

Radio-based Device-free activity recognition and implicit ad-hoc usable security

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Secure authentication from an Egocentric Camera







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Secure authentication from Egocentric camera





b)



c)





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Try and break it:

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











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Frame selection and challenge generation







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	Key Frames	Processing Time
Tablet-class (AMD E2-1800 1.7GHz)	118	51 sec
Desktop (Intel Core I5-2400 3.1GHz)	118	9 sec

Segmentation













Figure 3. Images selected by eye fixations (bottom) and frame sampling $(\ensuremath{\mathsf{top}})$

clustering



Figure 6. Feature values extracted from video frames (We only show absolute values of a part of feature vectors for better visualization)





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RF-based device-free activity recognition





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RF-based device-free activity recognition







Signal:

Active SDR-based DFAR (USRP1)

900MHz (RFX900 board), Vert900 Antenna), 4dBi antenna gain Freauency: 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 Environmental FM radio captured from a nearby radio station Signal: Sample rate: 64Hz



Active RSSI-based DFAR (INGA wsn nodes, v1.4) Frequency: 2.4GHz IEEE802.15.4, PCB High Gain-Antenna RSSI samples from packets transmitted between nodes Transmission of 100 packets per second

Accelerometer-based activity recognition (lphone 4) Signal: 3-axis accelerometer Sample rate: 40 Hz

Walking standing Crawling





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Modelling CSI vectors via multivariate Gaussian



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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Situation and gestures from passive RSSI-DFAR





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(e) Sensing device inside pocket



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Situation and gestures from passive RSSI-DFAR







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Gesture recognition from RF







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Motivation: Computation during transmission^a

- Max. rate to compute & communicate functions
- Mention: Collisions might contain information



^aGiridhar et al, Toward a theory of in-network computation in wireless sensor networks, IEEE Comm. Mag., vol. 44, no 4, pp. 98-107, april 2006

Calculation of by means of post- and $x_{K(t)}$ $H_{k+1(t)}$ pre-processing^a $H_{K(t)}$ $H_{k+1(t)}$ $H_{k}(t)$ $H_{$





^aM. Goldenbaum, S. Stanczak, and M. Kaliszan, On function computation via wireless sensor multiple-access channels, IEEE Wireless Communications and Networking Conf., 2009

Utilising Poisson-distributed burst-sequences



- Addition, subtraction, division and multiplication at the time of wireless data transmission via Poisson-distributed burst-sequences
- ► Adding Poisson processes *i* with mean μ_i will result in a Poisson process with mean $\sum_{i=1}^{n} \mu_i$.





Case study to compare the calculation accuracy





- Utilise data from the Intel Berkeley laboratory network (here: temperature)¹
- Transmission of data by simple sensor nodes

http://db.csail.mit.edu/labdata/labdata.html





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Thank you!

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