

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 (Basic recognition, Bayesian, Non-parametric)
- 13.11.2013 Classification methods (Linear discriminant, Neural networks)
- 20.11.2013 –
- 27.11.2013 –
- 04.12.2013 –
- 11.12.2013 Classification methods (Sequential, Stochastic)
- 18.12.2013 Activity Recognition (Basics, Applications, Algorithms, Metrics)
- 08.01.2014 Security from noisy data (Basics, Entity, F. Commitment, F. Extractors)
- 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

Introduction

Applications

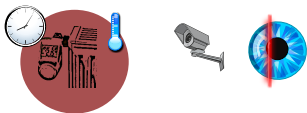
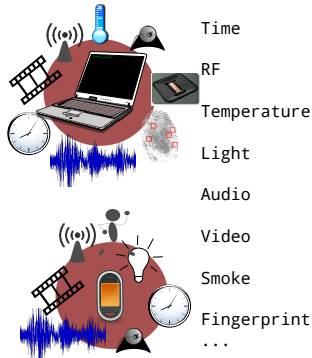
Conclusion

Sensors and sensor classes

- We are surrounded by a multitude of sensors

- Sensor readings utilised for

- Information provisioning
- Situation classification
- Authentication
- Cryptography

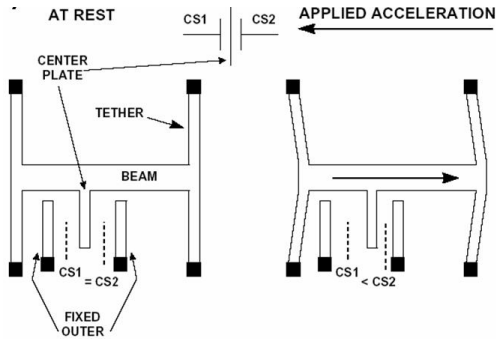


Sensors and sensor classes



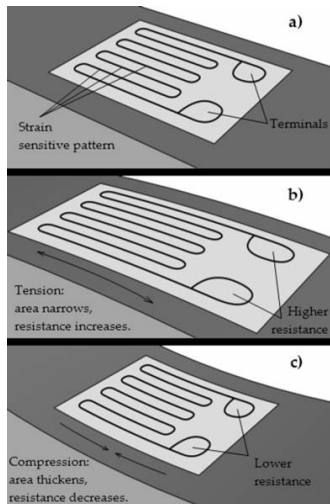
Sensors and sensor classes

- MEMS acceleration sensors
 - E.g. Analogue Devices ADXL
 - Low energy consumption, small, cheap, medium precision
 - MEMS = Micro-mechanical System: Mechanic in Silicon (Silizium)
 - Here: Comparison of capacity $CS1$ and $CS2$ leads to acceleration



Sensors and sensor classes

- Pressure sensors
 - Z.B. IEE about 3-10 Euro
 - Very imprecise



Sensors and sensor classes

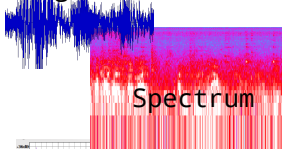
- Output of sensors has to be interpreted typically
 - Raw electrical signals
 - Interpretation of signals as electric values
 - Binary or Real valued representation
 - Further identification of features
 - Feature extraction
 - Interpretation of features and classification



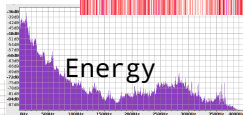
Features and feature extraction

- What is a feature and why do we need it?
 - Captured data might be hard to interpret
 - Many aspects can be contained in a single data stream
 - Example: Audio
 - Loudness
 - Energy on frequency bands
 - Zero crossings
 - Direction changes

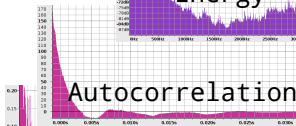
Signal over time



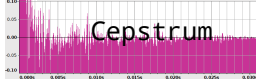
Spectrum



Energy



Autocorrelation



Cepstrum

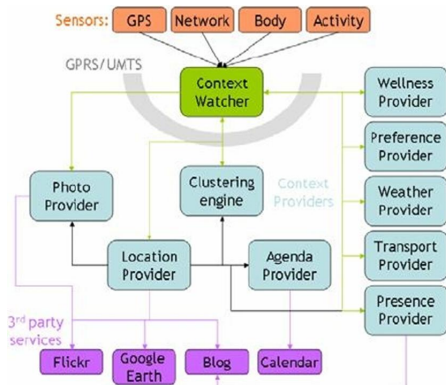
Examples and case studies: Media Cup

- Media Cup: Context recognition
 - Activity: Trigger sleep mode (save energy)
 - Level of activity
 - Own context: Object movement, person is nervous, specific handling of objects
 - Environmental context: Vibration, earthquake
- Sensor: Ballswitch
 - (nearly) no quiescent current
 - Various types, filled with gas/liquid
 - e.g. Acceleration with fixed value (liquid)
 - Vibration (filled with gas)




