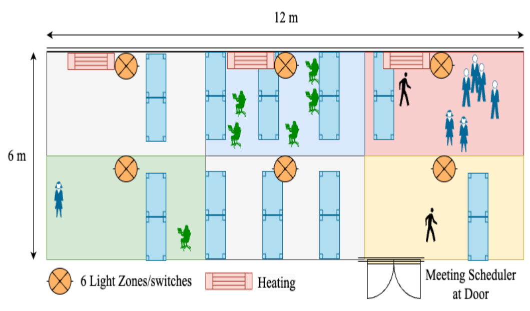
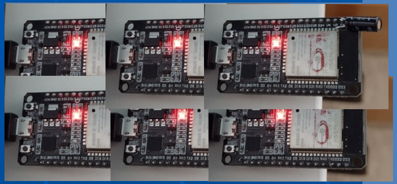
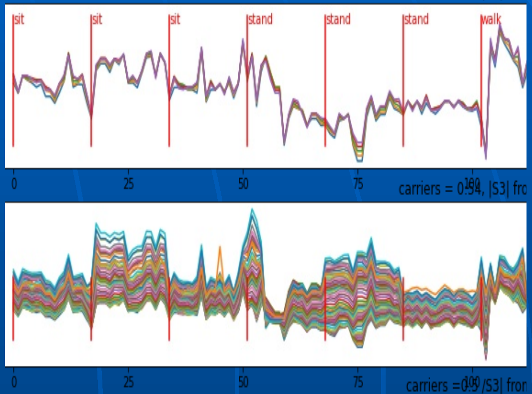
Pos Doc - ITIV-KIT Karlsruhe
Jan. 2022 – Mar. 2023







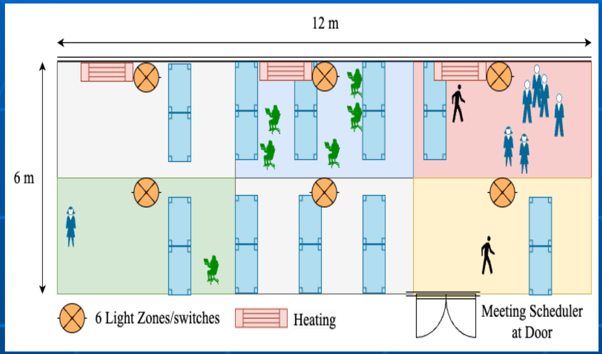
Few Shot CSI Learning for Occupancy-based Energy Efficient Smart Buildings

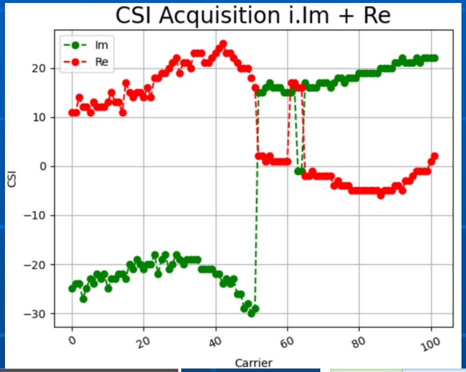
Auditório ENE – 7/7/2023 15:00

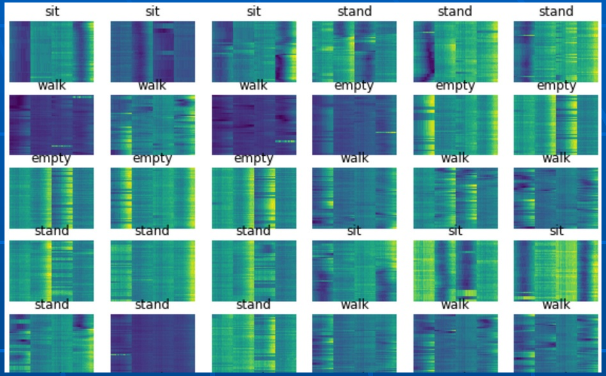
Prof. Adolfo Bauchspiess

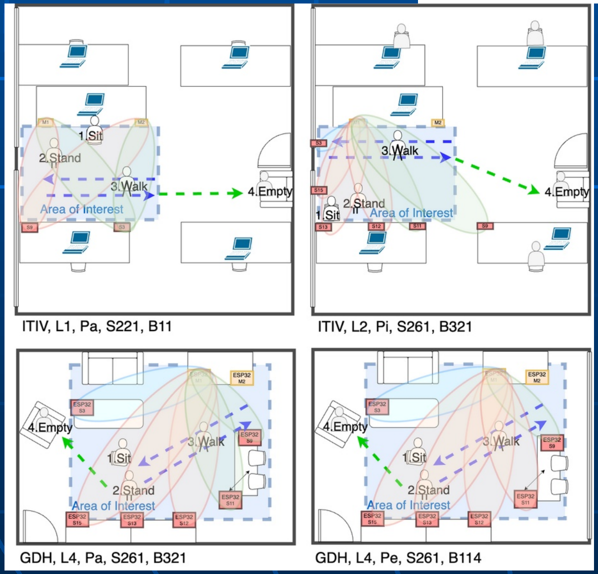
Comissão de IA do Departamento de Engenharia Elétrica
Universidade de Brasília - Brazil

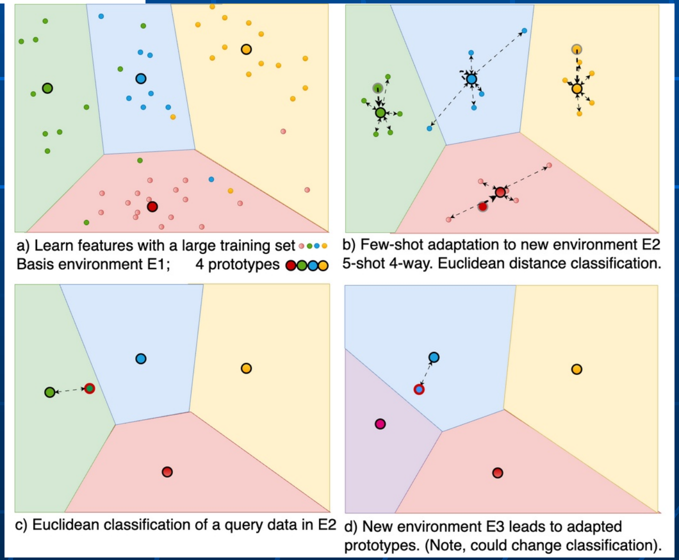
Visual Summary











Summary

1 – IITIV KIT Karlsruhe Germany

2 – Background (Some previous UnB Projects)

- MBPC Sensor-guided robotic manipulators
- PROBRAL – AmI Ambient Intelligence
- Energy Savings in Buildings (Hybrid Climatization)
- Zero Energy Buildings

3 – WiFi Sensing

- CSI
- HAR
- CC

4 – Research at itiv.kit.edu

- ESP32 CSI ESP-Now
- MIMI CSI with Wireless Sensor Network
- CNN/Few Shot activity estimation
- Cross-Domain – Location/Person/Environment

5 – Machine Learning Challenges & Perspectives

ITIV KIT Karlsruhe

Karlsruhe - Germany

ITIV-KIT

GDH (Hotel Tr.)
Heinrich Hertz

Karlsruher Institut für Technologie

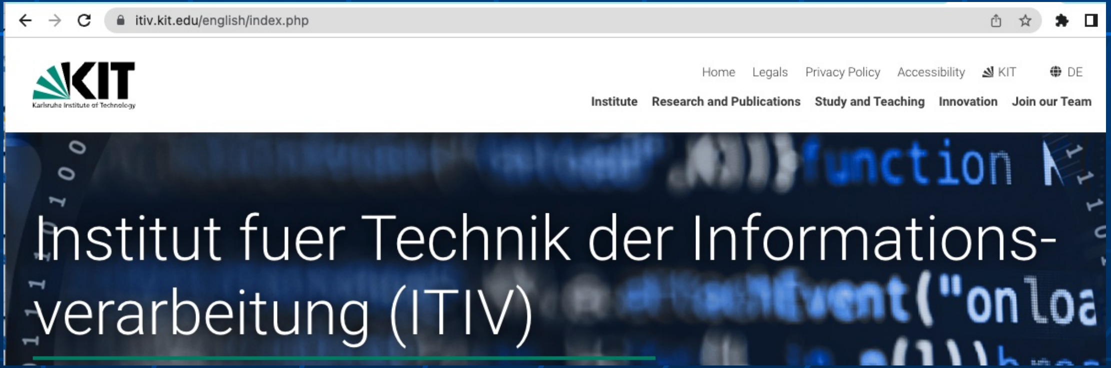
11 Faculdades
43 cursos
~23.500 Alunos

kit.edu 2009
Univ. Karlsruhe:
1824

6 prêmios Nobel

- Matemática
- Química e Biologia
- Sociologia
- Arquitetura
- Física
- Engenharia Civil, Geologia e Ecologia
- Engenharia Mecânica
- Engenharia Química
- Engenharia Elétrica
- Informática
- Administração

Heinrich Hertz – descoberta das ondas eletromagnéticas (comprovação experimental das leis de Maxwell)



ITIV-KIT (Christmas confraternization 2022)

Background

(Some previous UnB Projects)

Short CV - Adolfo Bauchspiess

- Electrical Engineering, M.Sc. ENE/UnB (1986, 1990)
- NOVADATA Sistemas e Computadores (1986-1990)
- Dr.-Ing. Universität Erlangen-Nürnberg/Germany (1991-1995)
- Electrical Engineering Department – FT – UnB (1995 -)

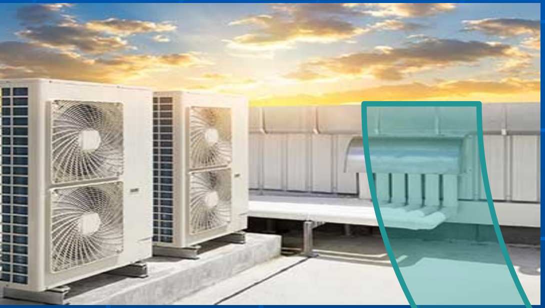
Post Doc:

Karlsruhe 2005-2006 – Prof. Litz, Ambient Intelligence
Santa Barbara 2014 – Prof. Hespanha, Networked Control Systems, RL
Karlsruhe 2022-2023 – Prof. Becker, CSI Few Shot ESP32

Lectures at UnB

- Control of Dynamic Systems
- Identification of Dynamic Systems
- Computational Inteligence
- Building Automation with IoT

Buildings Sub-Systems



- ✓ HVAC
- ✓ Illumination
- ✓ Fire
- ✓ Energy Management
- ✓ Back-Up Power Gen.
- ✓ CC-TV
- ✓ Access Control
- ✓ Elevator/Escalator
- ✓ …

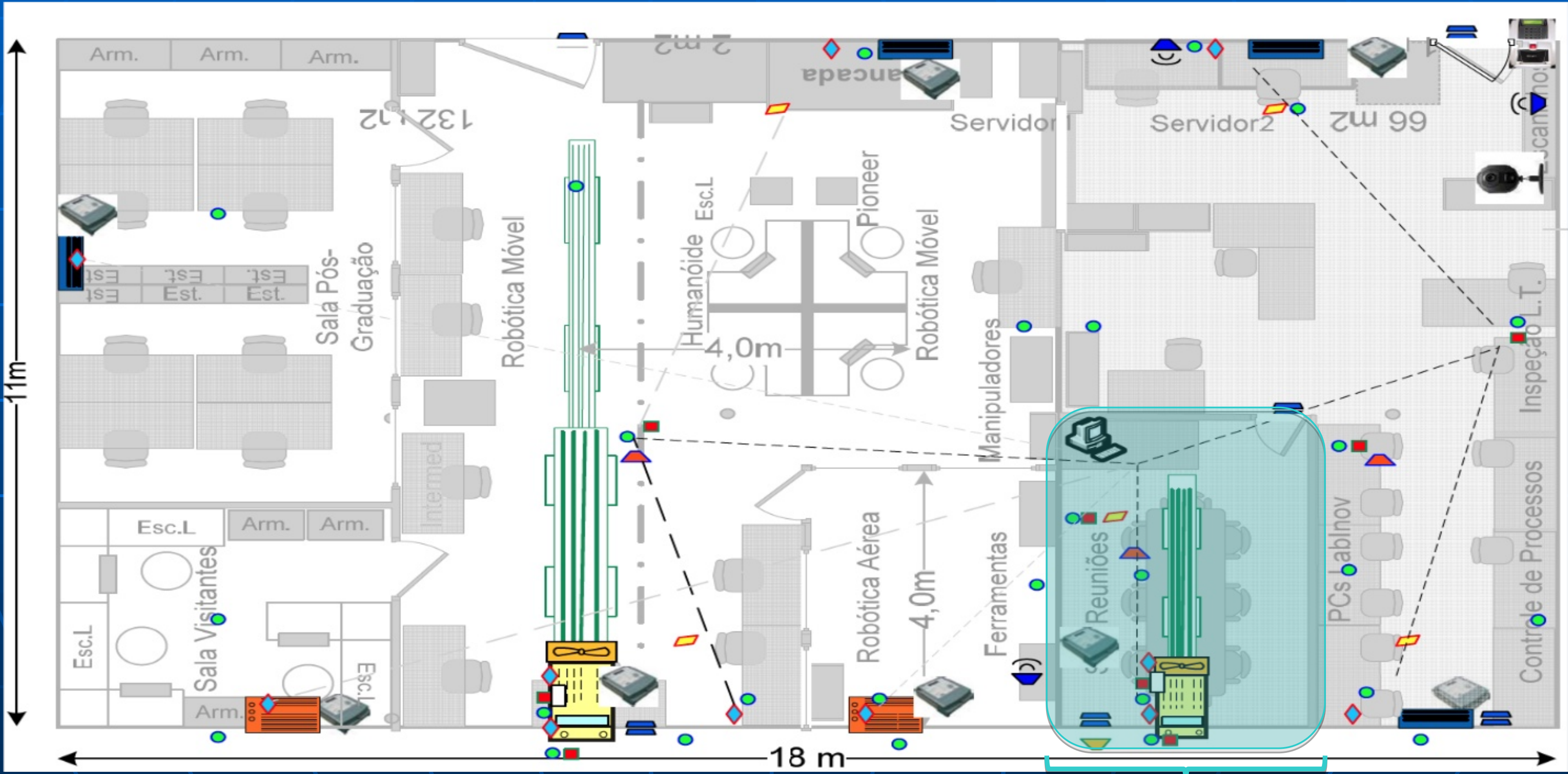
Building Automation- **Objectives**

- Safety
- access control
- CC-TV
- Fire detection
- Comfort (Productivity)
- temperature, humidity,… (PMV)
- illumination,
- waiting time for elevators, …
- Health issues
- air quality (renovation, filters…)
- CO_2

