Selected Topics of Pervasive Computing

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Overview and Structure

- 30.10.2013 Organisational
- 30.10.3013 Introduction
- 06.11.2013 Classification methods (Feature extraction, Metrics, machine learning)
- 13.11.2013 Classification methods (Basic recognition, Bayesian, Non-parametric)
- 20.11.2013 –
- 27.11.2013 –
- 04.12.2013 –
- 11.12.2013 Classification methods (Linear discriminant, Neural networks)
- 18.12.2013 Classification methods (Sequential, Stochastic)
- 08.01.2014 Features from the RF channel (Effects of the mobile radio channel)
- 15.01.2014 Security from noisy data (Error correcting codes, PUFs, Applications)
- 22.01.2014 Context prediction (Algorithms, Applications)
- 29.01.2014 Networked Objects (Sensors and sensor networks, body area networks)
- 05.02.2014 Internet of Things (Sensors and Technology, vision and risks)

Outline

Aspects of the mobile radio channel

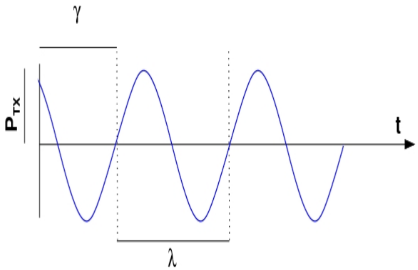
RF transmission

- Electromagnetic signals
- Transmitted in wave-Form
- Omnidirectional transmission
- Speed of light
  - $c = 3 \cdot 10^8 \frac{m}{s}$

Aspects of the mobile radio channel

RF signal

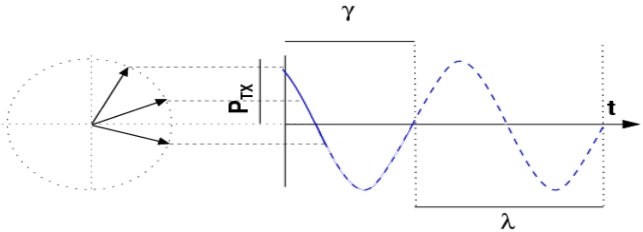
- Transmission power:
  - $P_{TX}[W]$
- Frequency:
  - $f[\frac{1}{sec}]$
- Phase offset:
  - $\gamma[\pi]$
- Wavelength:
  - $\lambda = \frac{c}{f}[m]$



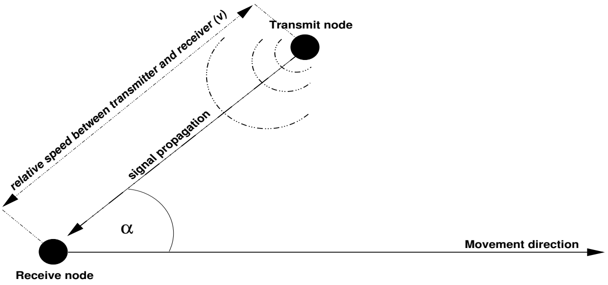
Aspects of the mobile radio channel

RF signal

- Real part of rotating vector
  - $\zeta = \Re\left(e^{j(ft+\gamma)}\right)$
- Instantaneous signal strength:
  - $\cos(\zeta)$
- Rotation Speed: Frequency f



Aspects of the mobile radio channel



Doppler Shift

- Frequency of received and transmitted signal may differ
- Dependent on relative speed between transmitter and receiver
- $f_d = \frac{v}{\lambda} \cdot \cos(\alpha)$

Aspects of the mobile radio channel

Noise

- In every realistic setting, noise can be observed on the wireless channel
- Typical noise power:[1]

$$P_N = -103dBm$$

- Value observed by measurements

[1] 3GPP: 3rd generation partnership project; technical specification group radio access networks; 3g home nodeb study item technical report (release 8). Technical Report 3GPP TR 25.820 V8.0.0 (2008-03) (March)

Aspects of the mobile radio channel

Noise

- Thermal noise can also be estimated analytically as

$$P_N = \kappa \cdot T \cdot B$$

- $\kappa = 1.3807 \cdot 10^{-23} \frac{J}{K}$: Boltzmann constant
- T: Temperature in Calvin
- B: Bandwidth of the signal.

Aspects of the mobile radio channel

Example

- GSM system with $200kHz$ bands
- Average temperature: $300K$
- Estimated noise power:

$$
\begin{aligned}
P_N &= \kappa \cdot T \cdot B \\
&= 1.3807 \cdot 10^{-23} \frac{J}{K} \cdot 300K \cdot 200kHz \\
P_N &= -120.82dBm
\end{aligned}
$$

Aspects of the mobile radio channel

Path-loss

- Signal strength decreases while propagating over a wireless channel
- Order of decay varies in different environments
- Impact higher for higher frequencies
- Can be reduced by antenna gain (e.g. directed)

Location	Mean Path loss exponent	Shadowing variance σ^2 (dB)
Apartment Hallway	2.0	8.0
Parking structure	3.0	7.9
One-sided corridor	1.9	8.0
One-sided patio	3.2	3.7
Concrete Canyon	2.7	10.2
Plant fence	4.9	9.4
Small boulders	3.5	12.8
Sandy flat beach	4.2	4.0
Dense bamboo	5.0	11.6
Dry tall underbrush	3.6	8.4

Aspects of the mobile radio channel

Path-loss

- For analytic consideration: Path-loss approximated
- Friis free-space equation:

$$P_{TX} \cdot \left(\frac{\lambda}{2\pi d}\right)^2 \cdot G_{TX} \cdot G_{RX}$$

Aspects of the mobile radio channel

Path-loss

$$P_{RX} = P_{TX} \cdot \left(\frac{\lambda}{2\pi d}\right)^2 \cdot G_{TX} \cdot G_{RX}$$

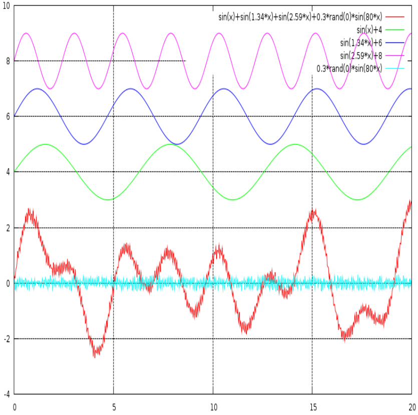
- Utilised in outdoor scenarios
  - Direct line of sight
  - No multipath propagation
- d impacts the RSS quadratically
- Other values for the path-loss exponent α possible.
- Path-loss:

$$PL^{FS}(\zeta_i) = \frac{P_{TX}(\zeta_i)}{P_{RX}(\zeta_i)}$$

Aspects of the mobile radio channel

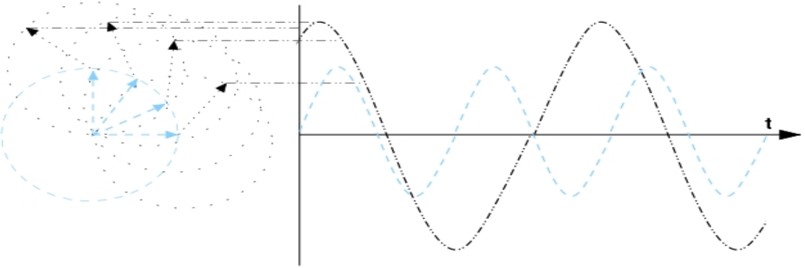
Superimposition of RF signals

- The wireless medium is a broadcast channel
- Multipath transmission
  - Reflection
  - Diffraction
  - Different path lengths
  - Signal components arrive at different times
- Interference



$$\zeta_{\text{sum}} = \sum_{i=1}^{\iota} \Re\left(e^{j(f_i t + \gamma_i)}\right)$$

