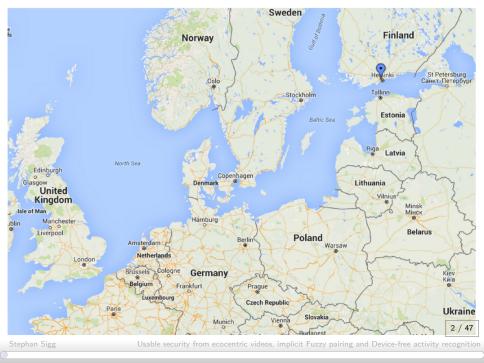
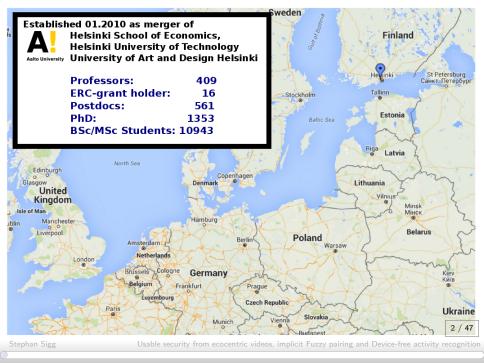
# Usable security from ecocentric videos, implicit Fuzzy pairing and Device-free activity recognition

Stephan Sigg

Aalto University, Communications and Networking





Established 01.2010 as merger of
Helsinki School of Economics,
Helsinki University of Technology
Aulto University of Art and Design Helsinki

Professors: 409 ERC-grant holder: 16 Postdocs: 561 PhD: 1353

BSc/MSc Students: 10943







Personnel: ~115

Authenticatication

- 11 + 2 Professors
- budget ~7.8 M€
- 60% external funding
- ~ 55 M.Sc thesis annually
- ~ 8 D.Sc thesis annually





Comnet is a multi-disciplinary unit of research and higher education covering communications and networking technology, networking business and human aspects of communications. In its area, Comnet is the largest unit in Finland.

#### http://comnet.aalto.fi/en/



Comnet 6/8/16



# **Professors**



Xiao Yu Networking software and applications



Stephan Sigg Ubiquitous computing



Antti Oulasvirta Human-Computer Interaction

(User Interfaces)



Heikki Hämmäinen Network Economics



Juuso Töyli Network economics Adjunct Prof.



Jarno Limnell Cyber security PoP



Information theory



Patric Östergard Olav Tirkkonen Communications theory

Riku Jäntti

Commuications Engineering Head of department



Jyri Hämäläinen Radio communications Dean of ELEC



Raimo Kantola Networking technology and privacy



Tarik Taleb Mobile Core Networks Network Function Virtualization and Cloud Communications



Jukka Manner Internet technologies Transport



**Aalto University** School of Electrical Engineering

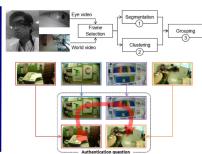
Comnet 6/8/16

Group











#### Stephan Sigg

Randomized Algorithms, Optimization, Usable security, Activity recognition, Machine learning, Pervasive Computing

Happiness



#### Bahareh Gholampooryazdi

Signal processing, RF-based Device-free activity recognition



### Visitors Dominik Schuermann

Security in DTN, Anonymity in decentralized networks, Authenticated Key Exchange Usable security



#### Le Ngu Nguyen

Usable Security, Activity recognition, Machine learning, Mobile applications



#### Muneeba Raja

Sentiment sensing, Device-Fre RF-based Activity recognition, Pervasive Computing



Information systems, Ad-hoc secure device pairing, Inertial sensors

Authenticatication

#### Secure authentication from an Egocentric Camera



# Secure authentication from Egocentric camera





b)



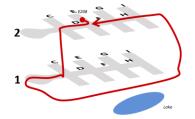
6 / 47

Usable security from ecocentric videos, implicit Fuzzy pairing and Device-free activity recognition

### PassFrame video

Device-authentication from egocentric videos

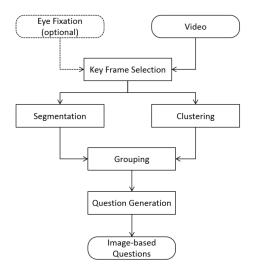
http://ambientintelligence.aalto.fi/passframe/