Energy Saving

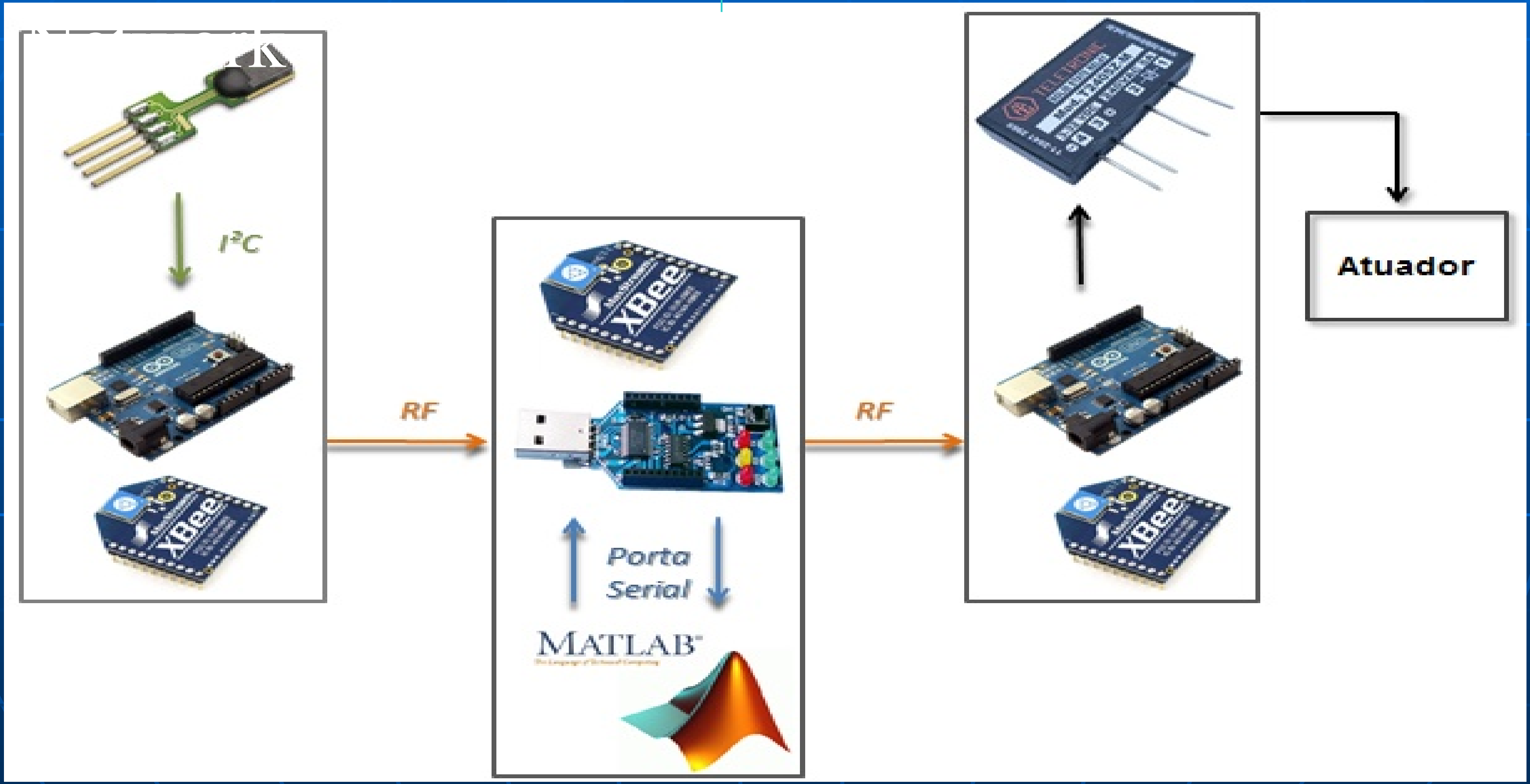
Adaptive Control

LARA/UnB
Brasília-BRAZIL



Meeting Room

ZigBee Automation



Adaptive Control

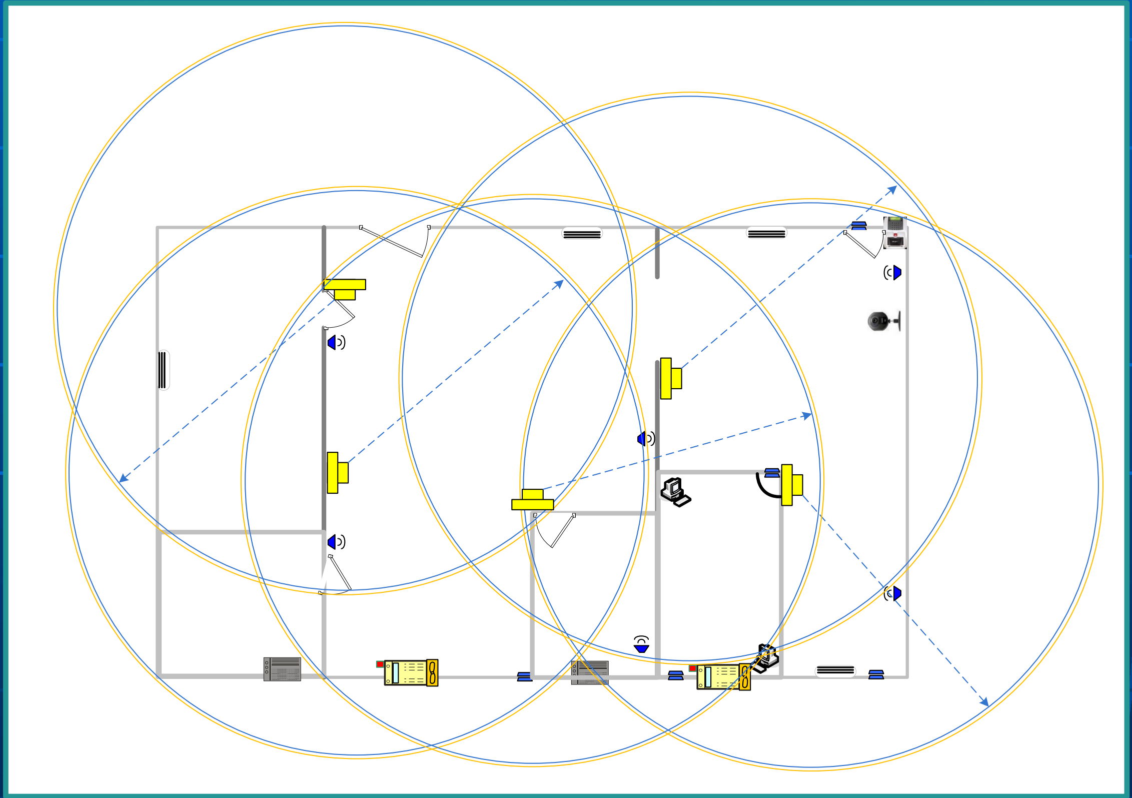
Thermal Load	ON-OFF Controller		PI Controller		Adaptive Controller	
	Error [RMS]	Energy [kWh]	Error [RMS]	Energy [kWh]	Error [RMS]	Energy [kWh]
Constant	0.14	6.69	1.55	3.12	0.53	3.42
Variable	0.12	7.89	1.18	4.84	0.43	4.63

Constant thermal load - empty meeting room's door kept closed. 8-hour runs

Variable thermal Load - occupancy change: meetings, studying, and vacancy periods.
Opening of the door -> large heat flow (process parameters change).

Adaptive controller: model based building climatization:
Lowest energy consumption (quick pay back)
Good thermal comfort
Extra hardware and software necessary