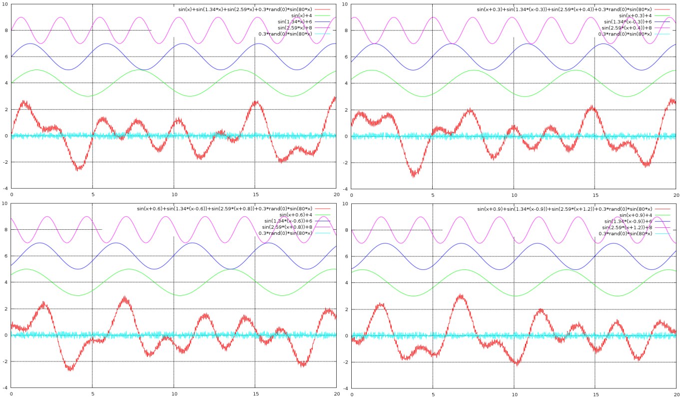
Aspects of the mobile radio channel



Superimposition of RF signals

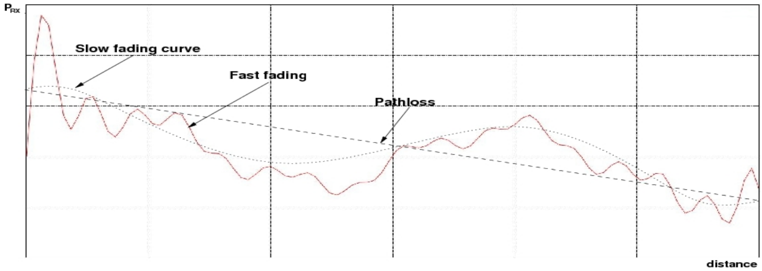
- At a receiver, all incoming signals add up to one superimposed sum signal
- Constructive and destructive interference
- Normally: Heavily distorted sum signal

Aspects of the mobile radio channel



- Channel conditions are dependent on time and location
- Independent channel conditions typically expected in a distance of $\frac{\lambda}{2}$

Aspects of the mobile radio channel



Fading

- Signal quality fluctuating with location and time
- Slow fading
- Fast fading

Aspects of the mobile radio channel

Slow fading

- Result of environmental changes
- Temporary blocking of signal paths
- Changing reflection angles
- Movement in the environment
  - Trees
  - Cars
  - Opening/closing doors
- Amplitude changes can be modelled by log-normal distribution

Aspects of the mobile radio channel

Fast fading

- Signal components of multiple paths
- Cancellation of signal components
- Fading incursions expected in the distance of $\frac{\lambda}{2}$
- Channel quality changes drastically over short distances
- Example: Low radio reception of a car standing in front of a headlight is corrected by small movement
- Stochastic models are utilised to model the probability of fading incursions
  - Rice
  - Rayleigh

Aspects of the mobile radio channel

Fast fading

- Fast fading weakened when direct signal component observed

- Density of amplitude distribution modelled by Rice distribution:

$$f(A) = \frac{A}{\sigma^2} e^{-\frac{A^2+s^2}{2\sigma^2}} I_0\left(\frac{As}{\sigma^2}\right)$$

- s: Dominant component of received signal
- σ: Standard deviation
- Modified Bessel function with order 0:

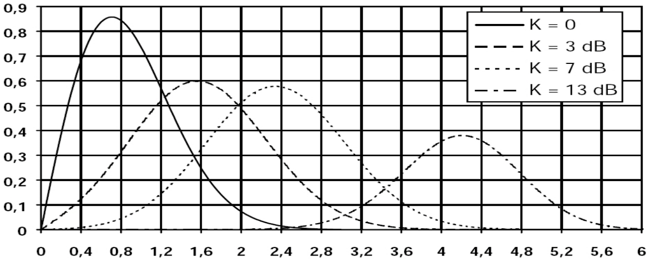
$$I_0(x) = \frac{1}{2\pi}\int_0^{2\pi} e^{x\cos(\Psi)} d\Psi$$

Aspects of the mobile radio channel

- Ricean factor:

$$K = \frac{s^2}{2\sigma^2}$$

  - Impacts probability density function of Rice distribution
  - Most probable outcome impacted

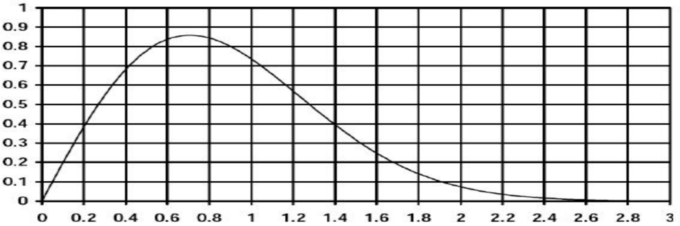


Aspects of the mobile radio channel

- For $K = 0$, Rice distribution migrates to Rayleigh distribution:

$$
\begin{aligned}
\lim_{K\to 0} f(A) &= \lim_{K\to 0} \frac{A}{\sigma^2} e^{-\frac{A^2}{2\sigma^2}-K} I_0\left(\frac{A\sqrt{2K}}{\sigma}\right) \\
&= \lim_{K\to 0} \frac{A}{\sigma^2} e^{-\frac{A^2}{2\sigma^2}-K} \frac{1}{2\pi} \int_0^{2\pi} e^{\frac{A\sqrt{2K}}{\sigma}\cos(\Psi)} d\Psi \\
&= \frac{A}{\sigma^2} e^{-\frac{A^2}{2\sigma^2}-0} \frac{1}{2\pi} \int_0^{2\pi} e^{\frac{A\sqrt{2\cdot 0}}{\sigma}\cos(\Psi)} d\Psi \\
&= \frac{A}{\sigma^2} e^{-\frac{A^2}{2\sigma^2}}
\end{aligned}
$$

Aspects of the mobile radio channel



Rayleigh distribution

- Probability density function of received sum signal for $n \gg 1$
- Assumption:
  - No direct signal component exists
  - Received signal components of approximately equal strength
- Example: Urban scenarios with dense house blocks