Examples and case studies: Context Watcher

- Context Watcher
 - Location
 - GSM cell-ID; GPS
 - Mood
 - user input
 - Activity
 - calendar based
 - Bio-data
 - heart and foot sensors
 - Weather
 - location based over internet
 - Photo/picture
 - camera



Examples and case studies: Context Watcher



Picture	Context Data
	cell id: 10571 altitude: 59.4 speed: 115.1 km/h course: 246.6 pos: (52.279, 6.503) range: 1 m street: E30 postal code: 7462 city: Rijssen (NL)

Johan's blog

Saturday, March 24, 2007

A day in Papendrecht

The weather that I enjoyed today: it has been rather cloudy in Alblasserdam, 1/9°C, with a relative humidity of 93%, a gentle breeze was blowing from north to northeast. The cities that I visited today: Papendrecht (7.4h), Dordrecht (1.6h), Alblasserdam (4.5h). The max of speed that I had today: 104.9. The photos that I took today:



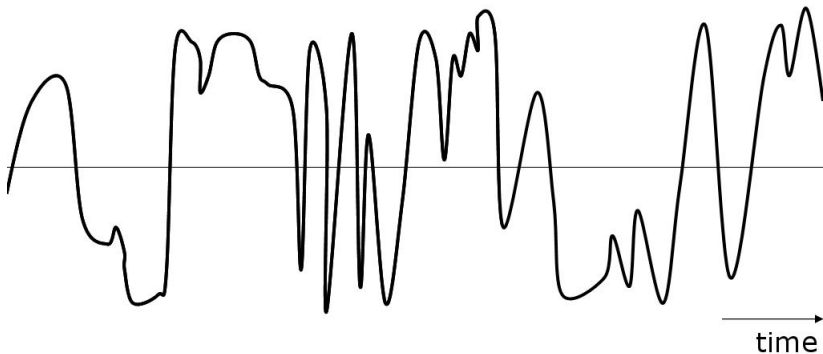

Examples and case studies: TEA

TEA-Audio

- Requirements
 - Restricted memory space
 - Computing power restricted
- Benefit
 - Many sensors → Many features
- Example approach
 - Utilise time domain (no transformation)
 - Utilise statistic measures
 - Feature extraction based on small amount of data