RFID occupancy identification for thermal load estimation

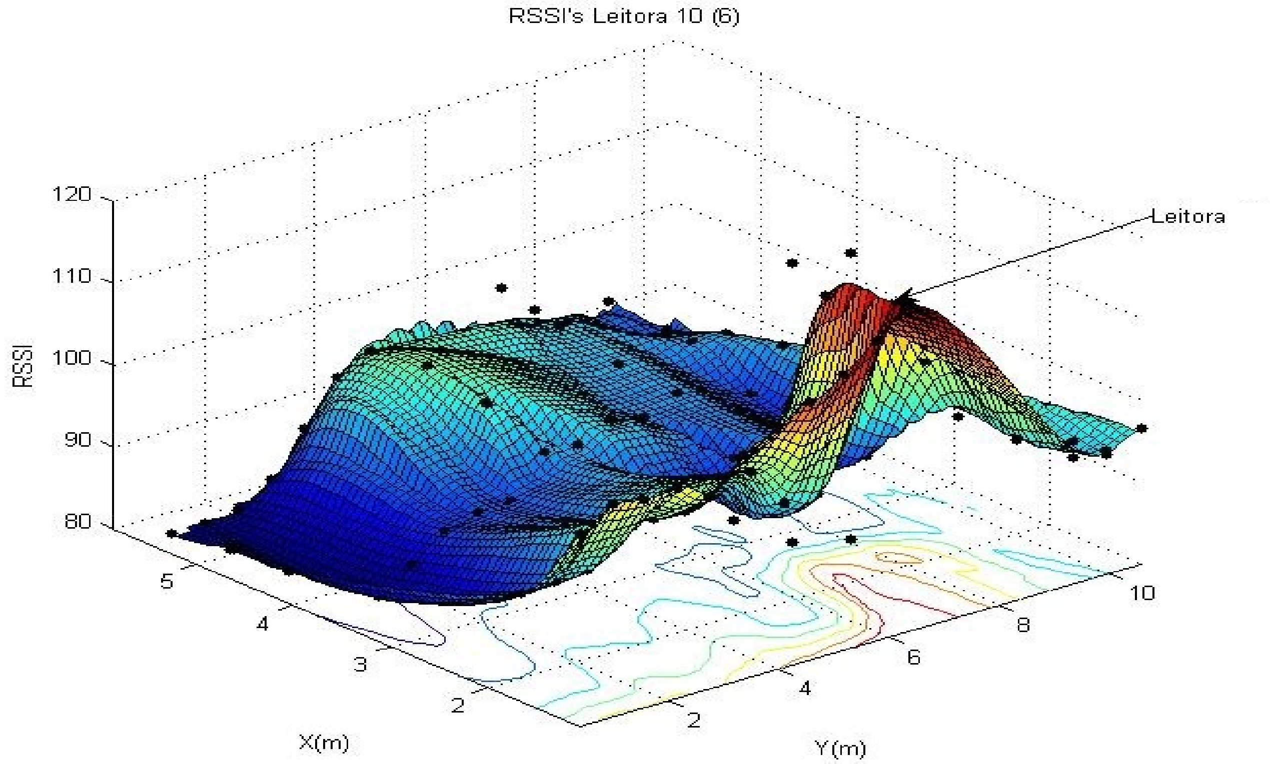


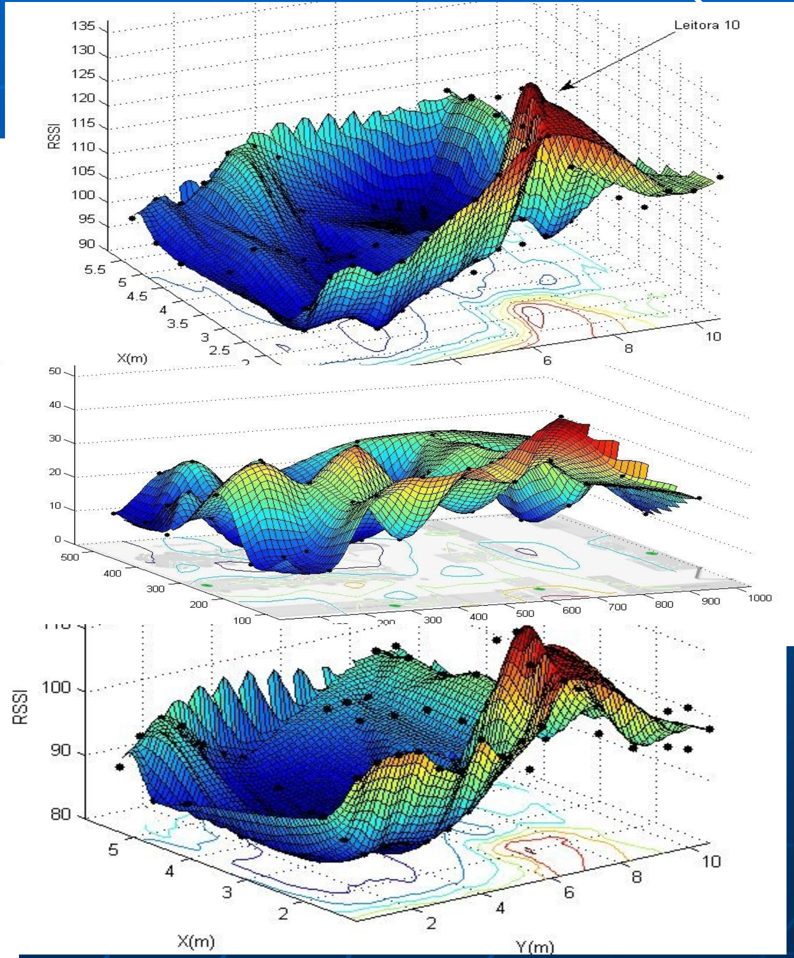
Active RFID Tags:
Battery, Microcontroller, Motion Detector

39 bytes datagram:
TagID, Age, RSSI, Interval

Eng. Josué Souza & Eng. Ariel Souza, 2011

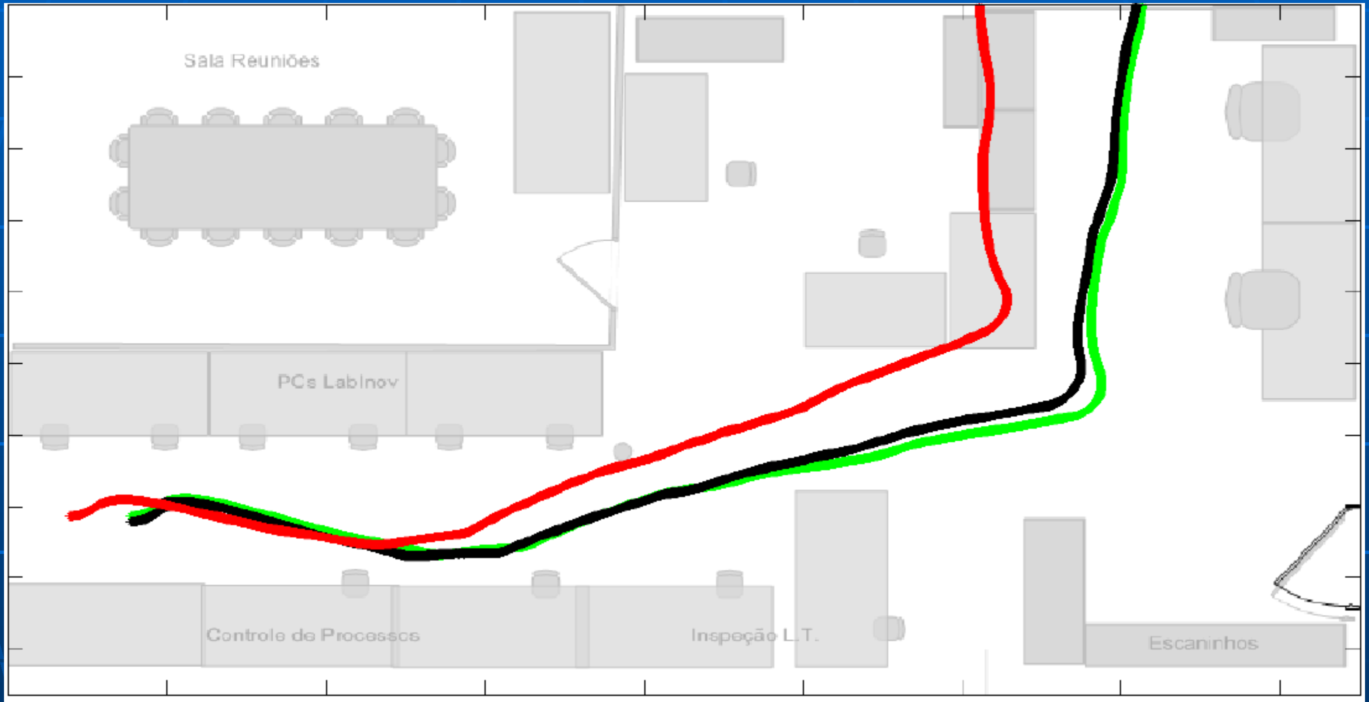
RSSI Mapping –
Data collected by Aramis Mobile Robot





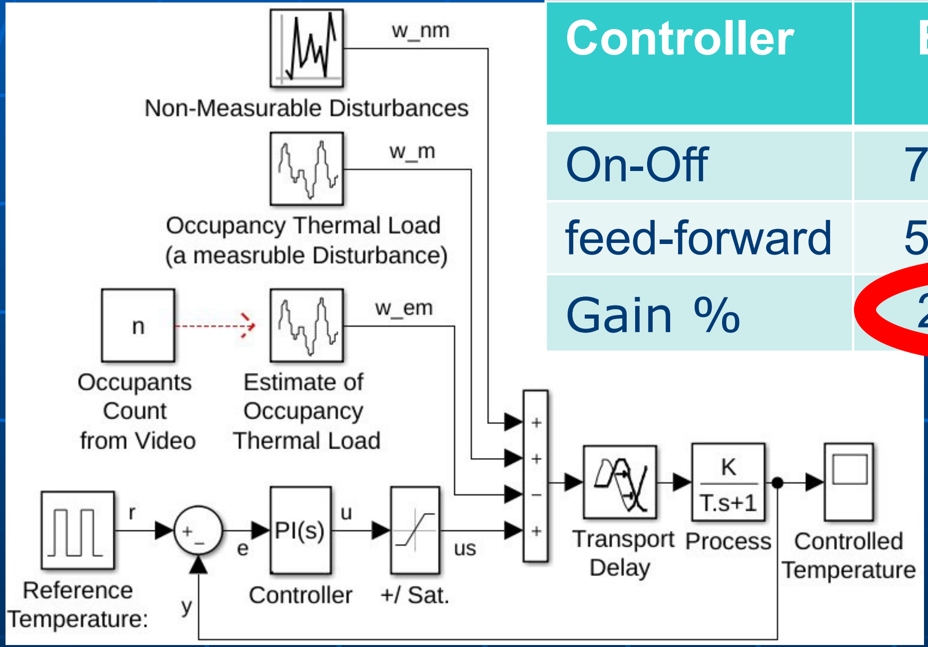
Interpolated Surfaces from measured RSSI

Comparison (Red: odometry, Black: +vision, Green: EKF Sensor Fusion)



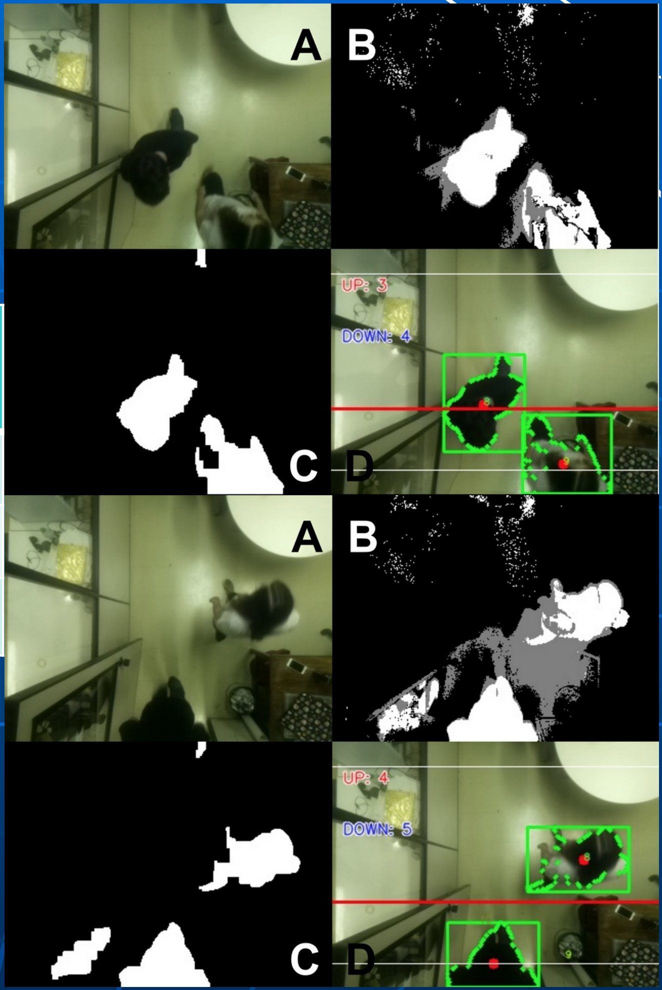
Odometry: mobile robot proprioceptive sensors
Vision: Augmented Reality with Beacons on the ceil
RFID RSSI system

Feed-Forward Disturbance Rejection by Video Thermal Load Estimation



Feed-forward thermal Control with video occupants estimate.

Controller	Energy	RMSE (Comfort)
On-Off	7,92 kWh	0,42
feed-forward	5,81 kWh	0,37
Gain %	26,64%	11,9%



Overhead camera-based occupants counting

1 Person = 0,116 kW

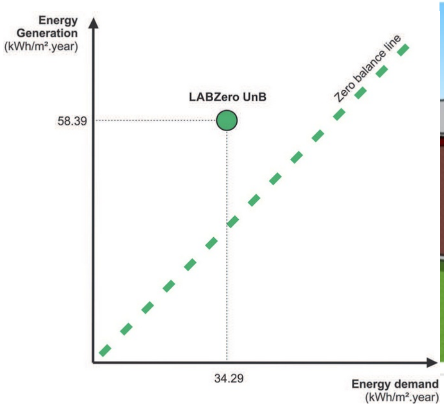
TG2018 Mariana Pimentel & Alexandre Saran

LabZero UnB – PROCEL Edifica Eletrobrás 2020

Demo Lab for nZEB
Buildings Energy Efficiency

Power to/from Power Company
  Photovoltaic (on-Grid)

Climatization (Zones):
- Ventilation nat./forced
- Evaporative
- Solar Chimney
- Geothermal
- Acqua Compressor