Aspects of the mobile radio channel

- With large K, Rice distribution evolves to Gauss distr.:

$$I_0(x) \rightarrow_{x \gg 1} \rightarrow \frac{e^x}{\sqrt{2\pi}}$$

$$\Rightarrow f(A) \rightarrow_{x \gg 1} \rightarrow \frac{A}{\sigma^2} e^{-\frac{A^2}{2\sigma^2} - K} \frac{e^{\frac{A\sqrt{2K}}{\sigma}}}{\sqrt{2\pi \frac{A\sqrt{2K}}{\sigma}}}$$

$$f(A) = \frac{A}{\sigma^2 \sqrt{\frac{2\pi}{\sigma}} \sqrt{A\sqrt{2K}}} e^{-\frac{A^2}{2\sigma^2} - \frac{s^2}{2\sigma^2}} e^{\frac{A\sqrt{2K}}{\sigma}}$$

$$= \frac{A}{\sigma^2 \sqrt{\frac{2\pi}{\sigma}} \sqrt{A\sqrt{2K}}} e^{-\frac{A^2 + s^2 - 2As}{2\sigma^2}}$$

$$= \sqrt{\frac{A}{s}} \frac{1}{\sigma 2\pi} e^{-\frac{1}{2}\left(\frac{A-s}{\sigma}\right)^2}$$

Aspects of the mobile radio channel

- The term

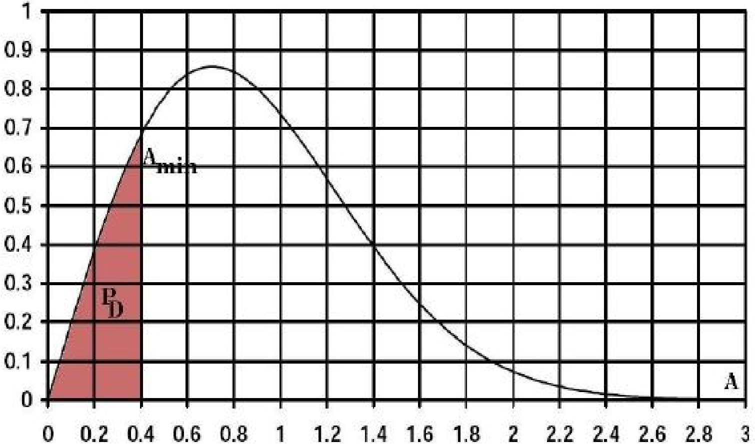
$$\sqrt{\frac{A}{s}}\frac{1}{\sigma 2\pi}e^{-\frac{1}{2}\left(\frac{A-s}{\sigma}\right)^2}$$

- differs from the Gauss distribution in $\sqrt{\frac{A}{s}}$:

$$f_{Gauss}(x) = \frac{1}{\sigma\sqrt{2\pi}}e^{-\frac{1}{2}\left(\frac{A-s}{\sigma}\right)^2}$$

- With $\sqrt{\frac{A}{s}} \approx 1$, Rice distribution can be approximated by Gauss distribution

Aspects of the mobile radio channel



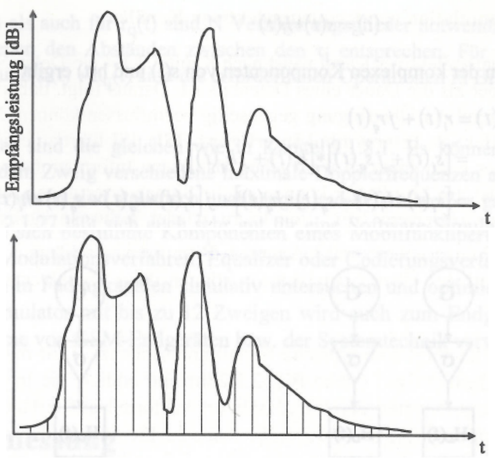
Aspects of the mobile radio channel

Simulation of frequency selective channels

- A common approach is to estimate he channel impulse response during a known training bit-sequence
- When the channel impulse response is known, signal distortions can be corrected
  - When the time axis is divided in discrete parts
  - We can derive discrete impulses for the energy in each of these parts

Aspects of the mobile radio channel

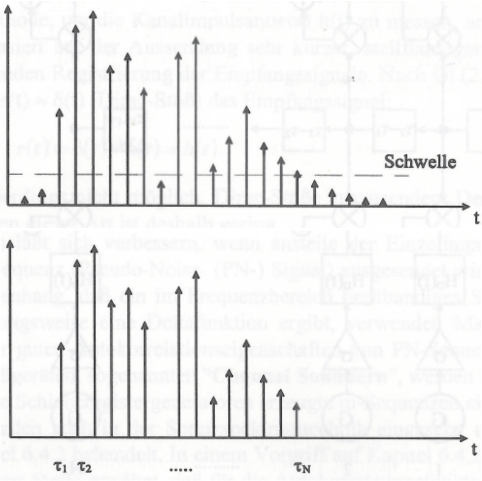
Simulation of frequency selective channels[2]



[2] David, Benkner, Digitale Mobilfunksysteme, Teubner, 1996

Aspects of the mobile radio channel

Simulation of frequency selective channels



Aspects of the mobile radio channel

Channel estimation

- The easiest approach to estimate $h(t)$ works in the time domain
- Based on sending very short impulses
- And registering the received signals
- The approach can be improved by utilising a pseudo-noise sequence instead of single identical impulses
- The inverse of the estimated impulse response is correlated $\overline{h(t)^{-1}}$ with the received signal:

$$r(t) \cdot \overline{h(t)^{-1}} = s(t) \cdot h(t) \cdot \overline{h(t)^{-1}} \approx s(t)$$

Outline

Features of the RF channel

Features specific for the RF-channel

- Wlan Access points
- Signal Strength
- Signal to noise ratio
- Fluctuation in signal strength
- Energy on several frequency bands
- Active Bluetooth devices
- GSM base stations/GSM active set
- ...

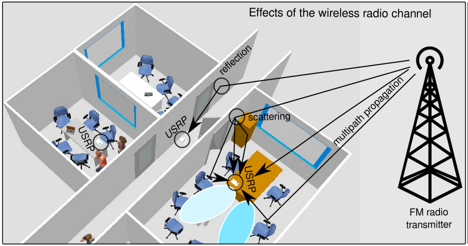
Features of the RF channel

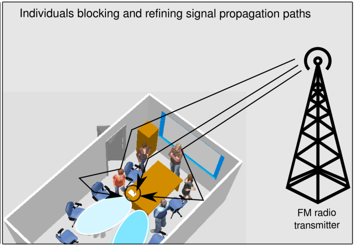
In the IoT wireless interfaces will be virtually everywhere

Can we re-use this hardware to gain additional value?

