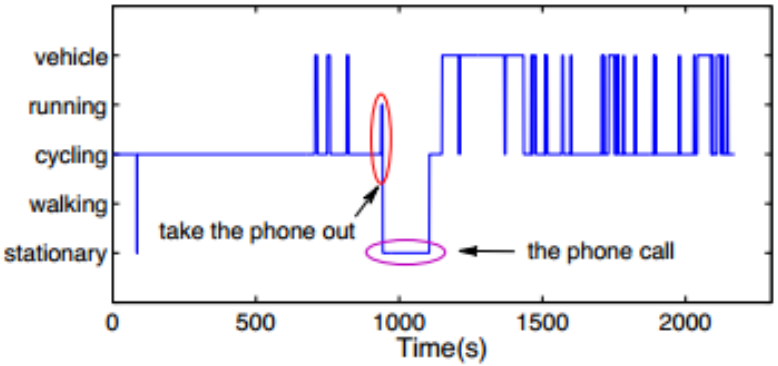


Figure 1: Activity inferences are inaccurate when the phone is in a backpack and the model was trained for a front pocket.

Accelerometer Pipeline

1) Calibration :

- Keep the phone absolutely steady (why?)
- $g_{axis} = K_{axis}a_{axis}+b_{axis}$
- Least squares
- can be made automatic

2) Normalize : Convert to units of g

3) Admission control

- filter out extraneous+transitions

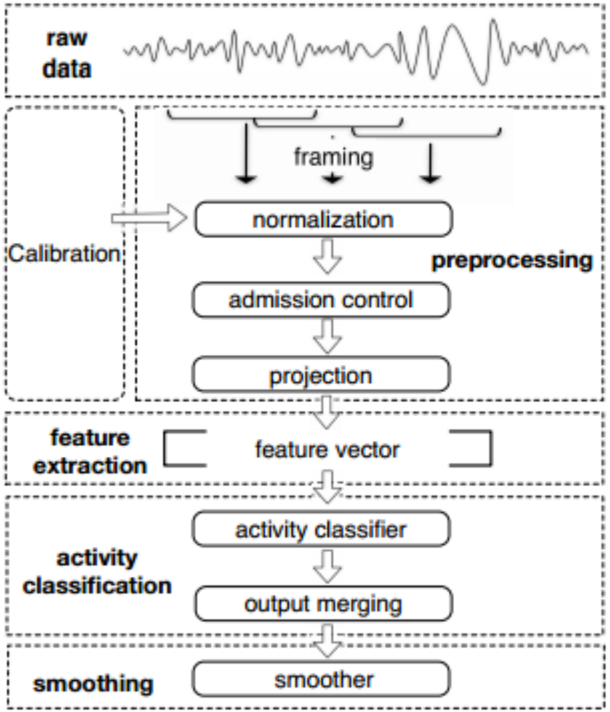


Figure 4: Jigsaw Accelerometer Pipeline

Accelerometer Pipeline

4) Projections :

- Convert from local to global coordinates
- Makes data insensitive to orientation

5) Feature Extraction :

Time domain	mean, variance, mean crossing rate
Frequency domain	spectrum peak, sub-band energy, sub-band energy ratio, spectral entropy