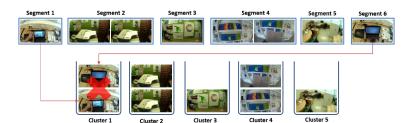






### Overview (Frame selection and challenge generation)





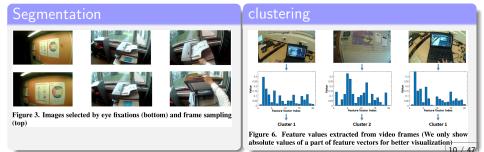
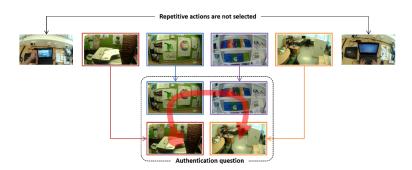




Figure 5. Non-informative images discarded from small clusters

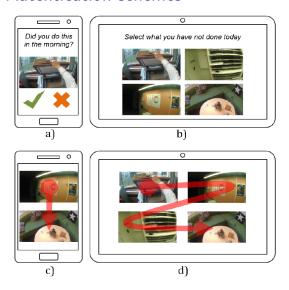
Authenticatication

### Secure authentication from Egocentric camera

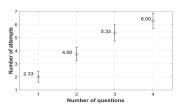


Authenticatication

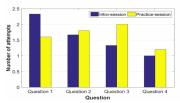
### Alternative Autentication schemes



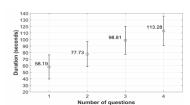
### Performance of subjects



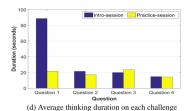
(a) Number of attempts to answer the challenges



(c) Average number of attempts on each challenge



(b) Time duration spent on answering the challenges



#### Similar images

Authenticatication







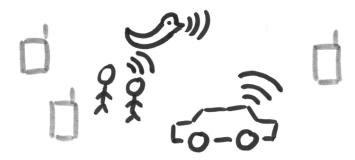
Figure 11. Some images that are difficult for the users to recall

• Robustness against an active attacker

Secure spontaneous authentication from ambient audio

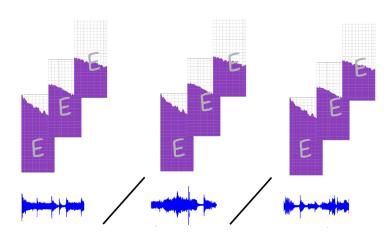


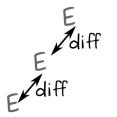




**DFAR** 

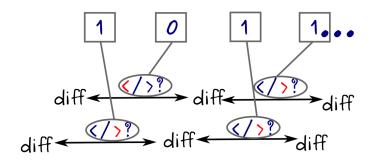




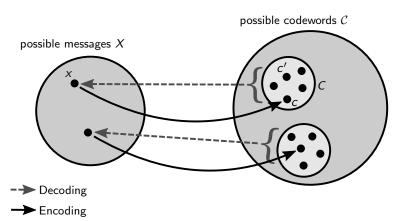








(Audio-based secure pairing)



### Audio-based ad-hoc secure pairing<sup>a</sup>

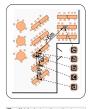
<sup>a</sup>S. Sigg et al., Secure Communication based on Ambient Audio, IEEE Transactions on Mobile Computing, vol. 12, no. 2, 2013

- Audio as common context source
- Fuzzy cryptography





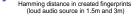


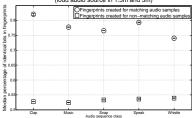


Only whistle

# Security from environmental stimuli Hamming distance in created fingerprints (loud audio source in 1.5m and 3m)

(Audio-based secure pairing)





that passed at >5% for Kuiper KS p-values of passed tests 0.9 Percentage 0.92053 (confidence value at  $\alpha = 0.03$ )

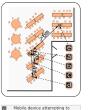
Test run

Percentage of tests in one test run









Position of person talking during fingerprint creation Audio source (FM radio)





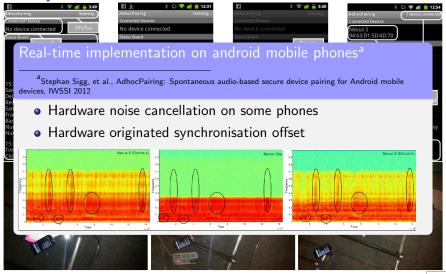












### How to synchronise audio without disclosing information?

No data shall be transmitted among devices

#### Hardware-originated synchronisation offset

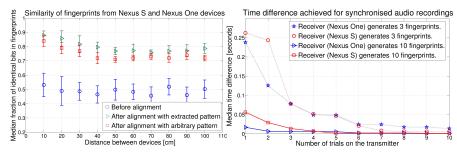
 Approximate pattern matching with arbitrary common sequence <sup>a</sup>