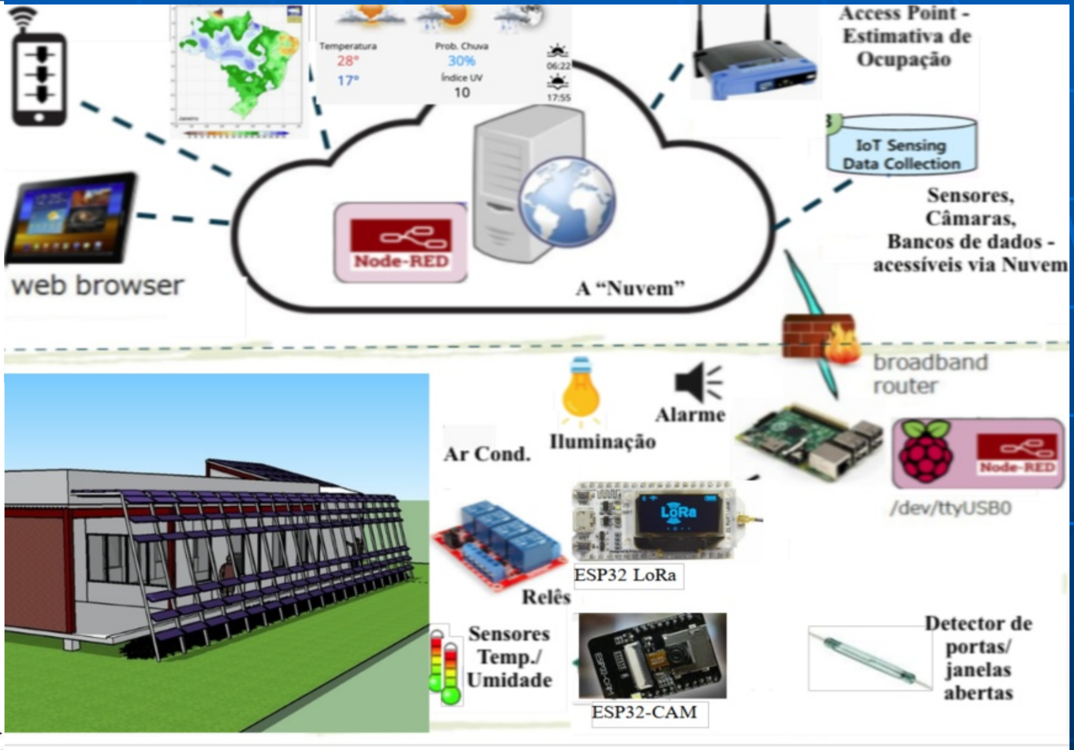
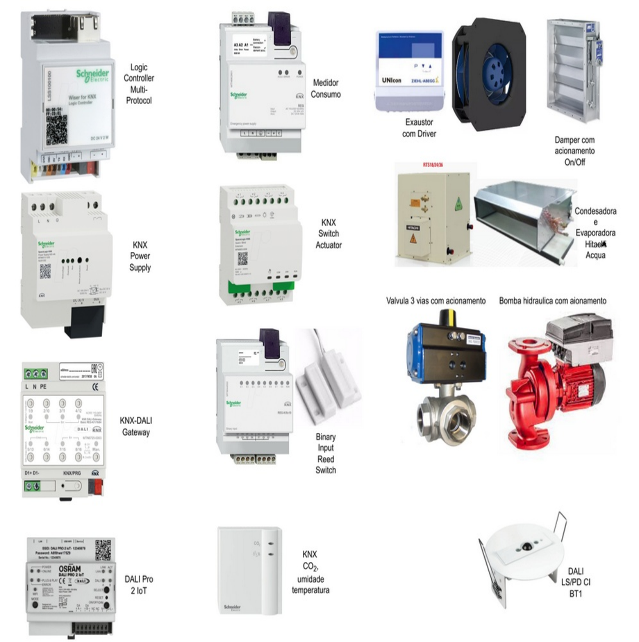
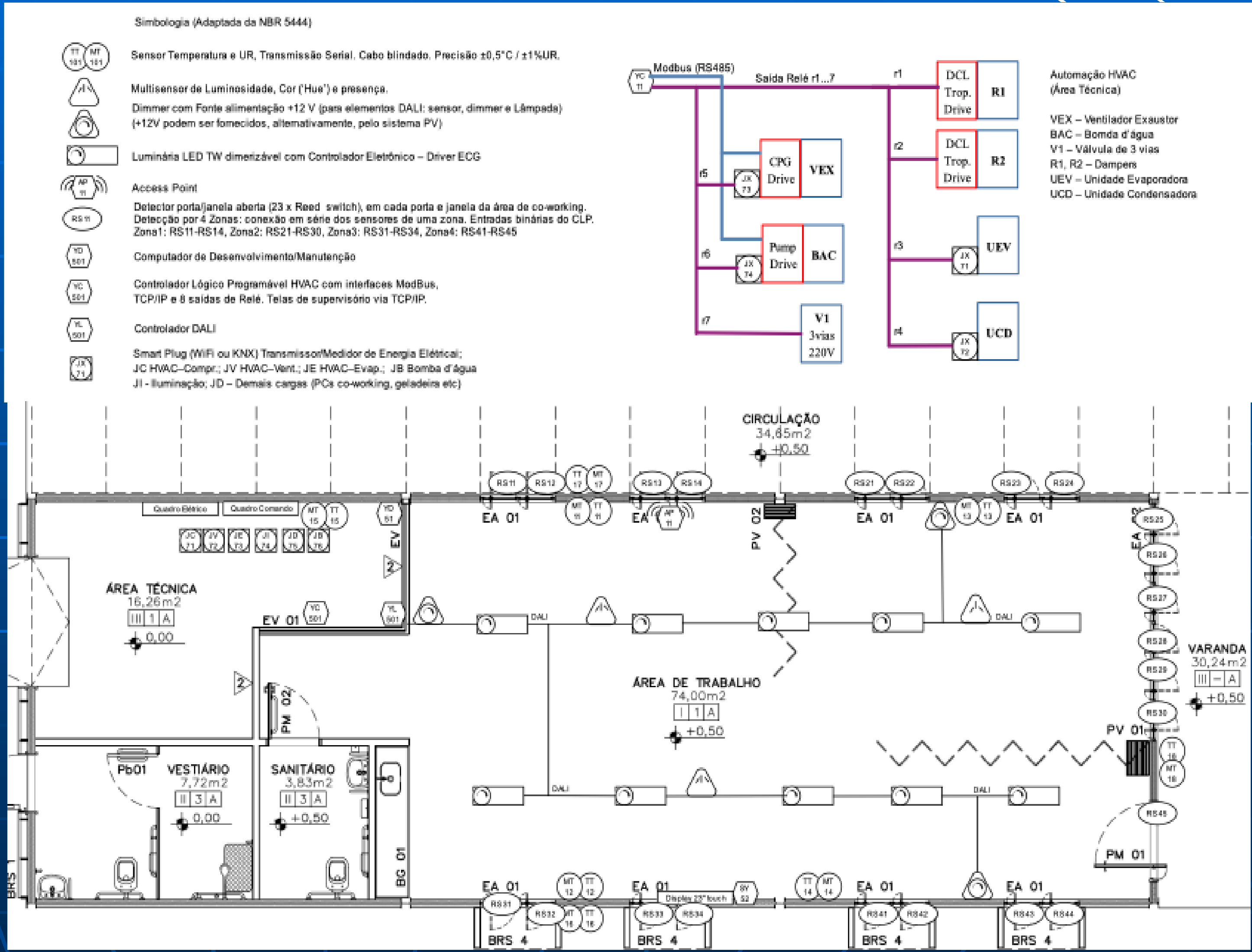


Figura 3.4.1 – Visão geral da automação do projeto Co-Working ZEB UnB.

LabZero UnB KNX automation





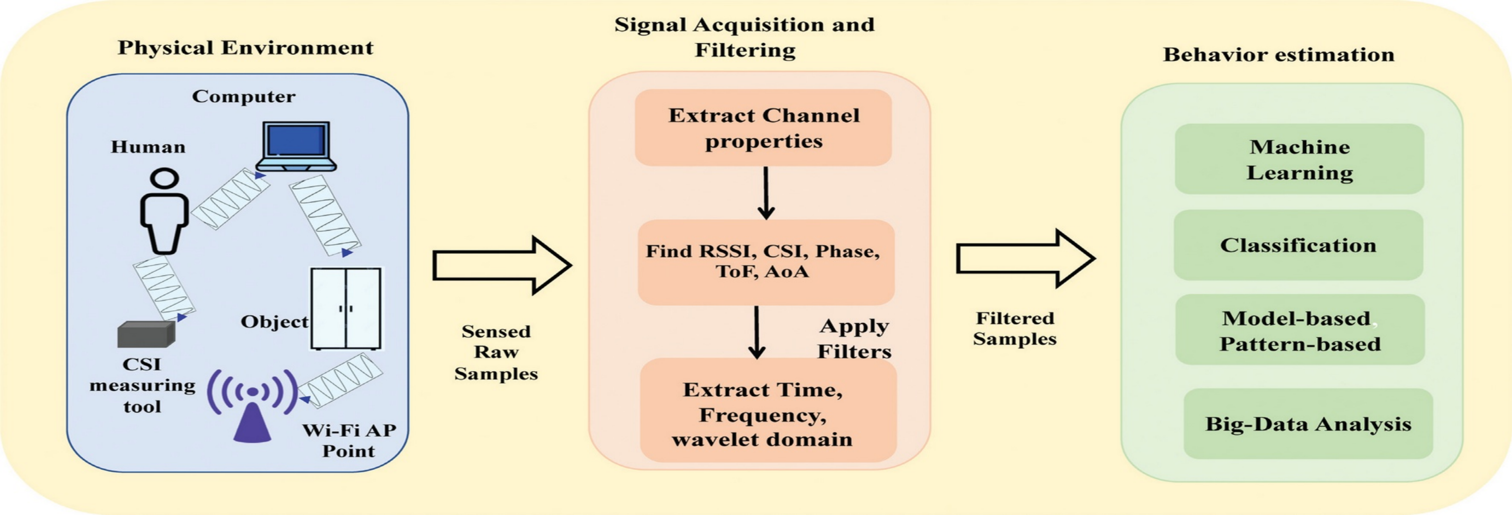
Cross Domain Transfer Learning

Ocupancy-Based Automation

WiFi-Sensing (CSI)

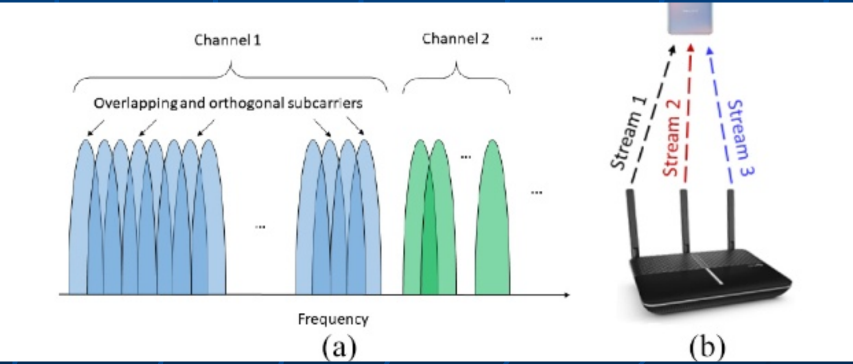
- HAR – Human Activity Recognition
- CC – Crowd Counting

CSI – Indoor Localization / Activity Detection



Atif et al., Wi-ESP—A tool for CSI-based Device-Free Wi-Fi Sensing (DFWS), Journal of Computational Design and Engineering, 2020, 7(5), 644–656 (KIST)

OFDM



WiFi – Sensing - Fresnel Zones

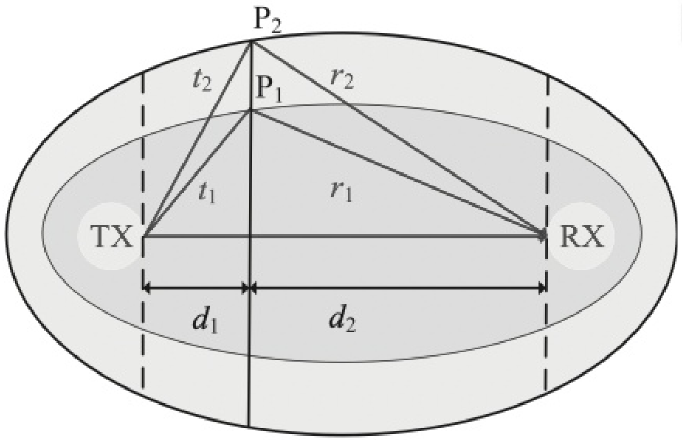
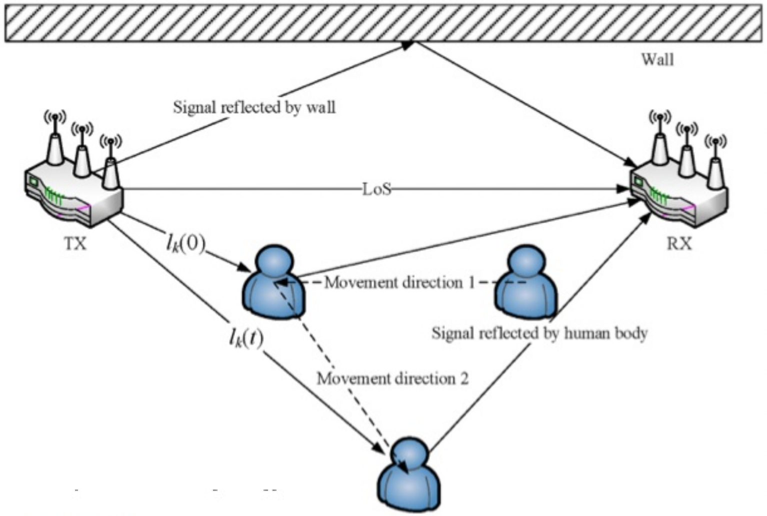
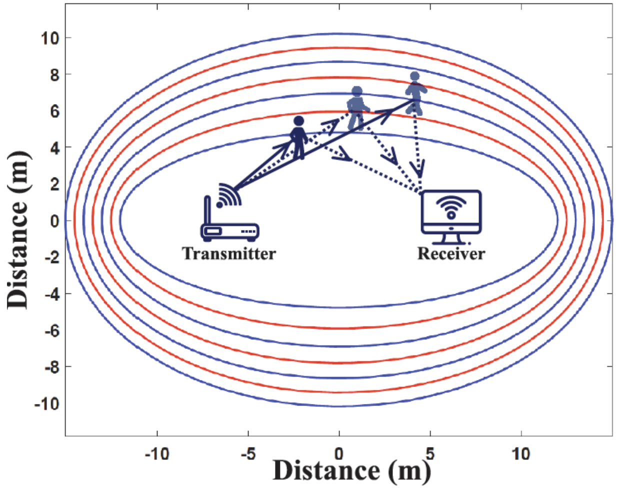
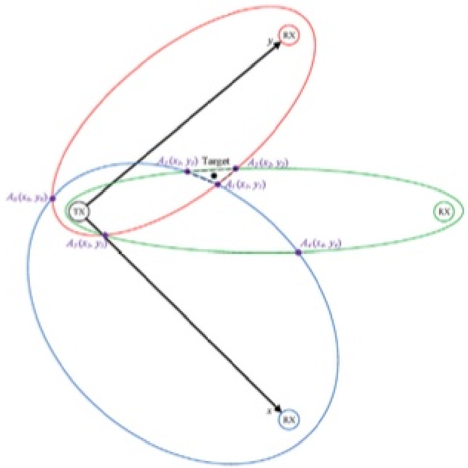


Fig. 4. Fresnel zones model.