Table 1: Motion Feature Set

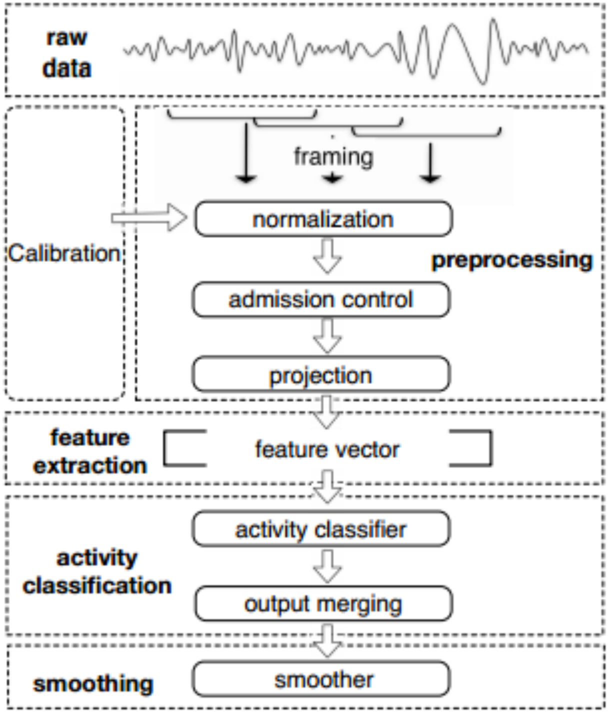


Figure 4: Jigsaw Accelerometer Pipeline

Accelerometer Pipeline

6) Activity Classification :

- Decision tree
- Sub-classes

stationary	
stationary	sitting, standing, on the table
walking	
lower body	front and back pants pockets
in hand	in hand when reading the screen, armband, in hand when swinging naturally
all others	jacket pocket, backpack, belt
cycling	
lower body	front and back pants pockets
upper body	jacket pocket, armband, backpack, belt
running	
running	all body postions
vehicle	
vehicle	car, bus, light rail

Table 2: Activity Subclasses

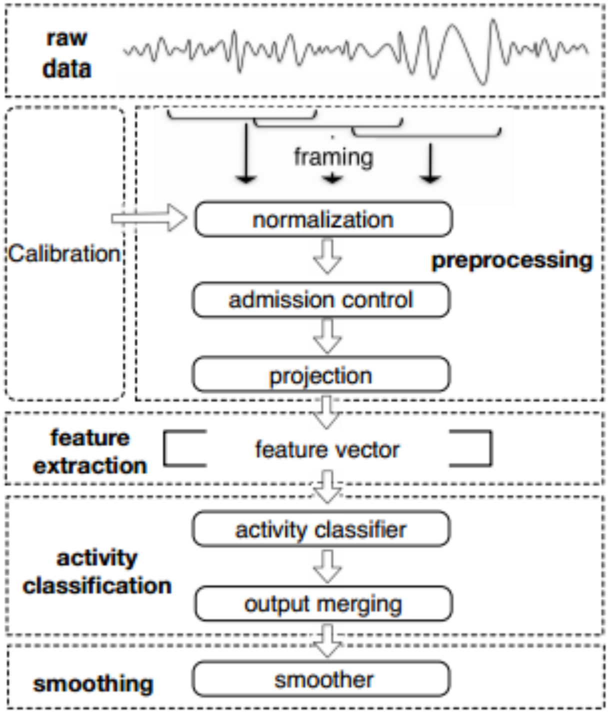


Figure 4: Jigsaw Accelerometer Pipeline

Microphone

- Sampling rate and sound classification increases load on CPU.

- Tasks are : “human voice or not”, and “reading”, “chatting”, “walking”, “toilet flush”. (20 classes)

Microphone Pipeline

1)Admission Control :

- If RMS intensity of sound below thresh. don't process.

2)Duty cycle :

- If user is sleeping, quiet, dont process

3) Features :

Category	Feature set
voice	Spectral Rolloff [12],Spectral Flux [25] Bandwidth [12],Spectral Centroid [12] Relative Spectral Entropy [6] Low Energy Frame Rate [25]
other activities	13 MFCC coefficient feature set [32] Spectral Centroid [12],Bandwidth [12] Relative Spectral Entropy [6] Spectral Rolloff [12]