<sup>a</sup>T. F. Smith and M. S. Waterman. Identification of common molecular subsequences. Journal of molecular biology, 147(1):195â197, Mar. 1981



### Hardware-originated synchronisation offset

Audio-based secure pairing



- Synchronisation in the order of 3ms possible
- No additional data transmitted among devices<sup>1 2</sup>

<sup>&</sup>lt;sup>1</sup>N. Nguyen, S. Sigg, A. Huynh and Y. Ji: Pattern-based Alignment of Audio Data for Ad-hoc Pairing, ISWC, 2012

N. Nguyen, S. Sigg, A. Huynh and Y. Ji: Using ambient audio in secure mobile phone communication, PerCom. 2012



- 8 Actions
- 7 Sensor-
- positions
- 6 Sensors



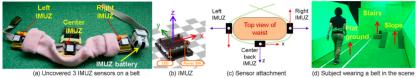
Sztyler et al.: On-body Localization of Wearable Devices [...]

### Osaka University (OU-ISIR Gait database)

- 460 participants aged between 8 and 78
- gender ratio almost 50:50
- max. 8 gait cycles
- Sensorpositions: Waist right, left, back
- 3D-Accelerometer and Gyroskope (100Hz)

URL: http://www.am.sanken.osaka-u.ac.jp/BiometricDB/SimilarActionsInertialDB.htm

#### Sensor Setup

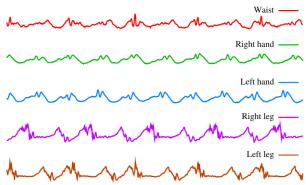


Thanh Trung Ngo, Yasushi Makihara, Hajime Nagahara, Yasuhiro Mukaigawa, Yasushi Yagi, "Similar gait action recognition using an inertial sensor," Pattern Recognition Vol. 48 (4), pp. 1289-1301, 2015

#### Dartmouth

- 7 Subjects
- 5 Accelerometers no Gyroscopes
- 13 hours at 255Hz
- waist, left wrist, right wrist, left ankle, right ankle

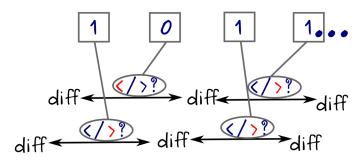
http://www.cs.dartmouth.edu/~dfk/papers/cornelius-same-body.pdf



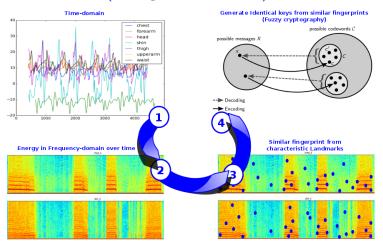
Cory Cornelius and David Kotz. 2011. Recognizing whether sensors are on the same body. In Proceedings of the 9th international conference on Pervasive computing (Pervasive'11), Kent Lyons, Jeffrey Hightower, and Elaine M. Huang (Eds.). Springer-Verlag, Berlin, Heidelberg, 332-349.

## Audio Fingerprinting (Haitsma & Kalker, ISMIR 2002)

Audio-based secure pairing

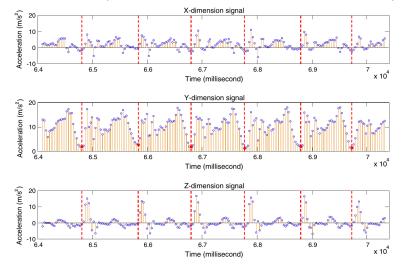


## Audio Landmarks (Wang, ISMIR 2003)



Wang: An Industrial Strength Audio Search Algorithm. ISMIR. 2003.

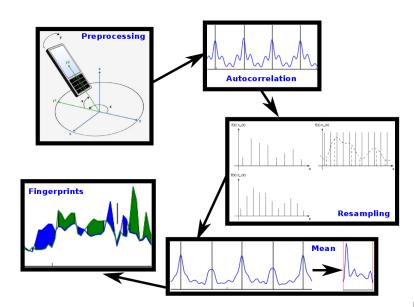
## Gait recognition (Hoang & Choi & Nguyen, IJIS 2015)