Multipath in indoor environment.





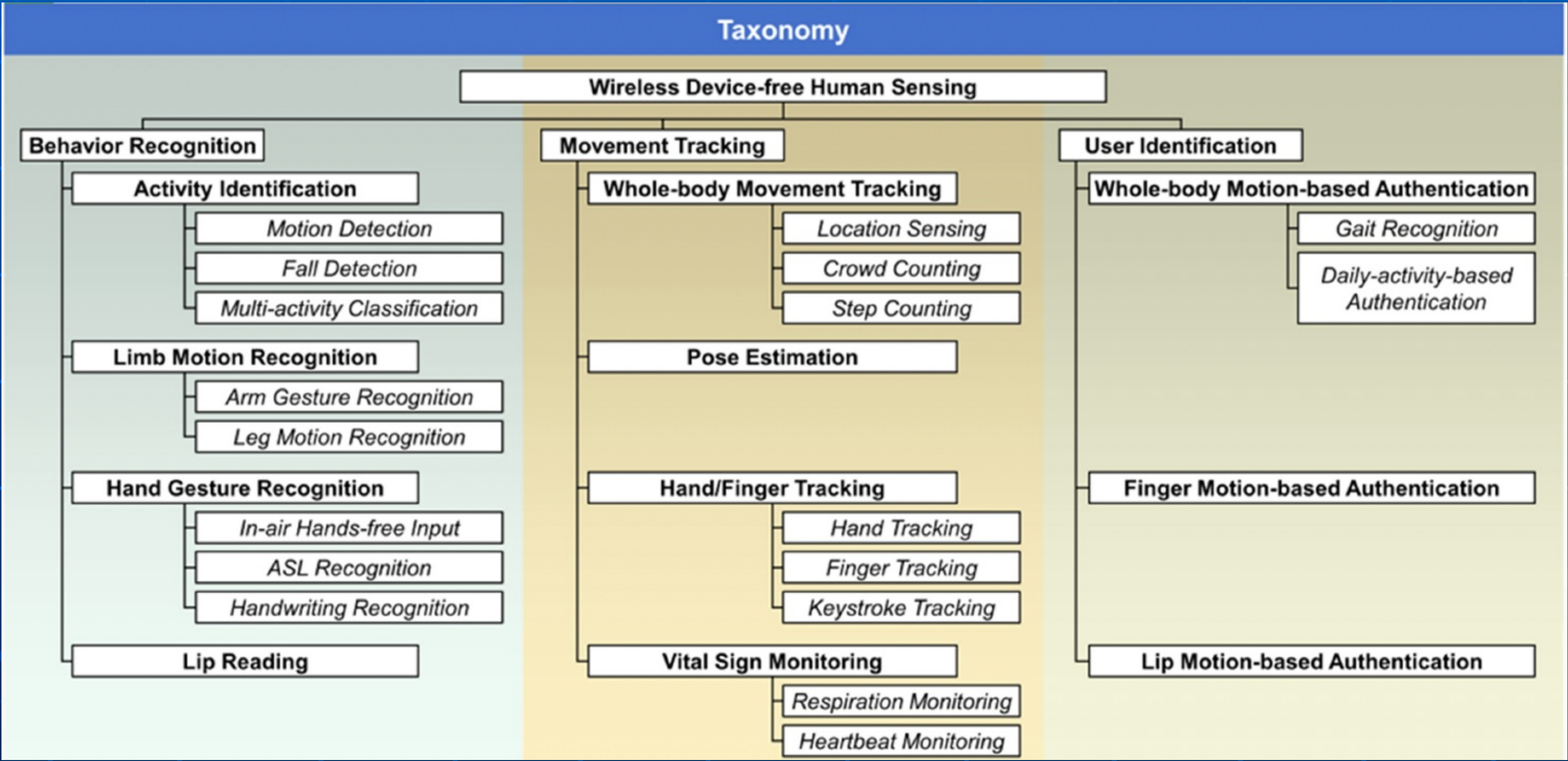
$$H = \begin{bmatrix} H_1(t_1) & H_1(t_2) & \cdots & H_1(t_N) \\ H_2(t_1) & H_2(t_2) & \cdots & H_2(t_N) \\ \vdots & \vdots & \ddots & \vdots \\ H_j(t_1) & H_j(t_2) & \cdots & H_j(t_N) \end{bmatrix}$$

$$t_n + r_n - (d_1 + d_2) = n \cdot \frac{\lambda}{2}$$

$$R_n = \sqrt{\frac{n \lambda d_1 d_2}{d_1 + d_2}}$$

2020 Fei et al., JNCA - Indoor static **localization** based on Fresnel zones model using COTS Wi-Fi

Taxonomy



Dec 2022 Xiao et al., ACM Computing Surveys, A Survey on **W**ireless **D**evice-free **H**uman **S**ensing: Application Scenarios, Current Solutions, and Open Issues

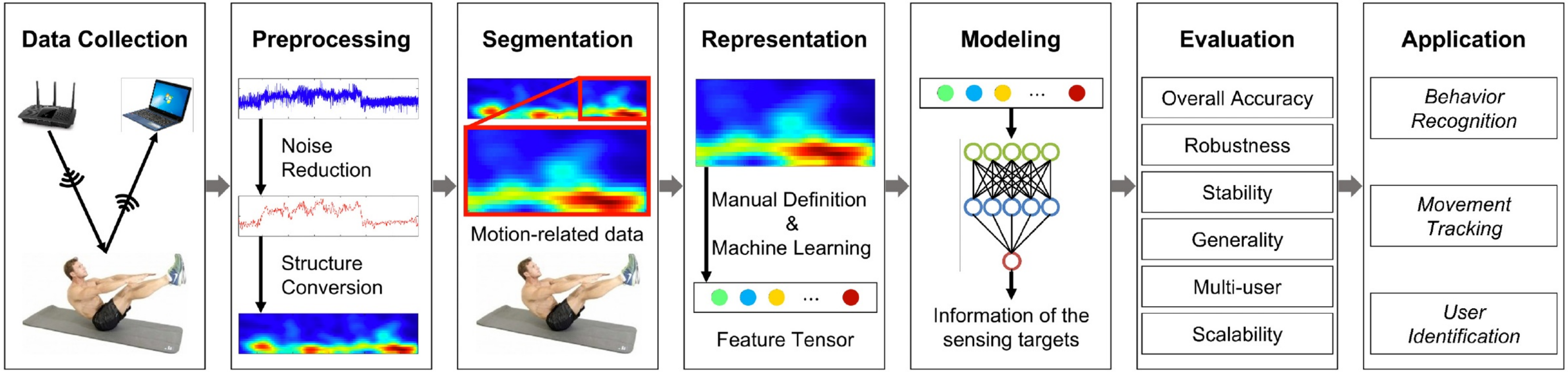
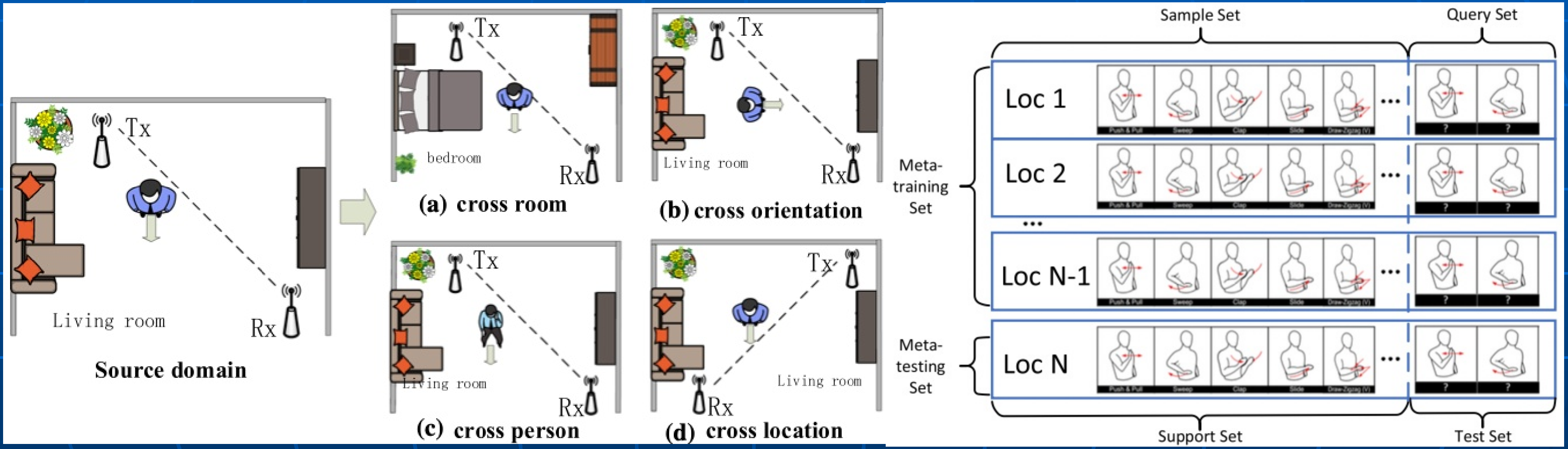


Fig. 2. Research framework of wireless device-free human sensing.

Cross-domain situations



2022 Gao, Soft Computing - ML-WiGR: a **meta-learning**-based approach for **cross-domain device-free gesture recognition**

CSI Counting

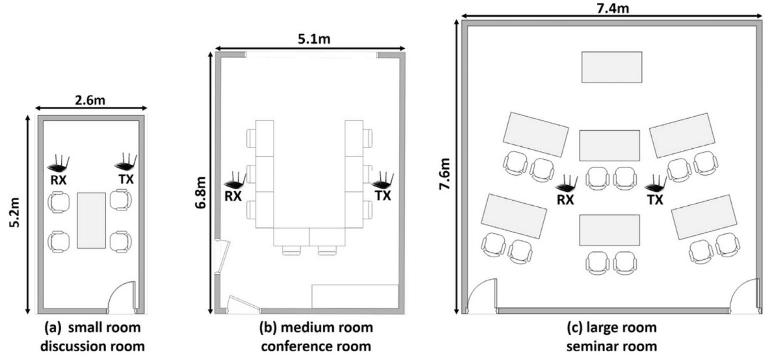


Fig. 5. Floor plans of the three indoor environments of disparate sizes where the experiments were conducted.

Fig. 6. System setup of WiFree.

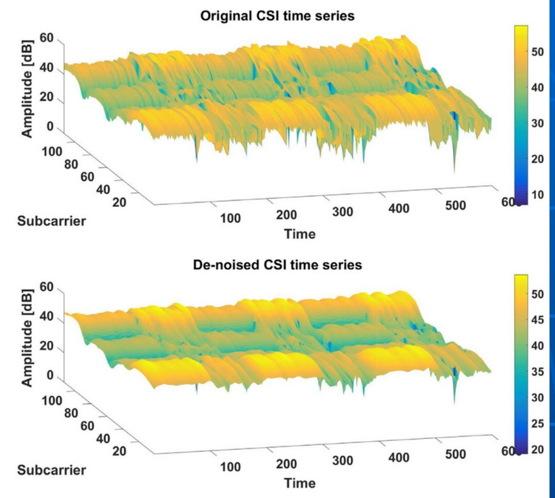


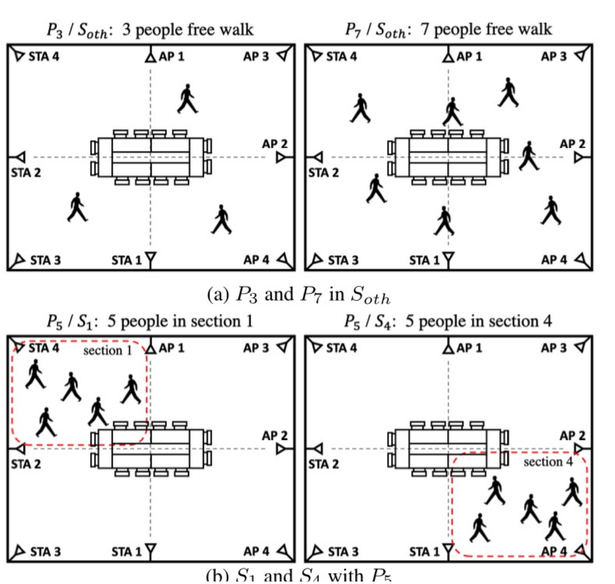
Fig. 7. De-noising performance of DWT.