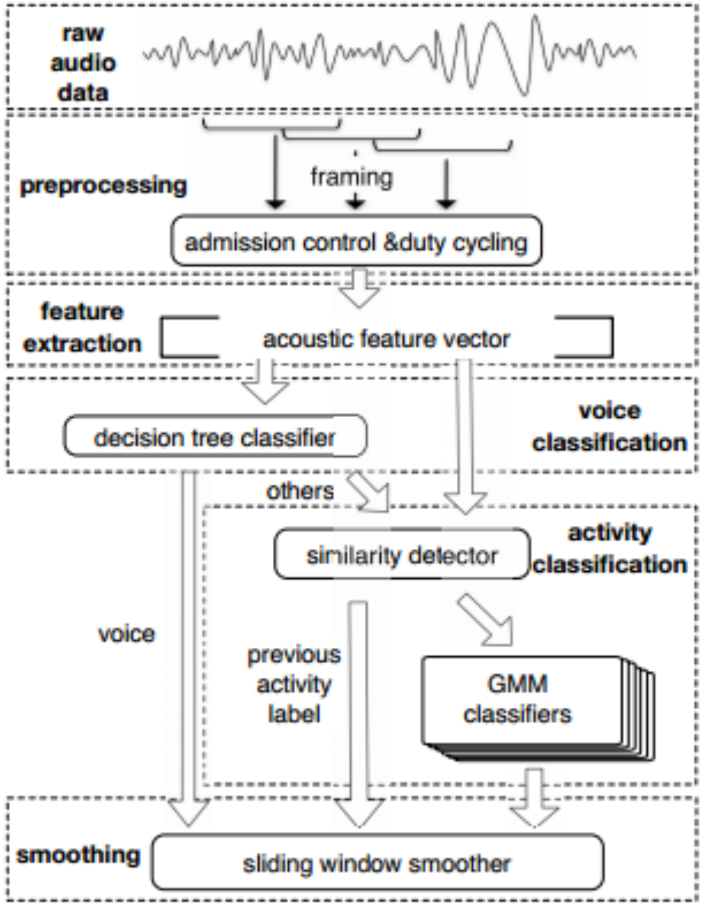


Figure 5: Jigsaw Microphone Pipeline

Microphone Pipeline

4)Voice Classification :

- Voice vs No Voice
- Decision tree

5) Activity Classification :

- GMM + Classifier

6) Similarity Detector

- If nearby samples are very similar (cosine distance), give them same labels.

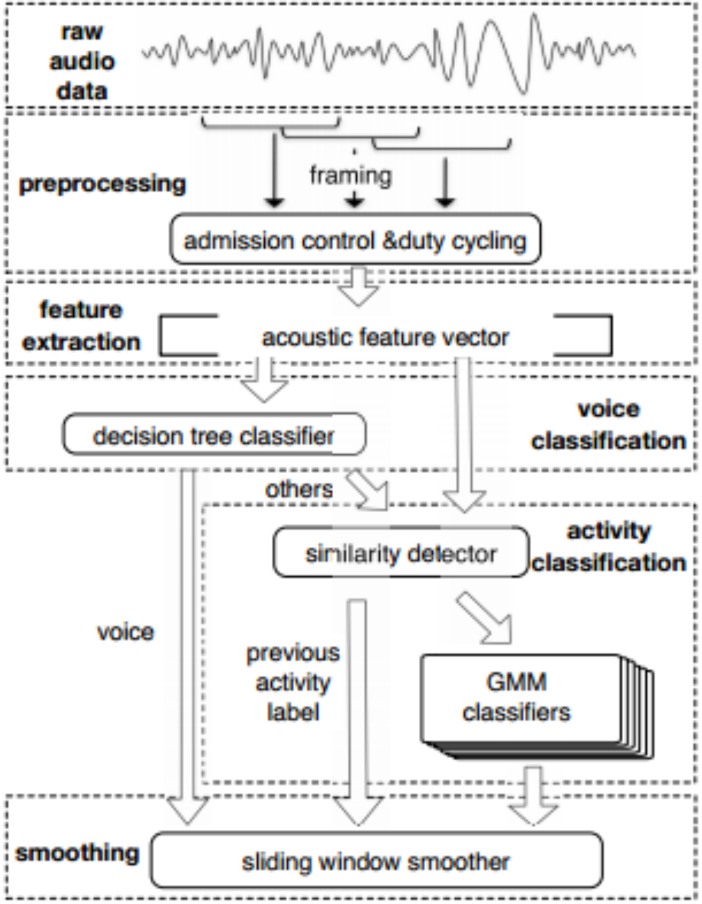
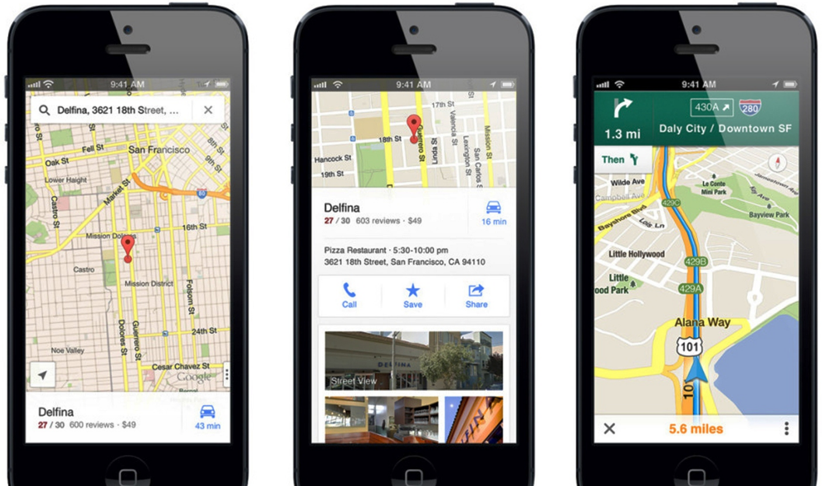