RF-channel: a ubiquitous source of environmental information

- Multi-path propagation
- Signal superimposition
- Scattering
- Reflection
- Blocking of signal paths
- Doppler Shift





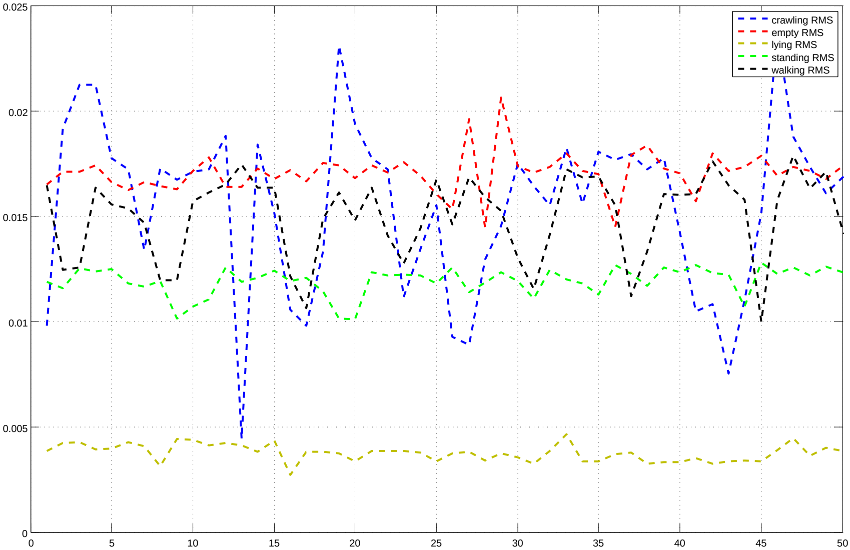
Features of the RF channel

Time-domain features

- Mean
- Median
- Variance, Standard deviation, RMS
- Central moments
- Zero crossings
- Direction changes
- Maximum, minimum
- Signal peaks within 10% of the maximum

Frequency-domain features

- Energy on various frequency bands
- Doppler-shift
- Information entropy in Freq. domain
- Lienar Correlation Coefficient
- Spectral roll-off
- Spectral centroid
- Spectral flux


0.025
0.02
0.015
0.01
0.005
0
0
5
10
15
20
25
30
35
40
45
50
crawling RMS
empty RMS
lying RMS
standing RMS
walking RMS

Assume that $\mid \mathcal{W}_t \mid$ samples s_i are taken on the signal strenth of an incoming signal for a window $\mathcal{W}_t = s_1^t, \ldots, s_{|\mathcal{W}_t|}^t$

Mean signal strength

The mean signal strength over a window of measurements represents static characteristic changes in the received signal strength.

It provides means to distinguish a standing person as well as her approximate location.

$$\text{Mean}(\mathcal{W}_t) = \frac{\sum_{s_i \in \mathcal{W}_t} s_i}{\mid \mathcal{W}_t \mid}$$

Variance of the signal's strength

The variance of the signal strength represents the volatility of the received signal.

It can provide some estimation on changes in a receiver's proximity such as movement of individuals

$$\text{Var}(\mathcal{W}_t) = \frac{\sum_{s_i \in \mathcal{W}_t} (s_i - \text{Mean}(\mathcal{W}_t))^2}{\mid \mathcal{W}_t \mid}$$

Standard deviation of the signal's strength

The standard deviation can be used instead of the variance. The interpretation of these two features is identical

$$\mathrm{Std}(\mathcal{W}_t) = \sqrt{\mathrm{Var}(\mathcal{W}_t)}$$

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Normalised spectral energy

The normalised spectral energy is a measure in the frequency domain of the received signal.

It has been used to capture periodic patterns such as walking, running or cycling.

$$\mathrm{E}_i = \sum_{k=1}^{n} \mathrm{P}_i(k)^2$$

Here, $\mathrm{P}_i(k)$ denotes the probability or dominance of a spectral band k:

$$\mathrm{P}_i(k) = \frac{\mathrm{FFT}_i(k)^2}{\sum_{j=1}^{n} \mathrm{FFT}_i(j)^2}$$

As usual, we calculate the k-th frequency component as

$$\mathrm{FFT}_i(k) = \sum_{t=(i-1)n+1}^{in} \mathrm{s}(t) e^{-j\frac{2\pi}{N}kt}$$

Standard deviation of the signal's strength

The standard deviation can be used instead of the variance. The interpretation of these two features is identical

$$\mathrm{Std}(\mathcal{W}_t) = \sqrt{\mathrm{Var}(\mathcal{W}_t)}$$

Median of the signal's strength

The median signal strenth over a window of measurements represents static characteristic changes in the received signal's strenth. It is more robust to noise than the mean.

It provides means to distinguish a standing person as well as her approximate location.

We define the ordered set of samples as

$$\mathcal{W}_{t,\mathrm{ord}} = \overline{s_1}, \ldots, \overline{s}_{|\mathcal{W}_t|} \; ; \; i < j \Rightarrow s_i \leq s_j$$

From this, the median is derived as

$$\mathrm{Med}(\mathcal{W}_t) = s_{\lceil |\mathcal{W}_{t,\mathrm{ord}}|/2 \rceil}$$

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Signal peaks within 10% of a maximum

Reflections at nearby or remote objects impact the signal strength at a receive antenna. When all peaks are of the similar magnitude, this is an indication that movement is farther away.

This feature can indicate near-far relations and activity of individuals.

$$h(s_i) = \begin{cases} 1 & \text{if } s_i \geq \max(s_1, \ldots, s_{|\mathcal{W}|}) \cdot 0.9 \\ 0 & \text{else} \end{cases}$$

$$\text{max}_{0.9}(\mathcal{W}_t) = \sum_{s_i \in \mathcal{W}_t} h(s_i)$$

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Minimum and maximum signal strength

The minimum/ maximum signal strength over a window represents extremal signal peaks.

It can be utilised as an indicator for movement and other environmental changes

$$\mathrm{Min}(\mathcal{W}_t) = s_i \in \mathcal{W}_t \text{ with } \forall s_j \in \mathcal{W}_t : s_i \leq s_j$$

$$\mathrm{Max}(\mathcal{W}_t) = s_i \in \mathcal{W}_t \text{ with } \forall s_j \in \mathcal{W}_t : s_i \geq s_j$$

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Mean difference between subsequent maxima

When the maximum peaks within a sample window are of similar magnitude, this indicates low activity in an environment or static activities. The opposite might be found with dynamic activities

$$\mathcal{W}_{\max}(\mathcal{W}_t) = \{s_i \mid s_i \in \mathcal{W}_t, s_{i-1} < s_i \wedge s_i > s_{i+1}\}$$

$$a(\mathcal{W}_t) = \sum_{\substack{\forall s_i, s_j \in \mathcal{W}_{\max}(\mathcal{W}_t); \\ i<j; \\ \nexists s_k \text{ with } i<k<j}} \frac{|\, s_i - s_j \,|}{|\, \mathcal{W}_{\max}(\mathcal{W}_t) \,|}$$

Direction changes over a set of features within a sample window

The direction changes over a signal period indicates the noise or interference in a received signal

It can, in particular, be utilised in relation to the count of zero crossings in order to express how significantly a received signal envelope is impacted by environmental effects.

$$\overline{g}(s_i) = \begin{cases} 1 & \text{if } s_{i-1} < si \wedge s_i > s_{i+1} \\ 0 & \text{else} \end{cases}$$

$$\text{dirChan}(\mathcal{W}_t) = \sum_{s_i \in \mathcal{W}_t} \overline{g}(s_i)$$

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Count of zero crossings

The count of zero crossings over a sample interval is a measure of the fluctuation in a received signal's strength.