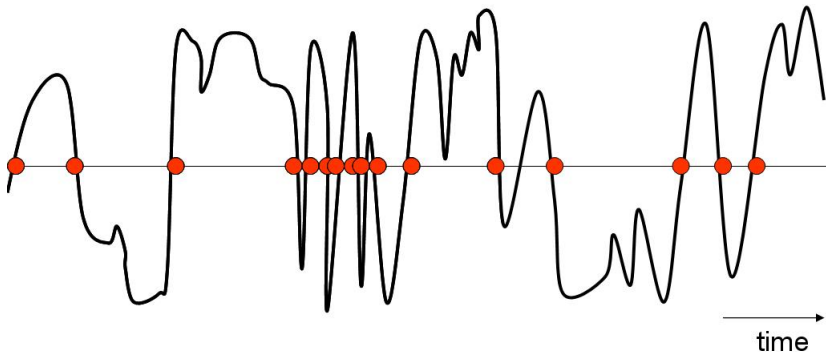
Examples and case studies: TEA

- Audio data in time domain



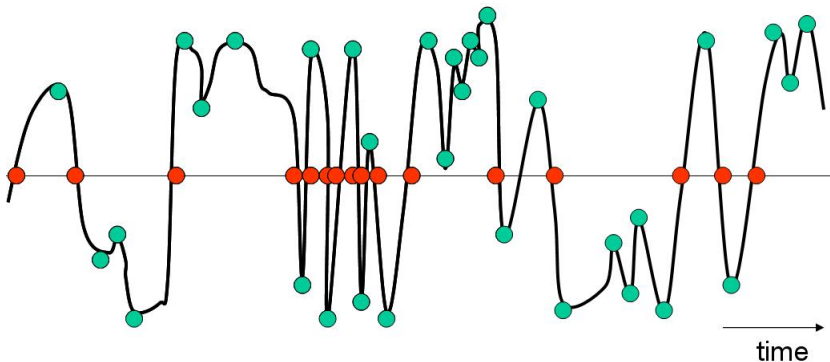
Examples and case studies: TEA

- Count zero crossings
- Distance between zero crossings



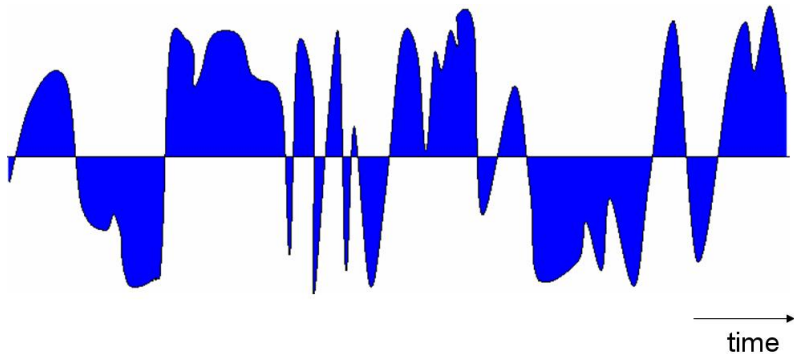
Examples and case studies: TEA

- ratio: $\frac{\text{direction changes}}{\text{zero crossings}}$



Examples and case studies: TEA

- Integral



Examples and case studies: TEA

- Several chunks for speech

whistling

```
Raw - Avg: 163.7 ; Abs Avg: 2368.5 ; ratio: 1.857 ; sd: 1.04
Spec - avg: 8.1 ; sd: 2055.67 ; avg dis: 315.8 ; sd dis: 102655.69
Prof - avg: 7954.4 ; sd: 2.15 ;
```

Whistling

speech

```
Raw - Avg: 170.5 ; Abs Avg: 471.0 ; ratio: 12.190 ; sd: 566179.8
Spec - avg: 12.5 ; sd: 4447.67 ; avg dis: 115.4 ; sd dis: 13669.85
Prof - avg: 1411.2 ; sd: 1673821.1 ;
```

1

2

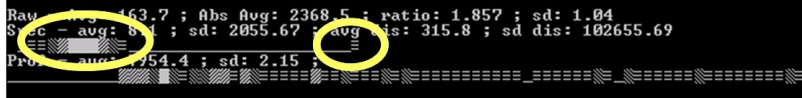
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4

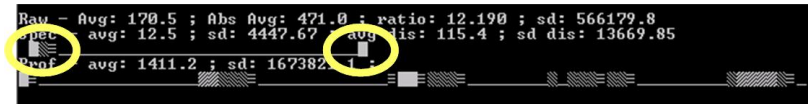
Examples and case studies: TEA

- Distance between zero crossings: distinct behaviour of oscillation at start and end

whistling



speech



Examples and case studies: TEA

- Distinct ratio: $\frac{\text{zero crossings}}{\text{direction changes}}$

whistling

```
Raw - Avg: 163.7 ; Abs Avg: 2368.5 ; ratio: 1.857 ; sd: 1.04
Spec - avg: 8.1 ; sd: 2055.67 ; avg dis: 315.9 ; sd dis: 102655.69
Prof - avg: 7954.4 ; sd: 2.15 ;
```

speech

```
Raw - Avg: 170.5 ; Abs Avg: 471.0 ; ratio: 12.190 ; sd: 566179.8
Spec - avg: 12.5 ; sd: 4447.67 ; avg dis: 115.4 ; sd dis: 13669.85
Prof - avg: 1411.2 ; sd: 1673821.1 ;
```

Examples and case studies: TEA

- Significant change in standard deviation of chunks

whistling

```
Raw - Avg: 163.7 ; Abs Avg: 2368.5 ; ratio: 1.857 ; sd: 1.04
Spec - avg: 8.1 ; sd: 2058.18 ; avg dis: 315.8 ; sd dis: 102655.69
Prof - avg: 7954.4 ; sd: 2.15 ;
```

speech

```
Raw - Avg: 170.5 ; Abs Avg: 471.0 ; ratio: 12.190 ; sd: 566179.8
Spec - avg: 12.5 ; sd: 4418.60 ; avg dis: 115.4 ; sd dis: 13669.85
Prof - avg: 1411.2 ; sd: 1673821.1 ;
```

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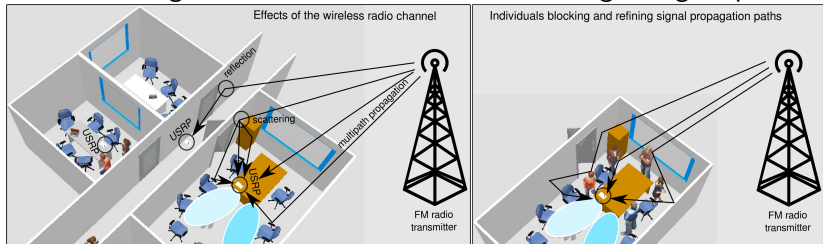
Conclusion

RF-based activity recognition

During propagation, radio signals experience a multitude of effects due to the environment

Can we learn about the environment from the signal evolution observed at a receiver?

