

School of Electrical Engineering

Neuron-inspired maintenance-free, distributed sensing – Challenges and algorithms

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Comnet

- Personnel: ~115
- 11 + 2 Professors
- budget ~7.8 M€
 - ~ 60% external funding
- ~ 55 M.Sc thesis annually
- ~ 8 D.Sc thesis annually



Commet 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.

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Professors



Xiao Yu Networking software and applications



Stephan Sigg Ubiquitous computing



Antti Oulasvirta Heikki Hämmäinen Human-Computer Network Economics Interaction (User Interfaces)





Juuso Töyli Network economics Adjunct Prof.



Jarno Limnell Cyber security PoP



Patric Östergård Olav Tirkkonen Information theory

Communications theory



Riku Jäntti Communications Engineering Head of department



Jvri Hämäläinen Radio communications Dean of ELEC



Raimo Kantola Networking technology Routing, trust, and privacy.



Mobile Core

Networks

Communications



Jukka Manner Internet technologies Virtualization and Cloud





Group members and recent related research RF-based activity recognition

Maintenance-free, intelligent distributed sensing

Sensor graphs for distributed mathematical operation Probabilistic superimposed mathematical operations Neuron-inspired communication between distributed nodes Artificial neural computation from implicit channel inputs

Conclusion





mbient Intelligence

Swipe right

Swipe left

Away

Towards







Authentication question



Stephan Sigg

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

Le Ngu Nguyen

Usable Security. Activity recognition. Machine learning, Mobile applications



Bahareh Gholampoorvazdi

Signal processing, **RF-based** Device-free activity recognition

Muneeba Raia

Sentiment sensing, Device-Free RF-based Activity recognition. Pervasive Computing

Visitors



Activity Recognition Lifelogging Web Contents Engineering





Exploiting the RF-channel for environmental preception

- Multi-path propagation
- Signal superimposition
- Scattering
- Signal Phase

- Reflection
- Blocking of signal paths
- Doppler Shift
- Fresnel effects







RF-based activity recognition

Sensewaves Video











RF-based device-free activity recognition







	And Annual States of Aug
Active SDR-ba Frequency: Signal: Sample rate:	sed DFAR (USRP1) 900MHz (RFX900 board), Vert900 Antenna), 4dBi antenna gain Sine signal, continuously modulated onto the carrier 80 Hz
Passive SDR-b Frequency: Signal: Sample rate:	ased DFAR (USRP N210) 82:5MHz (WBX board), Vert900 Antenna, 4dBi antenna gain Environmental FM radio captured from a nearby radio station 64Hz
Active RSSI-ba Frequency: Signal: Sample rate:	sed DFAR (INGA wsn nodes, v1.4) 2.4GHz IEEE802.15.4, PCB High Gain-Antenna RSSI samples from packets transmitted between nodes Transmission of 100 packets per second
Accelerometer Signal: Sample rate:	-based activity recognition (Iphone 4) 3-axis accelerometer 40 Hz

Walking Standing Crawling





RF-based device-free activity recognition

			and Naga Mend And Natary	er dire and local signals	
	on top of an USRP 1	Acti	ive SDR-based DFAR (USRP1)	And Michael Bergt, Mercler, MEC	
		Fred	guency: 900MHz (RFX900 board), Vert900 Antenna),	4dBi antenna gain	
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	1 3	g wa .955 .045	g wa .013 .962 .025	IO SIATION	
-	, Transmitter:	<u>ğ</u> cr .253 .748	ĝ cr .038 .212 .75		
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	Active	recognition by a k-NN	NN algorithm	ues	
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a Na					
S.S	I RX	Classification	Classification		
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_	TX	2 cr .01 .439 .551	₫ cr .044 .144 .811	Nina	
0		(c) Classification accuracy for	(d) Classification accuracy for	10	
se	Rx	active RSSL-based DFAR by a	passive SDR-based DEAR by a		
- Pa	Rx	k-NN algorithm	k NN algorithm		
4		K-IVIV algorithm	k-iviv argoritimi		
SS	speed multiple Utilities accomise	Speed multime Udining			
Ŕ	dynamic frequency in new activities	dynamic/frequency in new activities			
	Ci. [14]				





Monitoring attention from RF







Monitoring attention from RF









Situation and gestures from passive RSSI-based **DFAR**







Situation and gestures from passive RSSI-based DFAR







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Energy-harvesting from Ambient RF noise

Efficiency: DC-conversion possible at about 70% efficiency¹ 7cm·7cm rectenna : transmissions at 0.2Hz for 3.4ms each² $0.5m^2$ rectenna : RF-activity at 20Hz for 300 μ s each



¹ Doan et al. 'Design and Fabrication of Rectifying Antenna Circuit for Wireless Power Transmission System Operating At ISM Band.' International Journal of Electrical and Computer Engineering, 2016

²Nishimoto et al. 'Prototype implementation of ambient RF energy harvesting wireless sensor networks.' IEEE Sensors, 2010.