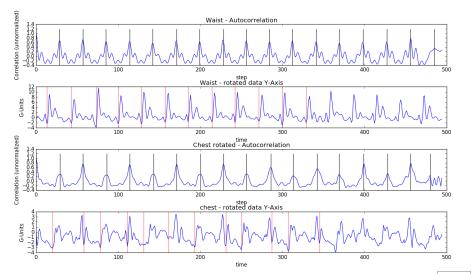
Hoang, Choi, Nguyen: Gait authentication on mobile phone using biometric cryptosystem and fuzzy commitment

30 / 47

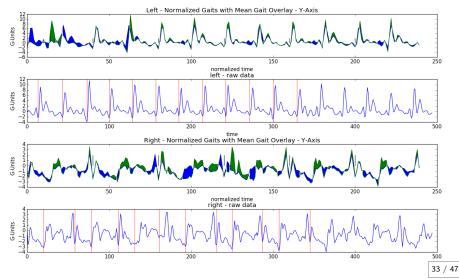
Usable security from ecocentric videos, implicit Fuzzy pairing and Device-free activity recognition



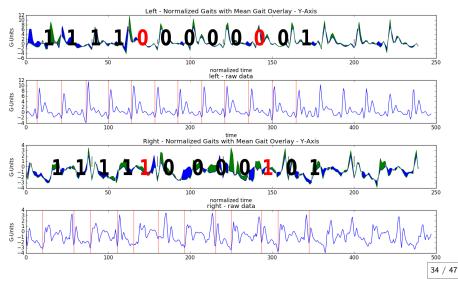
#### Results



#### Results



#### Results



#### Project:

RF-based device-free activity recognition

## RF-based device-free activity recognition



**Passive** 

receive devices

multiple

subjects

Incalise activitie

multiple

subjects Localise activities

ecognise

environ. cf. [19] receive devices

#### Stephan Sigs, Momber, IEEE and Makus School, Momber, IEE and Yashing J., Monber, IEEE and Michael Beef, Mon Active SDR-based DFAR (USRP1)

Frequency: 900MHz (RFX900 board), Vert900 Antenna), 4dBi antenna gain Signal: Sine signal, continuously modulated onto the carrier

Sample rate: 80 Hz



#### Passive SDR-based DFAR (USRP N210) Frequency:

82.5MHz (WBX board), Vert900 Antenna, 4dBi antenna gain Signal: Environmental FM radio captured from a nearby radio station

Sample rate: 64Hz



#### Active RSSI-based DFAR (INGA wsn nodes, v1.4)

Frequency: 2.4GHz IEEE802.15.4, PCB High Gain-Antenna

Signal: RSSI samples from packets transmitted between nodes

Sample rate: Transmission of 100 packets per second



#### Accelerometer-based activity recognition (lphone 4)

Signal: 3-axis accelerometer

Sample rate: 40 Hz

Walking Standing Crawling

36 / 47

multiple

subjects

Active

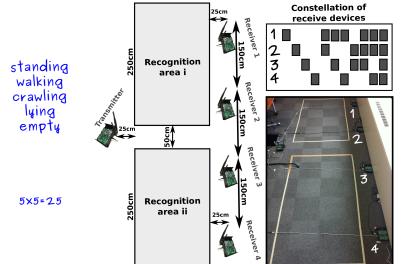
Sontinuous

## RF-based device-free activity recognition

Saighan Siga, Member, IEEE and Markus Schola, Member and Yesheng J., Member, IEEE and Michael Belgi. Active SDR-based DFAR (USRP1) 200MHz (REX900 board), Vert900 Antenna), 4dBi antenna gain Classification Classification lving standing walking crawling lying standing walking crawling By 904 .096 .096 .096 wa .013 .962 .025 cr .038 .212 .75 (b) Classification accuracy for Ground truth .976 .024 1.0 gain o station .955 .045 wa .253 .748 (a) Classification accuracy for accelerometer-based activity active SDR-based DFAR by a krecognition by a k-NN NN algorithm Act Continuous signa Classification Classification lying standing walking crawling lying standing walking crawling Ground truth Ground truth en ct st ly .882 .118 1.0 .056 .98 .12 .869 .004 .022 .007.953 .047 wal.023 .874 .102 439 .551 cr |.044 .811 01 144 RSSI-based (c) Classification accuracy for (d) Classification accuracy for active RSSI-based DFAR by a passive SDR-based DFAR by a k-NN algorithm k-NN algorithm

activities) bands

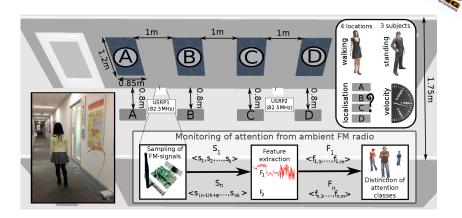
## Recognition of multiple activities simultaneously