Figure 5: Jigsaw Microphone Pipeline

GPS Pipeline

- What is the factors to take into consideration when sampling GPS ?



GPS Pipeline

- What is the factors to take into consideration when sampling GPS ?

Ans :

1) User’s mobility
2) Battery remaining

GPS Pipeline

If the energy budget is breached too quickly, there is a penalty. Reward = -penalty.

- Markov Decision Process
- Sampling freq : Every 20min, 10min, 5 min, 2 min, 1 min, 5 sec
- The bottomline is :
    - for every (accelerometer, battery, time) tuple, a sampling rate is available
    - stored as table

GPS Pipeline example

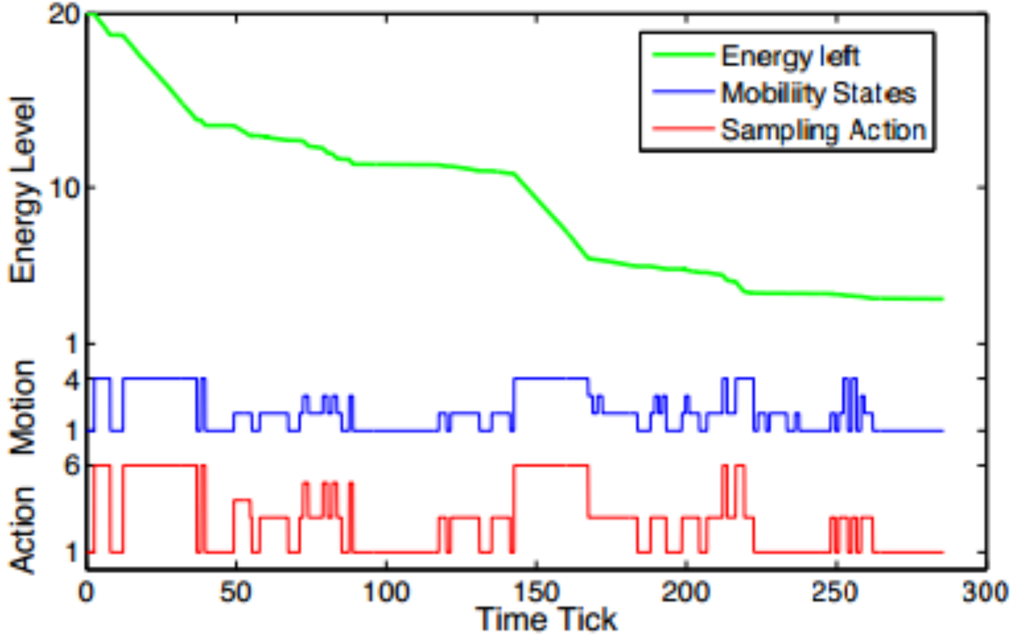


Figure 14: Jigsaw Emulated on a Weekend Trace

iPhone and N95

Results - Read the paper !