It can be leveraged in order to estimate the count of individuals or movement in proximity of a receiver.

$$g(s_i) = \begin{cases} 0 & \text{if } \mathsf{sgn}(s_{i-1}) = \mathsf{sgn}(s_i) \\ 1 & \text{else} \end{cases}$$

$$\mathsf{ZeroCross}(\mathcal{W}_t) = \sum_{s_i \in \mathcal{W}_t} g(s_i)$$

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$$\mathrm{ZeroCross}(\mathcal{W}_t) = \sum_{s_i \in \mathcal{W}_t} g(s_i)$$

Distance between Zero Crossings

The distance between zero crossings defines, for periodic carrier signals, a base-line on the signal data against which other features can be normalised.

We denote the set of zero crossing samples

$$\overline{\mathcal{W}_t} = \{s_i | g(s_i) = 1\}$$

$$\text{distZeroCross}(\mathcal{W}_t) = \sum_{\substack{s_i, s_j \in \overline{\mathcal{W}_t}; \\ \nexists s_k \in \overline{\mathcal{W}_t} \text{with } i<k<j}} \frac{j-i}{|\overline{\mathcal{W}_t}|}$$

RF-based activity recognition

RF-channel-based situation classification

Sensewaves Video

Recognising RF-fluctuation due to movement

Challenges: Device-free Passive Localization for Wireless Environments

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ABSTRACT

Typical location determination systems require the presence of a physical device that is attached to the person that is being tracked. In addition, they usually require the tracked device to participate actively in the localization process. In this paper, we introduce the concept of Device-free Passive (DfP) localization. A DfP system is envisioned to be able to detect, track, and identify entities that do not carry any device, nor participate actively in the localization process. The system works by monitoring and processing changes in the received physical signals at one or more monitoring points to detect changes in the environment. Applications for DfP systems include intrusion detection and *tracking*, protecting outdoor assets, such as pipelines, railroad tracks, and perimeters.

Keywords

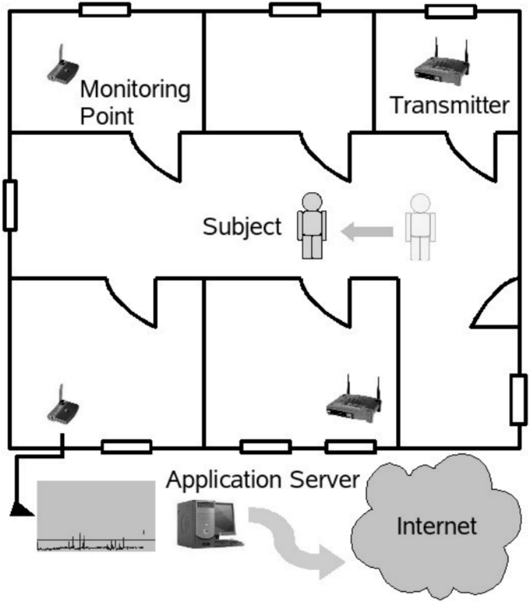
Device-free localization, passive localization, passive radio map

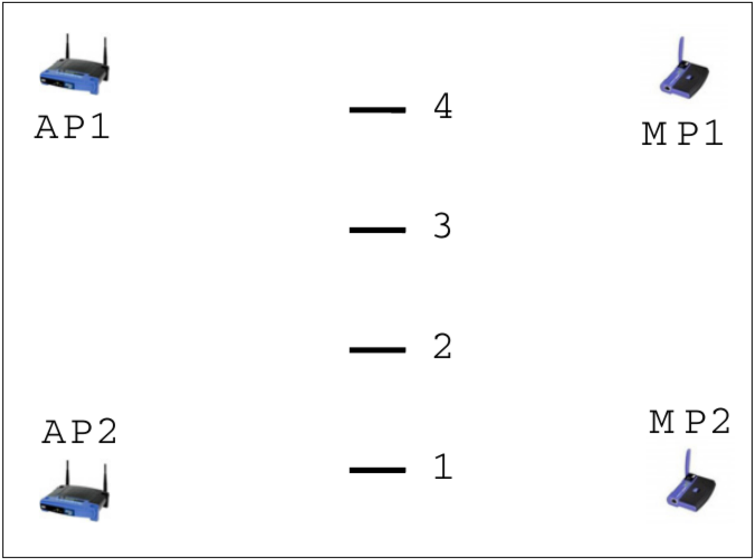
1. INTRODUCTION

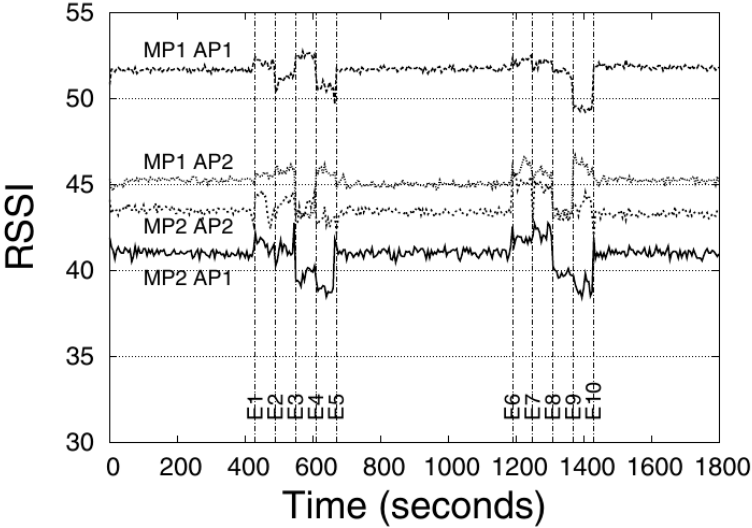
Many location determination technologies have been proposed over the years, including: the GPS [3], infrared [13], ultrasonic [10], and radio frequency (RF) [2]. All these technologies share the requirement for a tracked object to carry a device to be tracked. In addition many of these technologies require the device being tracked to actively participate in the localization process by running part of the localization algorithm. This allows the system to provide the user with its location and other services related to the estimated

[3]

[3] M. Youssef, M. Mah, A. Agrawala. 2007. Challenges: device-free passive localization for wireless environments. MobiCom '07


Monitoring
Point
Transmitter
Subject
Application Server
Internet


AP1
4
MP1
3
2
AP2
MP2
1


MP1 AP1
MP1 AP2
MP2 AP2
MP2 AP1
RSSI
55
50
45
40
35
30
0 200 400 600 800 1000 1200 1400 1600 1800
Time (seconds)
E1 E2 E3 E4 E5
E6 E7 E8 E9 E10