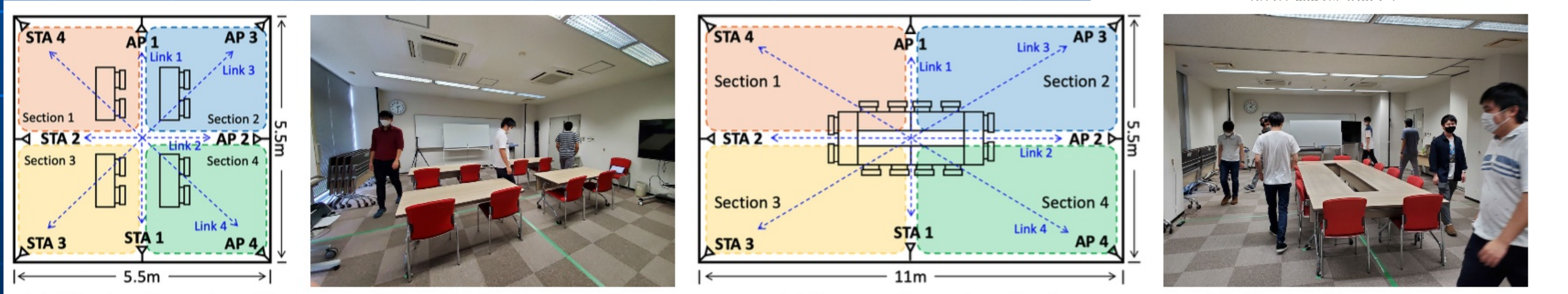
Ground Truth \ Estimation	Empty	O1	O2	O3	O4	O5	O6	O7	O8	O9	10	11
Empty	100	0	0	0	0	0	0	0	0	0	0	0
O1	0	99.7	0.2	0.1	0	0	0	0	0	0	0	0
O2	0	0.4	99.3	0.2	0.1	0	0	0	0	0	0	0
O3	0	0.3	0.1	98.8	0.7	0	0.1	0	0	0	0	0
O4	0	0.1	0	0.5	99.1	0.2	0	0	0.1	0	0	0
O5	0	0	0.2	0.3	0.3	98.4	0.6	0.2	0	0	0	0
O6	0	0	0.1	0.1	0	0.5	98.4	0.7	0	0	0.2	0
O7	0	0	0.1	0	0.1	0.4	0.2	98.1	0.6	0.5	0	0
O8	0	0	0	0	0.1	0	0	0.1	99.5	0	0.3	0
O9	0	0	0	0	0	0	0.2	0	1.1	97.8	0.4	0.5
10	0	0	0	0	0	0.1	0.2	0.1	0.3	1.3	97.6	0.4
11	0	0	0	0	0	0	0.1	0.1	0.1	1.1	1.3	97.3

(c) large room

2018 Zou et al. Energy&Buildings - Device-free occupancy detection and crowd counting in smart buildings with WiFi-enabled IoT.

ESP32 CSI Counting

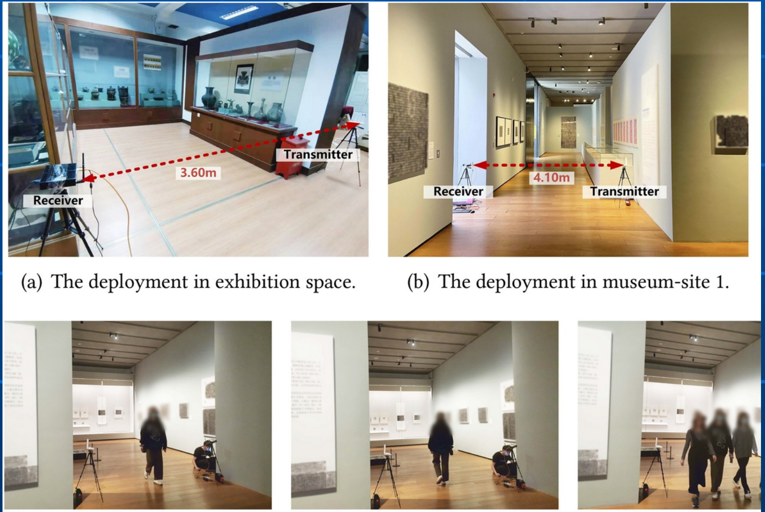




(a) Meeting Room (small) (b) Meeting Room (small) (c) Seminar Room (medium) (d) Seminar Room (medium)

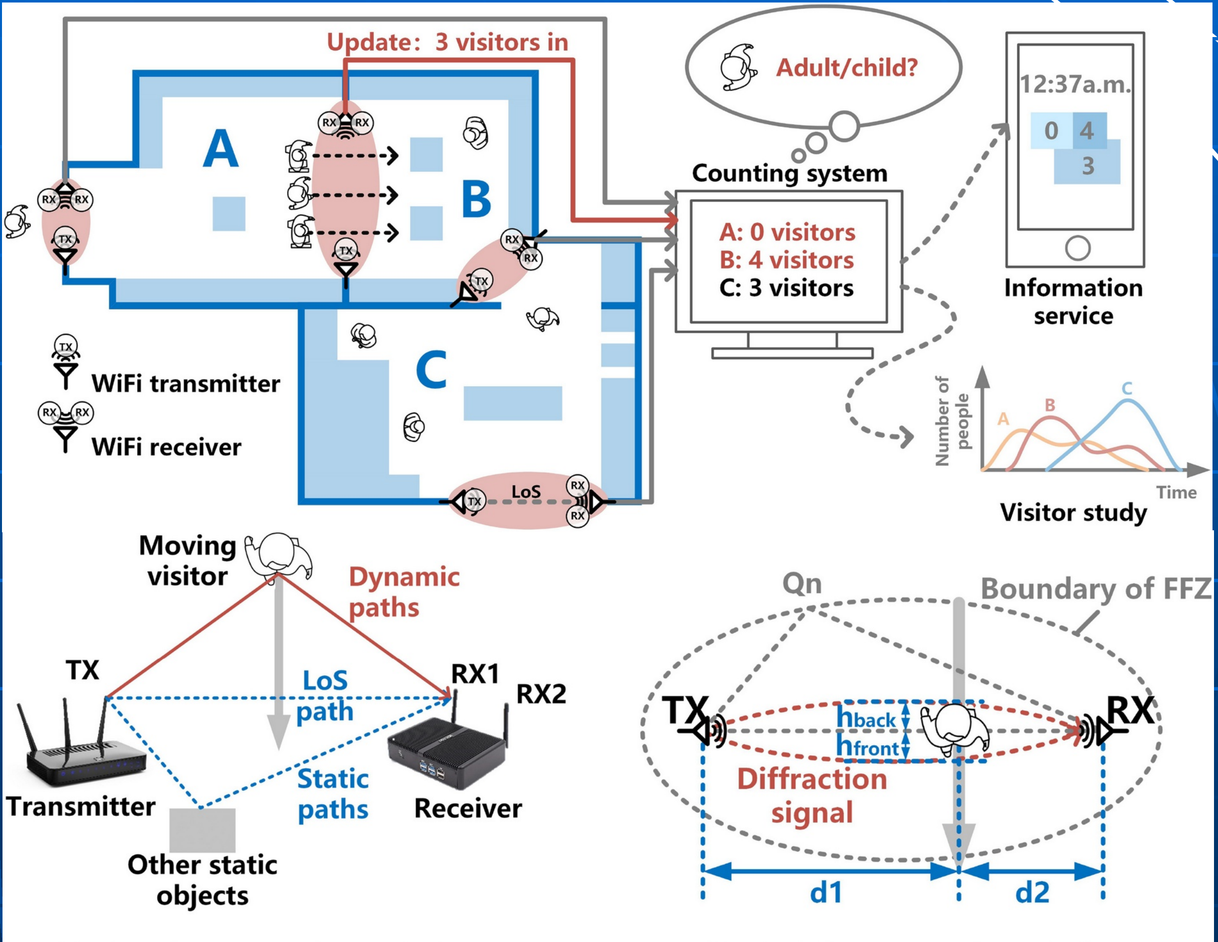
2022 Choi et al., IEEE Access, Wi-CaL_WiFi_Sensing_and_Machine_Learning_Based_Device-Free_Crowd_Counting_and_Localization

CSI Counting



(a) The deployment in exhibition space. (b) The deployment in museum-site 1.

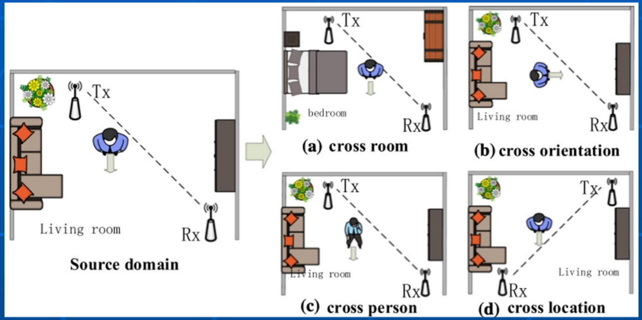
(d) Single target in. (e) Single target out. (f) 4 targets i

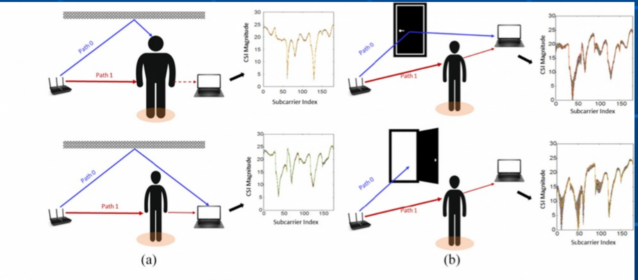


(a) The reflection signals outside the FFZ. (b) The diffraction signals inside the FFZ.

2023 Jiang et al. ACM - Towards Multi-area Contactless Museum Visitor Counting with Commodity WiFi.

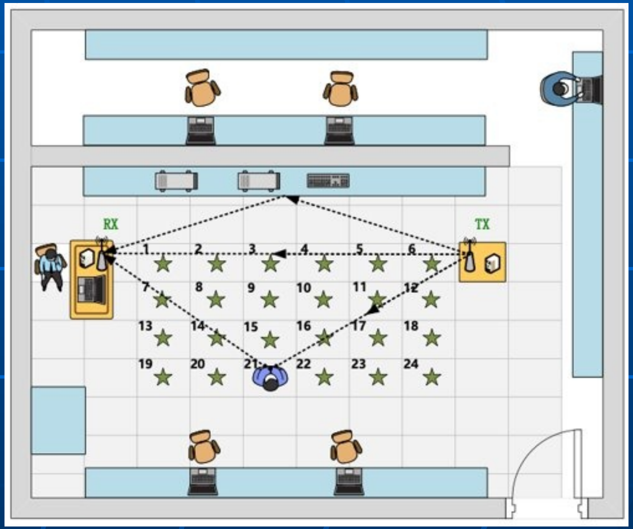
HAR - Human Activity Recognition





WiFi CSI fingerprint inconsistency across (a) different users and (b) environment changes.

Can **few shot** recognize Activities in different
- Locations?
- Orientations?
- Persons?
- Activities?
- Environments?