- Accelerometer - Close to 95% accuracy
- Microphone - ~85% on “voice vs no voice”
- GPS - low error, low power usage. (2nd best model after accelerometer augmented GPS)

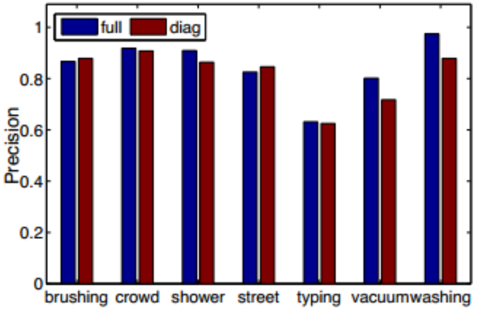


Figure 10: Precision of Two Types of GMM

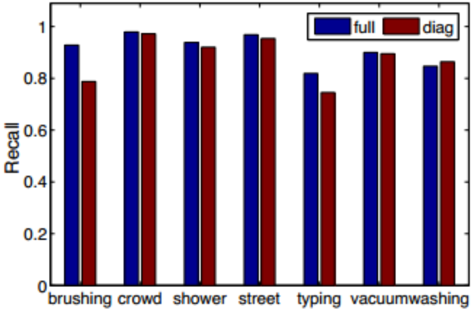
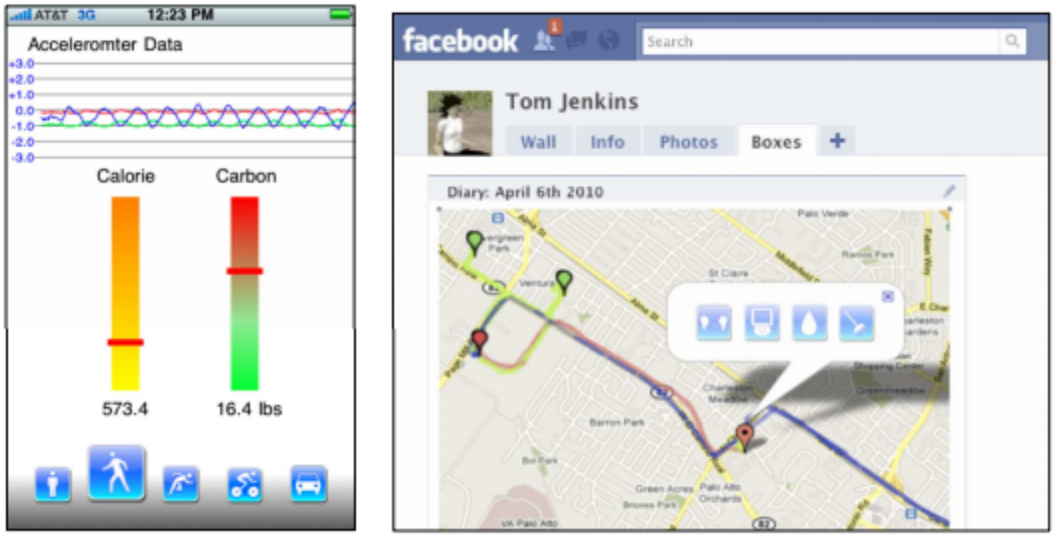


Figure 11: Recall of Two Types of GMM

Case Study

- JigMe - an automatic log of daily activities
- GreenSaw - daily calorie expenditure and carbon footprint (accelerometer)



(a) (b)

Figure 16: (a) The GreenSaw application provides carbon footprint and caloric expenditure information, and (b) The JigMe application provides a log of daily activities, significant places, and transportation methods.

Questions ?