Tracking location from RSS

2012 Proceedings IEEE INFOCOM

On Distinguishing the Multiple Radio Paths in RSS-based Ranging

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Department of Computer Science and Engineering, Hong Kong University of Science and Technology[2]
Third Research Institute of Ministry of Public Security[3]
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***Abstract*—Among the various ranging techniques, Radio Signal Strength (RSS) based approaches attract intensive research interests because of its low cost and wide applicability. RSS-based ranging is apt to be affected by the multipath phenomenon which allows the radio signals to reach the destination through multiple propagation paths. To address this issue, previous works try to profile the environment and refer this profile in run-time. In practical dynamic environments, however, the profile frequently changes and the painful retraining is needed. Rather than such static ways of profiling the environments, in this paper, we try to accommodate the environmental dynamics automatically in real-time. The key observation is that given a pair of nodes,**

however, this model is far from reality. It has been well known that the function is a dynamic, complex one that depends on many factors [14]. The most significant one is the multipath propagation phenomenon [2], which refers to the radio propagation nature that radio signals reach the receiver by two or more physical paths. The causes are many such as the atmospheric duct, refraction and reflection. Signals from different paths combine at the receiver constructively or destructively depending on signal phases. As the phases are environment-dependent, the RSS of combined signals is

4

[4] D. Zhang, Y. Liu, X. Guo, M. Gao, L.M. Ni. 2012. On distinguishing the multiple radio paths in RSS-based ranging, INFOCOM, 2012

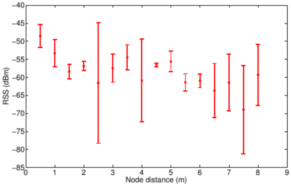


Fig. 1. RSS measurement in different environments

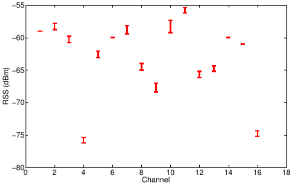


Fig. 2. RSS measurement in different channels: node distance=$2m$

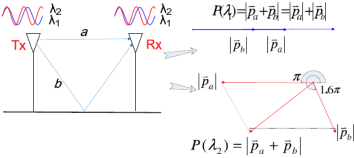
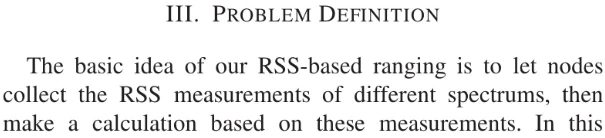


Fig. 3. An illustrative example; there are two paths a and b; The signals of two frequencies λ_1, λ_2 will have different RSS values at the receiver end because of the phase-shift difference between paths (i.e.,$P(\lambda_1 \neq P(\lambda_2))$


III. PROBLEM DEFINITION
The basic idea of our RSS-based ranging is to let nodes collect the RSS measurements of different spectrums, then make a calculation based on these measurements. In this

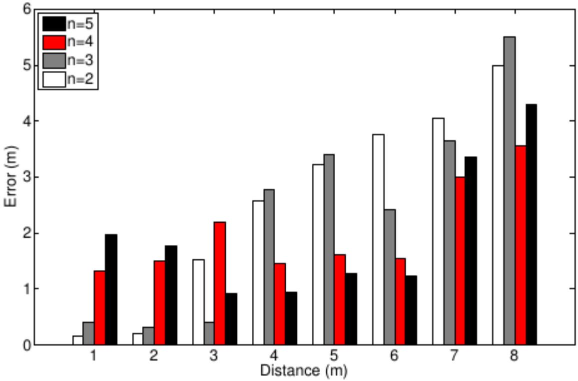


Fig. 8. Accuracy of individual ranging with different path number

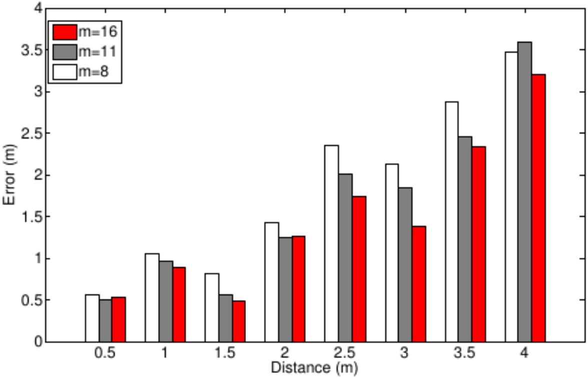


Fig. 12. Accuracy of individual ranging with different channel number

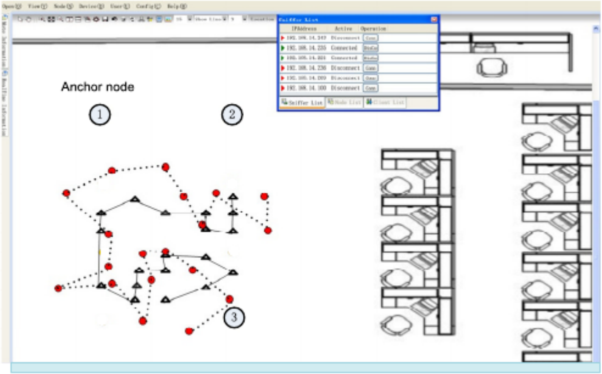


Fig. 16. Tracking example

Recognition of gestures via Doppler shift

Whole-Home Gesture Recognition Using Wireless Signals

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{qp, sidhant, gshyam, shwetak}@cs.washington.edu

Abstract – This paper presents WiSee, a novel gesture recognition system that leverages wireless signals (e.g., Wi-Fi) to enable whole-home sensing and recognition of human gestures. Since wireless signals do not require line-of-sight and can traverse through walls, WiSee can enable whole-home gesture recognition using few wireless sources. Further, it achieves this goal without requiring instrumentation of the human body with sensing devices. We implement a proof-of-concept prototype of WiSee using USRP-N210s and evaluate it in both an office environment and a two-bedroom apartment. Our results show that WiSee can identify and classify a set of nine gestures with an average accuracy of 94%.

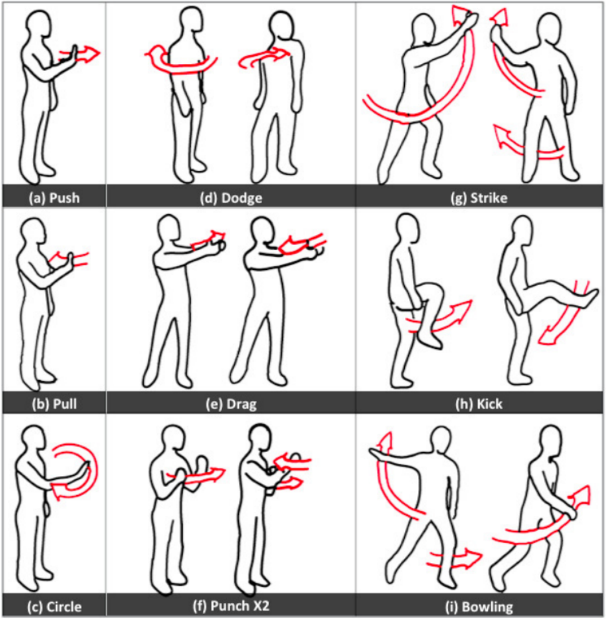
Categories and Subject Descriptors

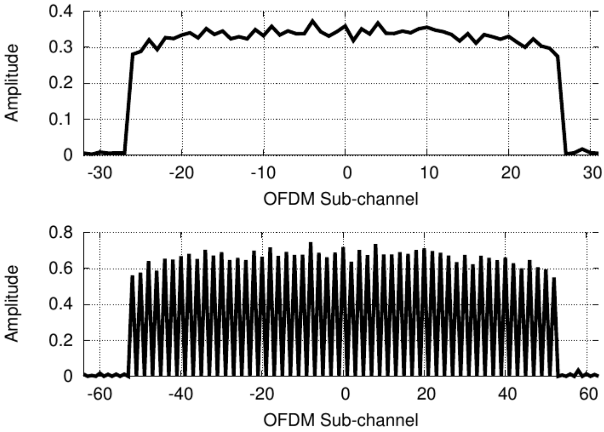
home or building. Given these limitations, researchers have explored ways to move some of the sensing onto the body and reduce the need for environmental sensors [8] [14] [13]. However, even on-body approaches are limited to what people are willing to constantly carry or wear, and may be infeasible in many scenarios (e.g., in a shower).