Classical Adjustments:
Fine2D reprojection of
the training configuration
Based on the localization estimation

Learning Strategies

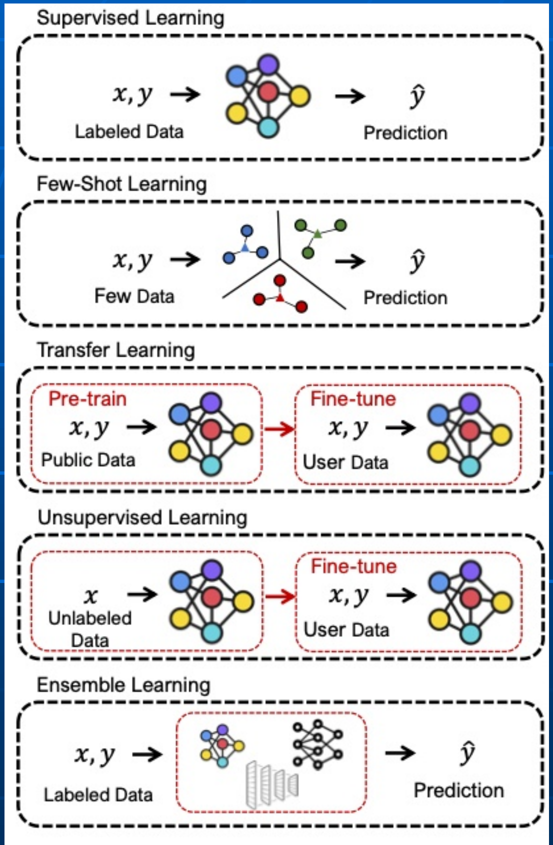
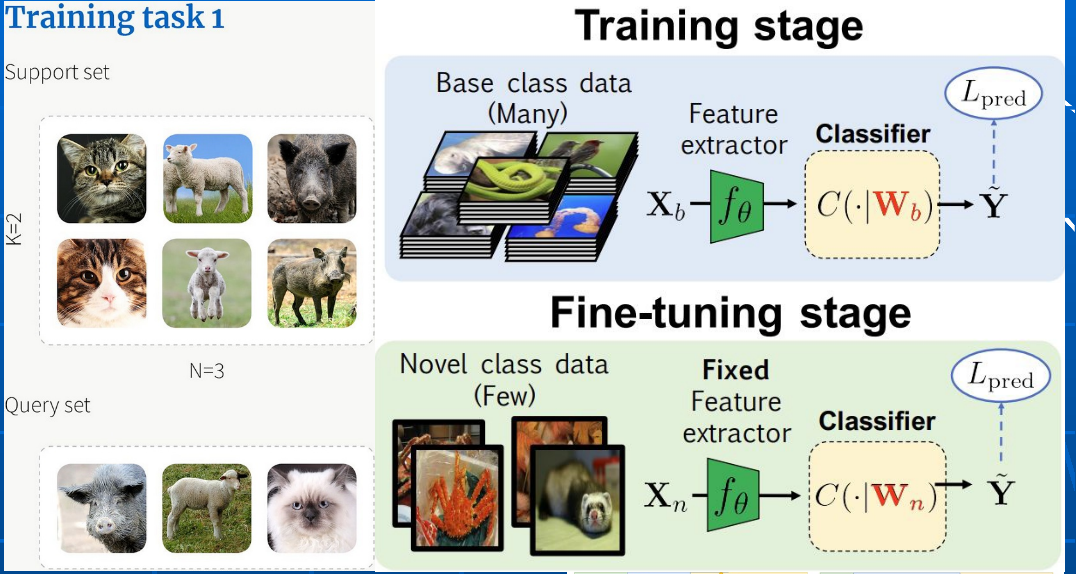


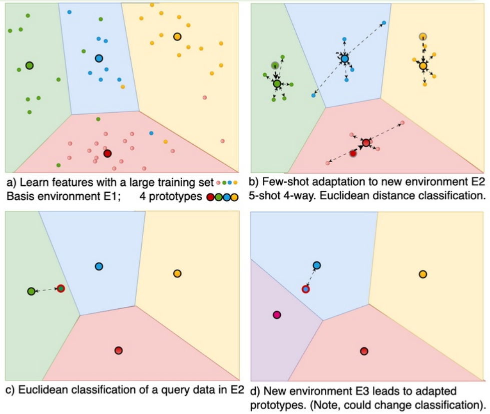
Fig. 4: The illustration of the learning strategies.



2019 Chen et al. ICLR, A Closer Look at Few-Shot Classification

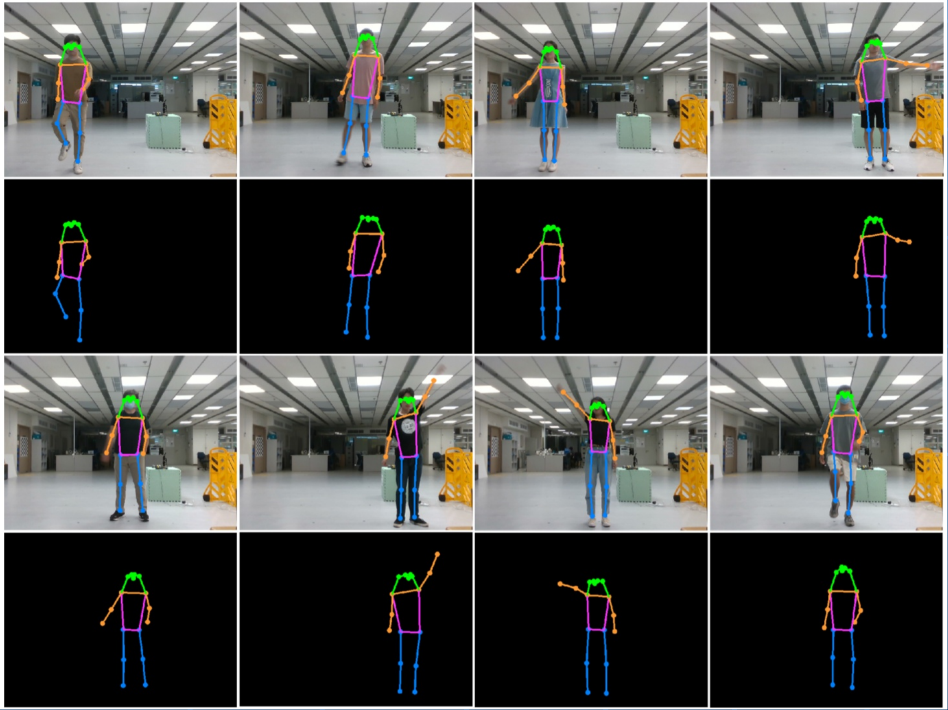
Few-shot classification
- ○ *N-way k-shot task*

- *Few-shot classification's training paradigms*
  - ○ *Baseline: transfer learning*
  - ○ *Meta-learning*
- *Meta-learning methods*
  - ○ *Distance metric based: Matching Net, Prototype Net, Relation Net*
  - ○ *Initialisation based: MAML (Model Agnostic Meta Learning)*
- *Empirical comparison between baseline and meta-learning methods*



2022 Yang, arXiv - Deep Learning and Its Applications to WiFi Human Sensing: A Benchmark and A Tutorial

2022 Yang Archive - MetaFi: Device-Free Pose Estimation via Commodity WiFi for Metaverse Avatar Simulation



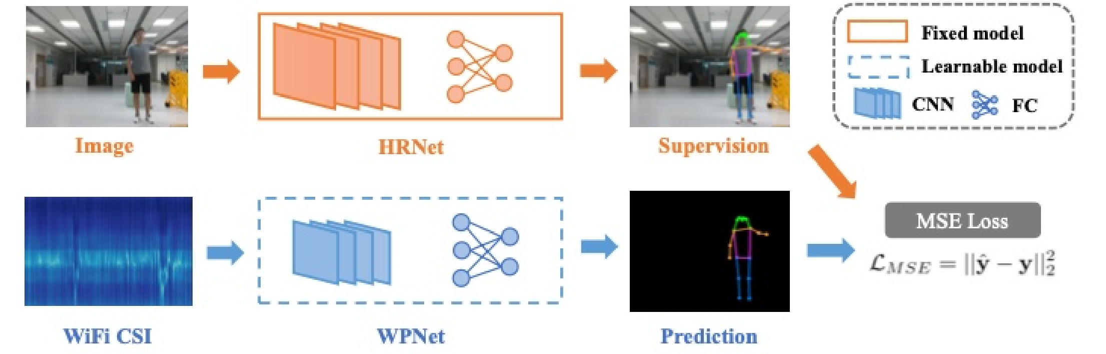


Fig. 2: Illustration of the MetaFi framework. The HRNet processes the video frame and extracts the pose annotation that is leveraged for cross-modal supervision of the WPNet.

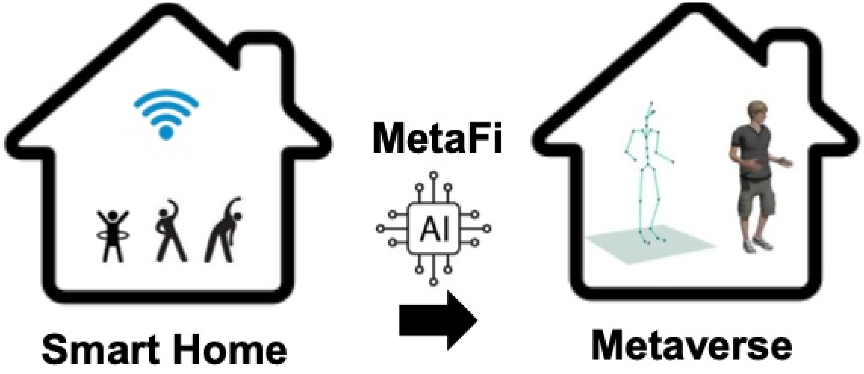
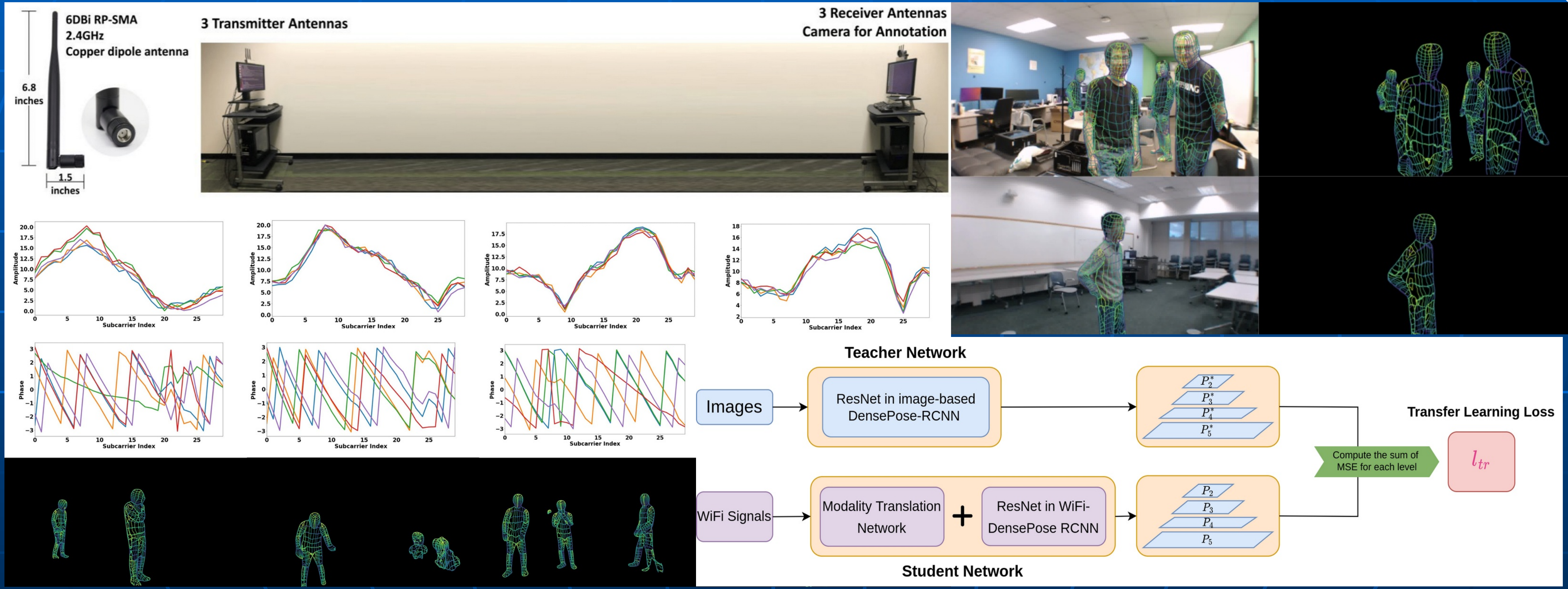


Fig. 1: Illustration of the MetaFi that connects smart home and metaverse using WiFi.

Geng2022 CMU-Archiv - Dense Pose From WiFi



deep neural network that maps the phase and amplitude of WiFi signals to UV coordinates within 24 human regions.

Deep Learning HAR

School of Electrical and Electronics Engineering, Nanyang Technological University, Singapore

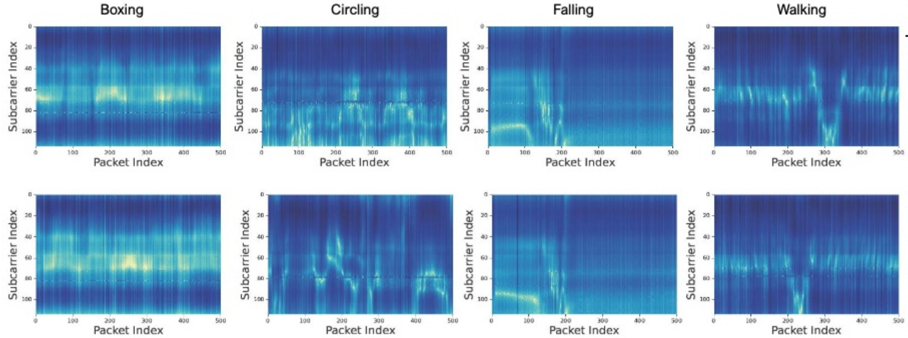


Fig. 2: The CSI samples of three human activities in NTU-Fi, collected by Atheros CSI Tool.