 3 Song et al. 'On the use of the intermodulation communication towards zero power sensor nodes.' EuMC 2013





Maintenance-free intelligent distributed sensing







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Envisioned paradigm shift in mobile computing

Parasitic operation Communication comes virtually for free Miniaturisation Processing and storage capabilities limited (passive, parasitic, backscatter)





Envisioned paradigm shift in mobile computing

Parasitic operation Communication comes virtually for free Miniaturisation Processing and storage capabilities limited (passive, parasitic, backscatter)

Potential: Trade processing load for communication load

 Shift computation towards the wireless communication channel





Envisioned paradigm shift in mobile computing

Parasitic operation Communication comes virtually for free Miniaturisation Processing and storage capabilities limited (passive, parasitic, backscatter)

Potential: Trade processing load for communication load

- Shift computation towards the wireless communication channel
- Computation below computational complexity possible?





Motivation: Computation during transmission^a

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



^aA. Giridhar and P. Kumar, Toward a theory of in-network computation in wireless sensor networks, IEEE Comm. Mag., vol. 44, no 4, pp. 98-107, april 2006





Requires identical absolute transmit power

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





Utilising Poisson-distributed burst-sequences







Utilising Poisson-distributed burst-sequences



Basic operations Addition, subtraction, division and multiplication at the time of wireless data transmission via Poisson-distributed burst-sequences





Utilising Poisson-distributed burst-sequences



Addition Adding Poisson processes *i* with mean μ_i will result in a Poisson process with mean $\sum_{i=1}^{n} \mu_i$.





Utilising Poisson-distributed burst-sequences



Multiplication Applying logarithm laws allows multiplication





Utilising Poisson-distributed burst-sequences



Division From two nodes, one transmits the Numerator and one the Denominator (fraction)





Utilising Poisson-distributed burst-sequences



Subtraction Combining division with logarithm laws allows subtraction (two nodes only)





Errors for calculating during transmission on the wireless channel

$t = 10^{6}; \kappa = 10^{3}$	10 nodes	20 nodes	30 nodes	40 nodes	50 nodes
mean err	.0322	.0466	.0609	.051	.0719
std-dev.	.0232	.0368	.0536	.0336	.0438
max N _i	9	14	18.5	26	31
median T	2653.5	5161.5	7393	101816	124179
$t = 10^7$; $\kappa = 10^3$	10 nodes	20 nodes	30 nodes	40 nodes	50 nodes
mean err	.0049	.0176	.0402	.0475	.0781
std-dev.	.0062	.0127	.0233	.0292	.0405
max N _i	12	18	23	27	31
median T	25708.5	52617.5	78502	101381	114348
$t = 10^7$; $\kappa = 10^2$	10 nodes	20 nodes	30 nodes	40 nodes	50 nodes
mean err	.0190	.1337	.2619	.4903	.6597
std-dev.	.0107	.0358	.0591	.0708	.1129
max N _i	9.5	16	19	24	27
median T	24165	50037	71686 5	96829	114383





Case study to compare the calculation accuracy





- Utilise data from the Intel Berkeley laboratory network (here: temperature)⁴
- Transmission of data by simple sensor nodes

⁴http://db.csail.mit.edu/labdata/labdata.html











Further mathematical operations

Utilising the mean of the minimum of a convolution

- Exploiting the CDF of the minimum of a distribution, further operations are possible
 - $\sim \sqrt{n}$
 - dn
 - . . .

transmitted burst sequences



First burst indicating the minimum





Environmental perception with CRFs









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Neural communication for sensor networks







Neural communication for sensor networks



Problem

- Communication in sensor networks is omnidirectional
- In neural networks, the missing of edges is vital for the network's computational power





Neural communication for sensor networks



Proposal

Transmit beamforming to establish dedicated links





Example closed-loop carrier synchronization



Too computationally expensive for parasitic operation

⁵Y. Tu and G. Pottie, Coherent Cooperative Transmission from Multiple Adjacent Antennas to a Distant Stationary Antenna Through AWGN Channels, Proceedings of the IEEE VTC, 2002





Example open-loop carrier synchronization



Too computationally expensive for parasitic operation







⁶ R. Mudumbai, G. Barriac and U. Madhow, On the feasibility of distributed beamforming in wireless networks, IEEE Transactions on Wireless Communications, 2007

⁷ Sigg, El Masri and Beigl, A sharp asymptotic bound for feedback based closed-loop distributed adaptive beamforming in wireless sensor networks, IEEE Transactions on Mobile Computing, 2013





- Weak multimodal fitness function
- Single local=global optimum



Stephan Sigo

February 24, 2017



















0.8-0.6-0.4-<u>E</u> 0.2-

-0.4 -0.6

0









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Thank you!

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