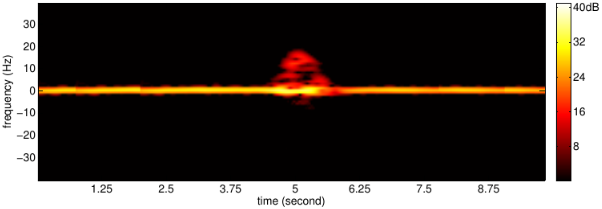
This paper presents WiSee, the first whole-home gesture recognition system that requires neither user instrumentation nor an infrastructure of cameras. WiSee achieves this by leveraging wireless signals (e.g. Wi-Fi) in an environment. Since these signals do not require line-of-sight and can traverse through walls, very few signal sources need to be present in the space (e.g., a Wi-Fi AP and a few mobile devices in the living room). WiSee works by looking at

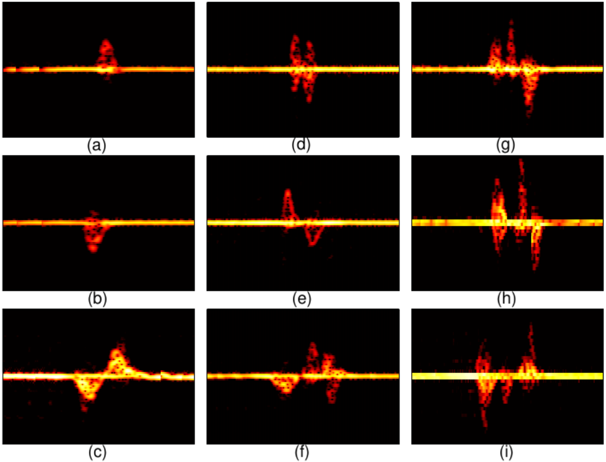
5

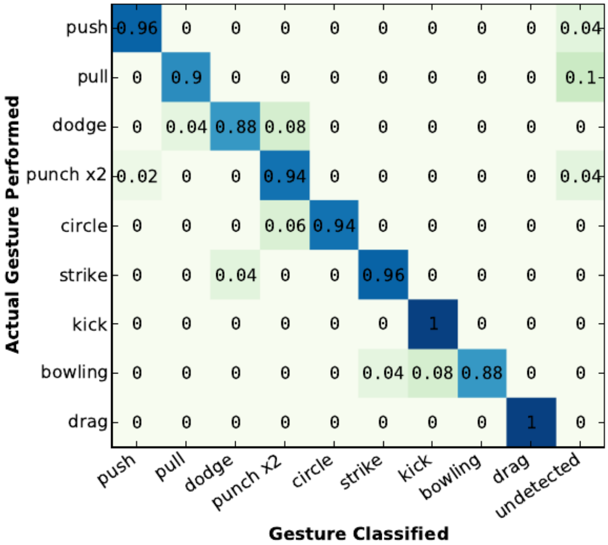
[5] Q. Pu, S. Gupta, S. Gollakota, S. Patel, Whole-Home Gesture Recognition Using Wireless Signals, Mobicom'13


(a) Push
(d) Dodge
(g) Strike
(b) Pull
(e) Drag
(h) Kick
(c) Circle
(f) Punch X2
(i) Bowling


0.4
0.3
0.2
0.1
0
Amplitude
-30
-20
-10
0
10
20
30
OFDM Sub-channel
0.8
0.6
0.4
0.2
0
Amplitude
-60
-40
-20
0
20
40
60
OFDM Sub-channel


frequency (Hz)
30
20
10
0
−10
−20
−30
1.25
2.5
3.75
5
6.25
7.5
8.75
time (second)
40dB
32
24
16
8


(a)
(d)
(g)
(b)
(e)
(h)
(c)
(f)
(i)


Actual Gesture Performed
push 0.96 0 0 0 0 0 0 0 0 0.04
pull 0 0.9 0 0 0 0 0 0 0 0.1
dodge 0 0.04 0.88 0.08 0 0 0 0 0 0
punch x2 0.02 0 0 0.94 0 0 0 0 0 0.04
circle 0 0 0 0.06 0.94 0 0 0 0 0
strike 0 0 0.04 0 0 0.96 0 0 0 0
kick 0 0 0 0 0 0 1 0 0 0
bowling 0 0 0 0 0 0.04 0.08 0.88 0 0
drag 0 0 0 0 0 0 0 0 1 0
push pull dodge punch x2 circle strike kick bowling drag undetected
Gesture Classified

RF-based activity recognition

RF-channel-based situation classification

Wisee Video

Recognition of gestures via time-domain features

The Telepathic Phone: Frictionless Activity Recognition from WiFi-RSSI

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***Abstract*—We investigate the use of WiFi Received Signal Strength Information (RSSI) at a mobile phone for the recognition of situations, activities and gestures. In particular, we propose a passive activity recognition system that does not require any device carried by the user. We discuss challenges and lessons learned for the design of such a system on a mobile phone and propose appropriate features for extracting activity characteristics from RSSI signals. We demonstrate the feasibility of recognising activities, gestures and environmental situations from RSSI information obtained by the mobile phone. The case studies were conducted during a period of about two months in which about 12 hours of continuous RSSI data has been sampled, in two countries and with 11 participants in total. Results demonstrate the potential to utilise RSSI information for the extension of the environmental perception of a mobile device as well as for the interaction with touch-free gestures. The system achieves an accuracy of 0.51 while distinguishing as many as 11 gestures and can reach 0.72 on average for four more disparate ones.**

I. Introduction

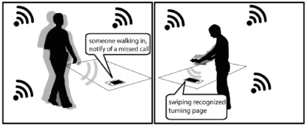
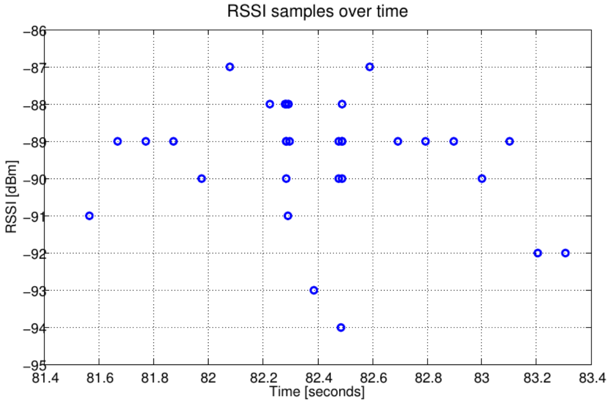