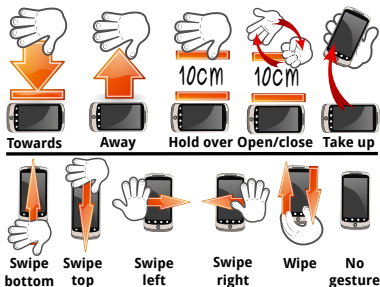
- Multi-path propagation
- Scattering
- Reflection
- Blocking of signal paths



RF-based activity recognition

Sensewaves Video

RF-based activity recognition



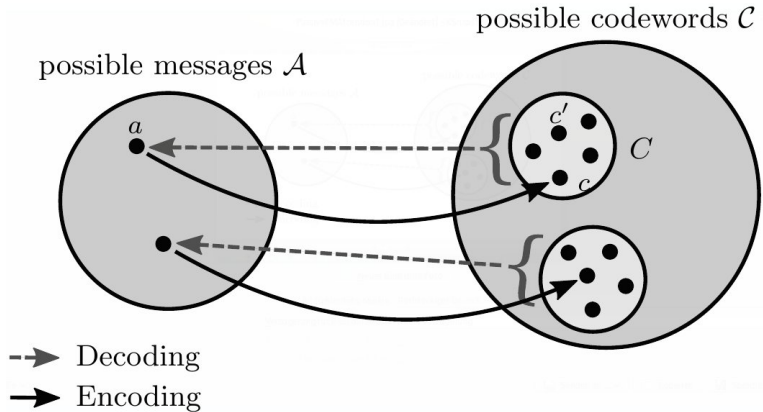
	Classification						recall	
	Aw	Ho	To	No	Op	Sr		St
Aw	.7	.02			.06	.09	.13	.70
Ho	.03	.28	.22	.05	.2	.16	.06	.28
To		.09	.76	.07	.06		.02	.76
No		.05	.06	.73	.14	.01	.01	.73
Op	.01	.15	.1	.14	.49	.04	.07	.49
Sr	.02	.01		.01	.06	.83	.07	.83
St	.12	.03	.01		.05	.14	.65	.65
prec	.795	.444	.661	.730	.462	.654	.644	

	Classification				recall
	Away	Towards	No gesture	S. top	
round truth	Away	.83		.17	.83
	Towards		.88	.09	.88
	No gesture	.01	.05	.92	.92
	S. top	.14	.02	.02	.82
precision		.847	.926	.893	.788

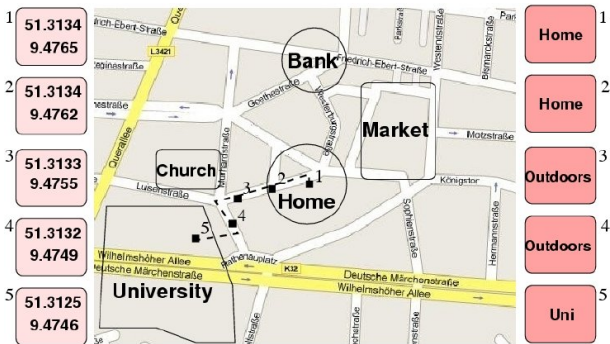
Context-based security



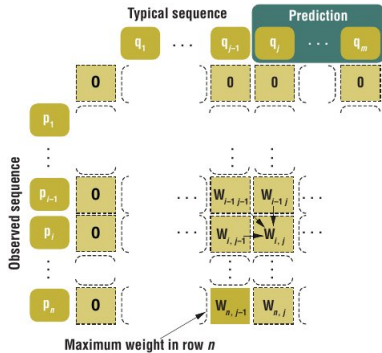
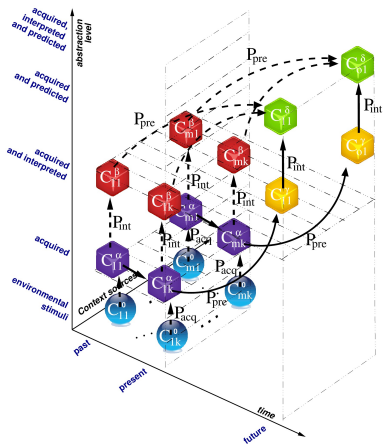
Context-based security



Context prediction



Context prediction



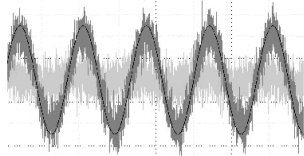
Collaborative transmission

Phase 4:

Feedback is broadcast to the network

Phase 3:

Receiver estimates the phase synchronisation level of the received sum signal



Phase 2:

Source nodes transmit to the destination as a distributed beamformer



Phase 1:

Source nodes adjust their carrier phase offset and frequency randomly



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Questions?

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Literature

- C.M. Bishop: Pattern recognition and machine learning, Springer, 2007.
- P. Tulyas, 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.