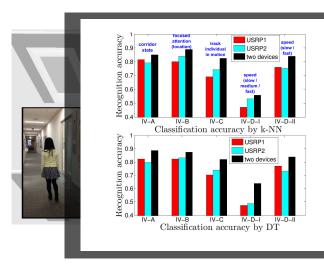
	Constellation of receive devices						
	1,2	1,3	1,4	2,3	1,2,3	1,2,4	1,2,3,4
CA	.697	.749	.726	.730	.787	.754	.838
IS	1.49	1.64	1.57	1.57	1.7	1.65	1.86
Brier	.421	.355	.388	.390	.318	.343	.229
AUC	.930	.946	.939	.928	.958	.960	.980

Table 5: Overall performance of the k-NN classifier

## Monitoring attention from RF



## Monitoring attention from RF





## Situation and gestures from passive RSSI-based DFAR









(a) Office environment at ETH

(b) Lecture room at TU-BS

(c) Scenario for the distinction of walking speed









(f) Meeting room at ETH



bottom





Hold over Open/close Take up

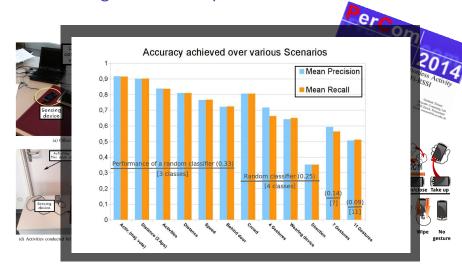




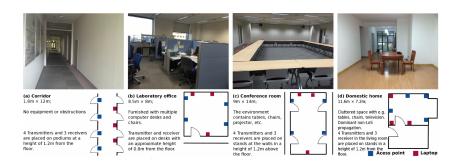


Authenticatication

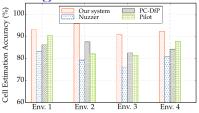
## Situation and gestures from passive RSSI-based DFAR

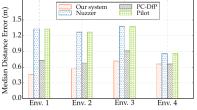


## Modelling CSI vectors via multivariate gaussian distribution



We model the amplitude of every CSI reading at location 'y' to approximately follow a multivariate Gaussian Distribution. Location is then predicted via the maximum likelihood estimate.





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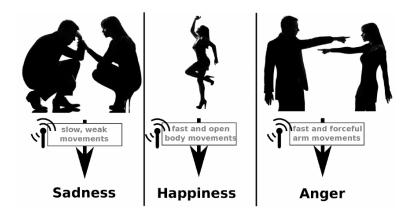
**Nuzzer**: Seifeldin, Saeed, Kosba, El-keyi, Youssef. Nuzzer: A large-scale device-free passive localization system for wireless environments. IEEE Transactions on Mobile Computing, 2013.

**Pilot**: Xiao, Wu, Yi, Wang, Ni. Pilot: Passive device-free indoor localization using channel state information. ICDCS, 2013.

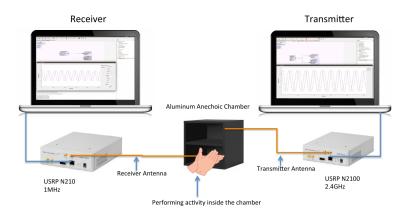
PC-DfP: Xu, Firner, Zhang, Howard, Li, Lin. Improving rf- based device-free passive

localization in cluttered indoor environments through probabilistic classification

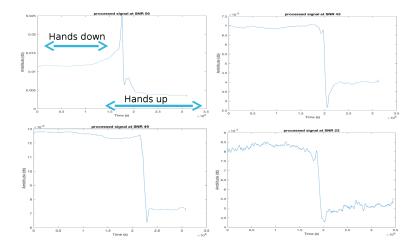
## Emotion recognition from RF



## Emotion recognition from RF

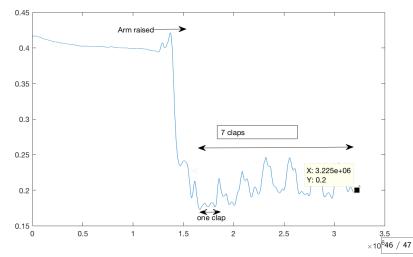


## Emotion recognition from RF



45 / 47

Usable security from ecocentric videos, implicit Fuzzy pairing and Device-free activity recognition



# Thank you!

Stephan Sigg stephan.sigg@aalto.fi