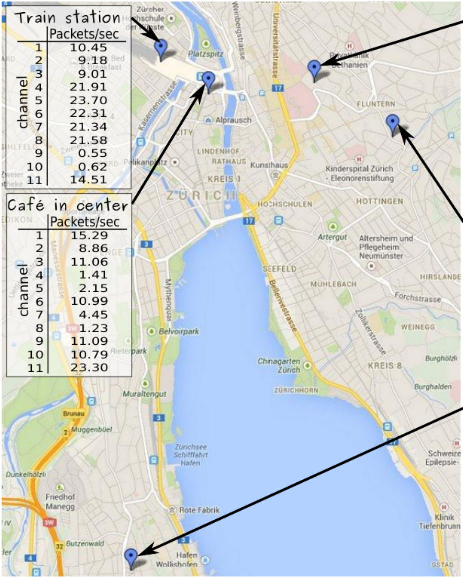
Fig. 1: Activity obtained from RSSI-signatures. Two example use-cases: user walking in with the smartphone implicitly reacting (left) and a no-touch explicit interaction (right).

received signal strength indicator (RSSI) that is calculated at

6

[6] S. Sigg, U. Blanke, G. Troester, The Telepathic Phone: Frictionless Activity Recognition from WiFi-RSSI, PerCom'14


RSSI samples over time
-86
-87
-88
-89
-90
-91
-92
-93
-94
-95
81.4
81.6
81.8
82
82.2
82.4
82.6
82.8
83
83.2
83.4
Time [seconds]
RSSI [dBm]



Train station

channel	Packets/sec
1	10.45
2	9.18
3	9.01
4	21.91
5	23.70
6	22.31
7	21.34
8	21.58
9	0.55
10	0.62
11	14.51

Café in center

channel	Packets/sec
1	15.29
2	8.86
3	11.06
4	1.41
5	2.15
6	10.99
7	4.45
8	1.23
9	11.09
10	10.79
11	23.30

University (ETH)

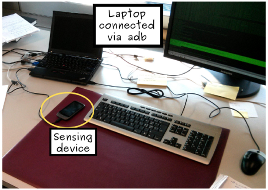
channel	Packets/sec ground	Packets/sec 3rd fl.
1	34.06	14.88
2	0.61	5.02
3	4.45	0.19
4	0.10	0.04
5	53.97	192.29
6	0.14	0.04
7	0.28	0.03
8	0.11	0.07
9	26.46	2.88
10	0.06	0.09
11	0.05	0.02

Dormitory

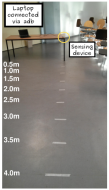
channel	Packets/sec
1	10.28
2	10.03
3	12.13
4	9.92
5	9.30
6	1.77
7	0.09
8	0.19
9	6.92
10	0.47
11	0.36

Suburban flat

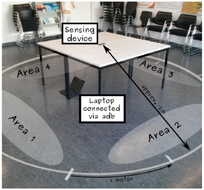
channel	Packets/sec
1	0.85
2	0.35
3	0.32
4	0.20
5	0.85
6	3.10
7	2.59
8	11.85
9	4.46
10	2.05
11	9.61



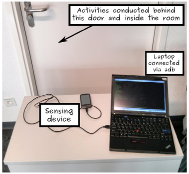
(a) Office environment at ETH



(b) Lecture room at TU-BS

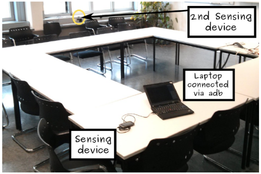


(c) Scenario for the distinction of walking speed

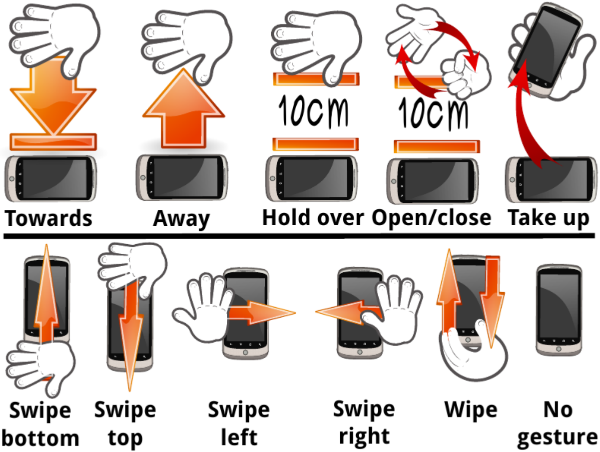


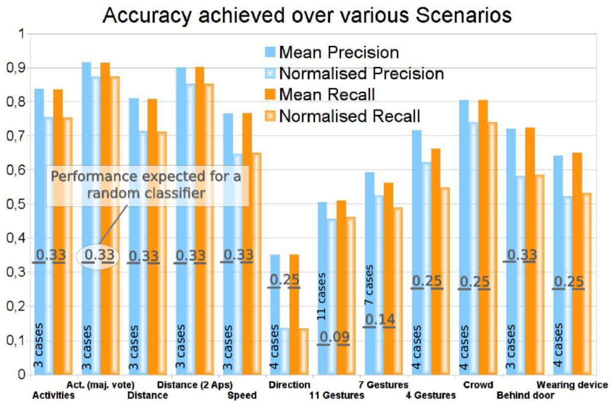
(d) Indoor environment with activities conducted behind a closed door

(e) Person wearing the sensing device (inside the pocket)



(f) Meeting room at ETH


10cm
10cm
Towards
Away
Hold over
Open/close
Take up
Swipe bottom
Swipe top
Swipe left
Swipe right
Wipe
No gesture


Accuracy achieved over various Scenarios
Mean Precision
Normalised Precision
Mean Recall
Normalised Recall
Performance expected for a random classifier
1
0,9
0,8
0,7
0,6
0,5
0,4
0,3
0,2
0,1
0
0.33
0.33
0.33
0.33
0.33
0.25
0.09
0.14
0.25
0.25
0.33
0.25
3 cases
3 cases
3 cases
3 cases
3 cases
4 cases
11 cases
7 cases
4 cases
4 cases
3 cases
4 cases
Activities
Act. (maj. vote)
Distance
Distance (2 Aps)
Speed
Direction
11 Gestures
7 Gestures
4 Gestures
Crowd
Behind door
Wearing device

Outline

Questions?

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stephan.sigg@cs.uni-goettingen.de

Literature

- C.M. Bishop: Pattern recognition and machine learning, Springer, 2007.
- P. Tulys, B. Skoric, T. Kevenaar: Security with Noisy Data – On private biometrics, secure key storage and anti-counterfeiting, Springer, 2007.
- R.O. Duda, P.E. Hart, D.G. Stork: Pattern Classification, Wiley, 2001.