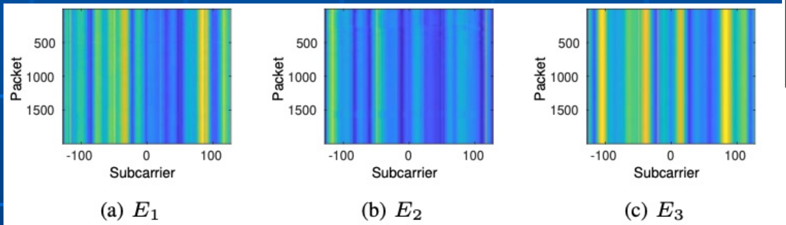
TABLE IV: Evaluations on Transfer Learning

Method	Accuracy (%)	Flops (M)	Params (M)
MLP	84.46	175.24	175.240
CNN-5	**96.35**	28.24	0.478
ResNet18	83.44	54.19	11.190
ResNet50	73.62	90.67	23.570
ResNet101	64.21	166.85	42.590
RNN	57.84	**13.09**	**0.027**
GRU	75.89	39.39	0.079
LSTM	71.98	52.54	0.105
BiLSTM	80.20	105.09	0.210
CNN + GRU	51.73	48.39	0.059
ViT	66.20	501.64	1.054

Method	Year	Task	Model
[30]	2017	Human Activity Recognition	RNN, LSTM
WiCount [40]	2017	People Counting	MLP
EI [41]	2018	Human Activity Recognition	CNN
CrossSense [29]	2018	Human Identification,Gesture Recognition	MLP
[42]	2018	Human Activity Recognition	LSTM
DeepSense [5]	2018	Human Activity Recognition	CNN-LSTM
WiADG [25]	2018	Gesture Recognition	CNN
WiSDAR [43]	2018	Human Activity Recognition	CNN-LSTM
WiVi [7]	2019	Human Activity Recognition	CNN
SiaNet [9]	2019	Gesture Recognition	CNN-LSTM
CSIGAN [44]	2019	Gesture Recognition	CNN, GAN
DeepMV [45]	2020	Human Activity Recognition	CNN (Attention)
WIHF [46]	2020	Gesture Recognition	CNN-GRU
DeepSeg [47]	2020	Human Activity Recognition	CNN
[48]	2020	Human Activity Recognition	CNN-LSTM
[35]	2021	Human Activity Recognition	LSTM
[49]	2021	Human Activity Recognition	CNN
[50]	2021	Human Activity Recognition	CNN
Widar [31]	2021	Human Identification, Gesture Recognition	CNN-GRU
WiONE [51]	2021	Human Identification	CNN
[52]	2021	Human Activity Recognition	CNN, RNN, LSTM
THAT [53]	2021	Human Activity Recognition	Transformers
WiGr [54]	2021	Gesture Recognition	CNN-LSTM
MCBAR [55]	2021	Human Activity Recognition	CNN, GAN
CAUTION [12]	2022	Human Identification	CNN
CTS-AM [56]	2022	Human Activity Recognition	CNN (Attention)
WiGRUNT [57]	2022	Gesture Recognition	CNN (Attention)
[58]	2022	Human Activity Recognition	LSTM
EfficientFi [33]	2022	Human Activity Recognition, Human Identification	CNN
RobustSense [59]	2022	Human Activity Recognition, Human Identification	CNN
AutoFi [60]	2022	Human Activity Recognition, Human Identification	CNN-MLP

2022 Yang, arXiv - Deep Learning and Its Applications to WiFi Human Sensing: A Benchmark and A Tutorial

Few Shot HAR
Majority Vote



(a) E_1 (b) E_2 (c) E_3

Fig. 3: CSI measurements of an empty room in the data collection environments described in Figure 5.

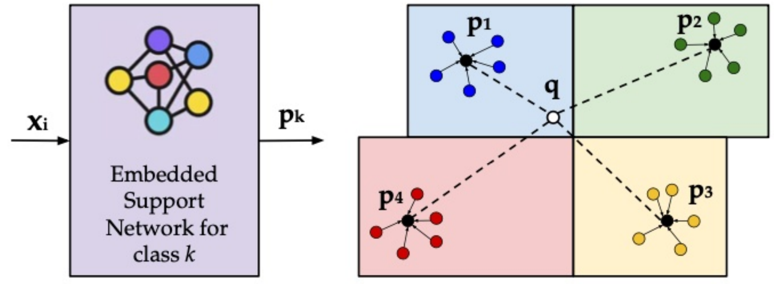
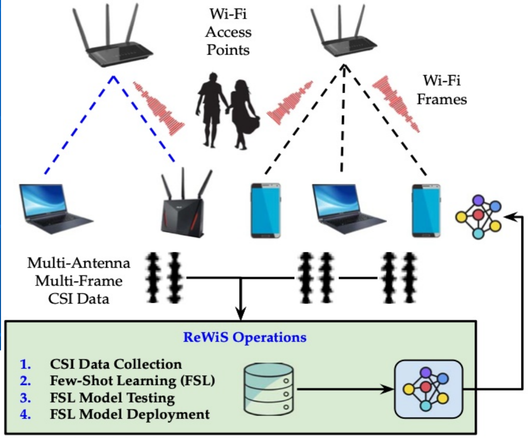


Fig. 4: Embedded Prototype Network.



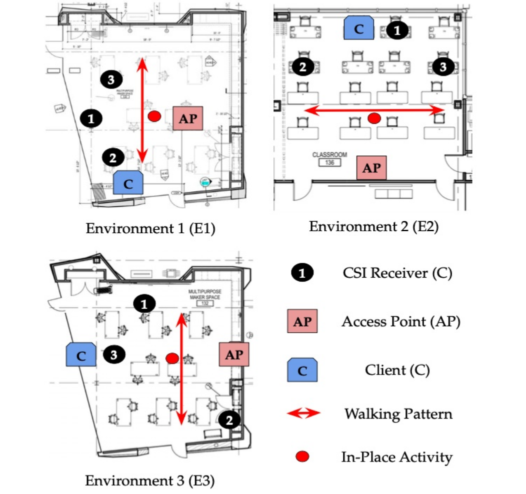
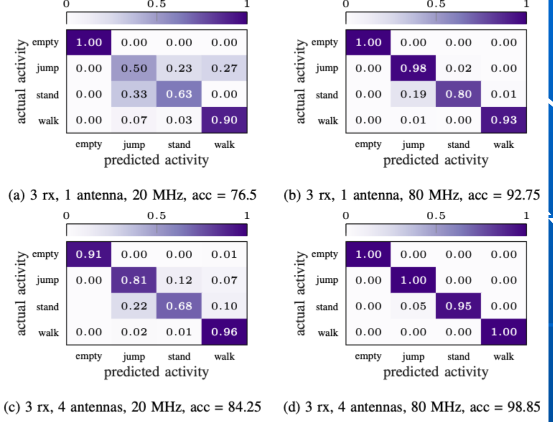


Fig. 5: Data collection and testing environments used in our experiments. We also report the legend of symbols used in the figure.



(a) 3 rx, 1 antenna, 20 MHz, acc = 76.5 (b) 3 rx, 1 antenna, 80 MHz, acc = 92.75

(c) 3 rx, 4 antennas, 20 MHz, acc = 84.25 (d) 3 rx, 4 antennas, 80 MHz, acc = 98.85

Fig. 8: Impact of frequency resolution and diversity, with one receiver. E_2 is the target environment.

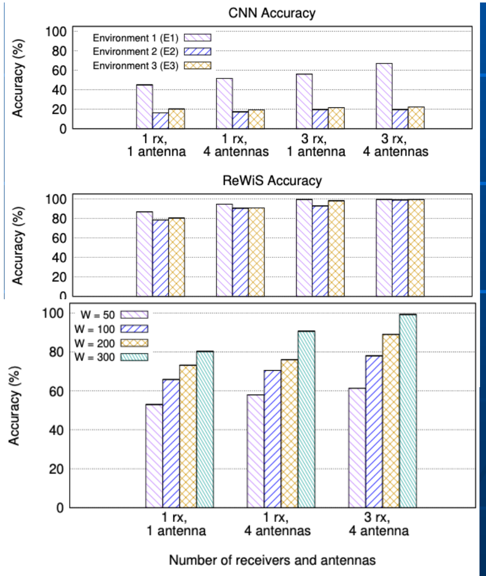


Fig. 10: Impact of diversity and window size.

2022 Bahadori WoWMoM - ReWiS_Reliable_Wi-Fi_Sensing_Through_Few-Shot_Multi-Antenna_Multi-Receiver_CSI_Learning

Research at ITIV.KIT

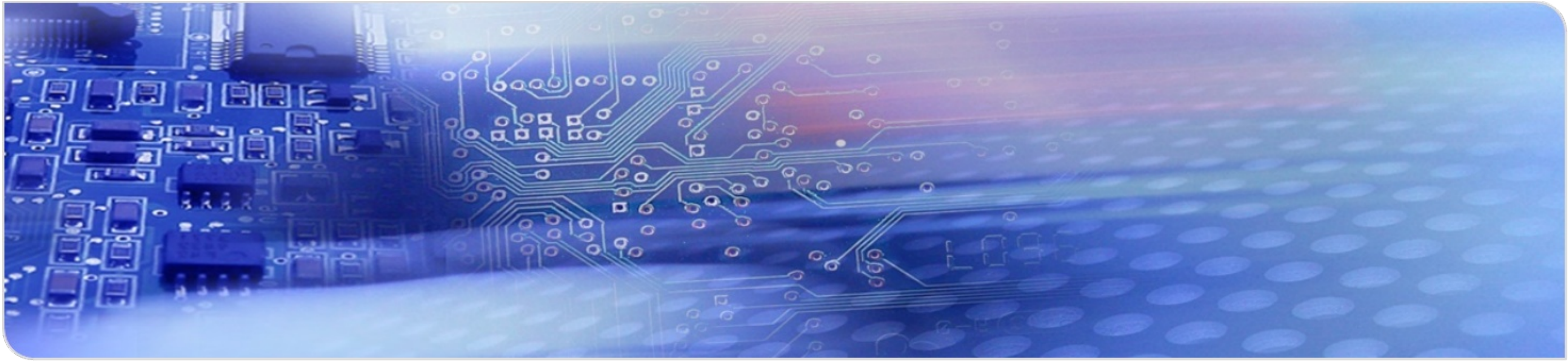
Occupancy-based Automation
- HAR Few Shot Transfer Learning

Karlsruhe Institute of Technology

Institut fuer Technik der Informationsverarbeitung

CSI-HAR261

- **Tanmay Mane** (cand. M.Sc.)
- **Boyang Li** (cand. M.Sc.)
- **Iris Fürst-Walter** (cand. Dr.-Ing.)
- **Adolfo Bauchspiess** (Post-Doc.)



Building Automation

Automation:
- Movement/Presence detector
- Radiators with individual thermostat
- Radiators with IoT connection
- Counting people at the door
- Counting people by zones
- **HAR by zones**
- Identify individual thermal load classes

Sensors:
- Presence Detector
- LUX Meters
- HCL - Human Centered Lighting by Zones
- WiFi "curtain" Counting (passing point monitoring)
- **CSI-based HAR - Human Activity Recognitiopn (area of interest)**
- Computer Vision

A combination of sensors could be used. Cameras rise privacy concerns.
In the illustration we expect the following, with growing accuracy, occupancy:

Occupancy Accounting:
- Door Sensor: 15 (total inside)
- By Zone: 0, 5, 7, 2, 0, 1
- By Activity: 6 Sitting 2 Walking 7 Standing 2 Empty Zones
- By Thermal Load: 9 small 6 medium

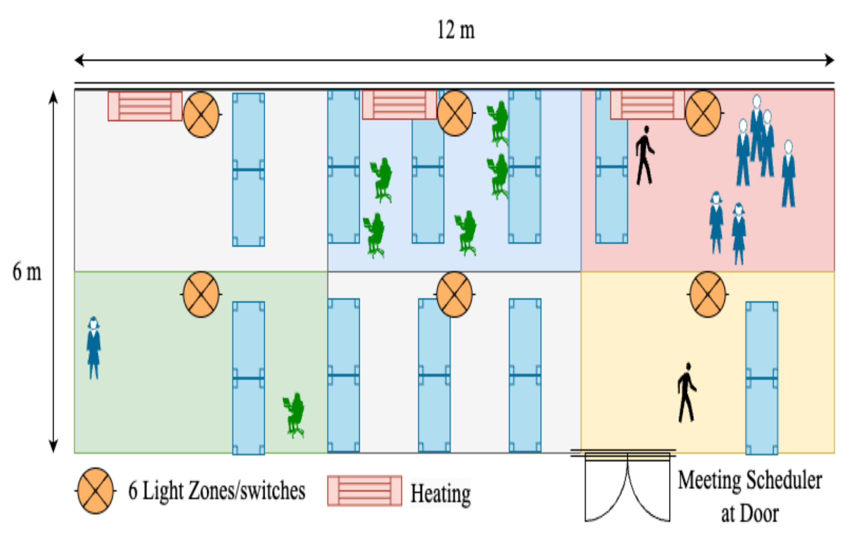
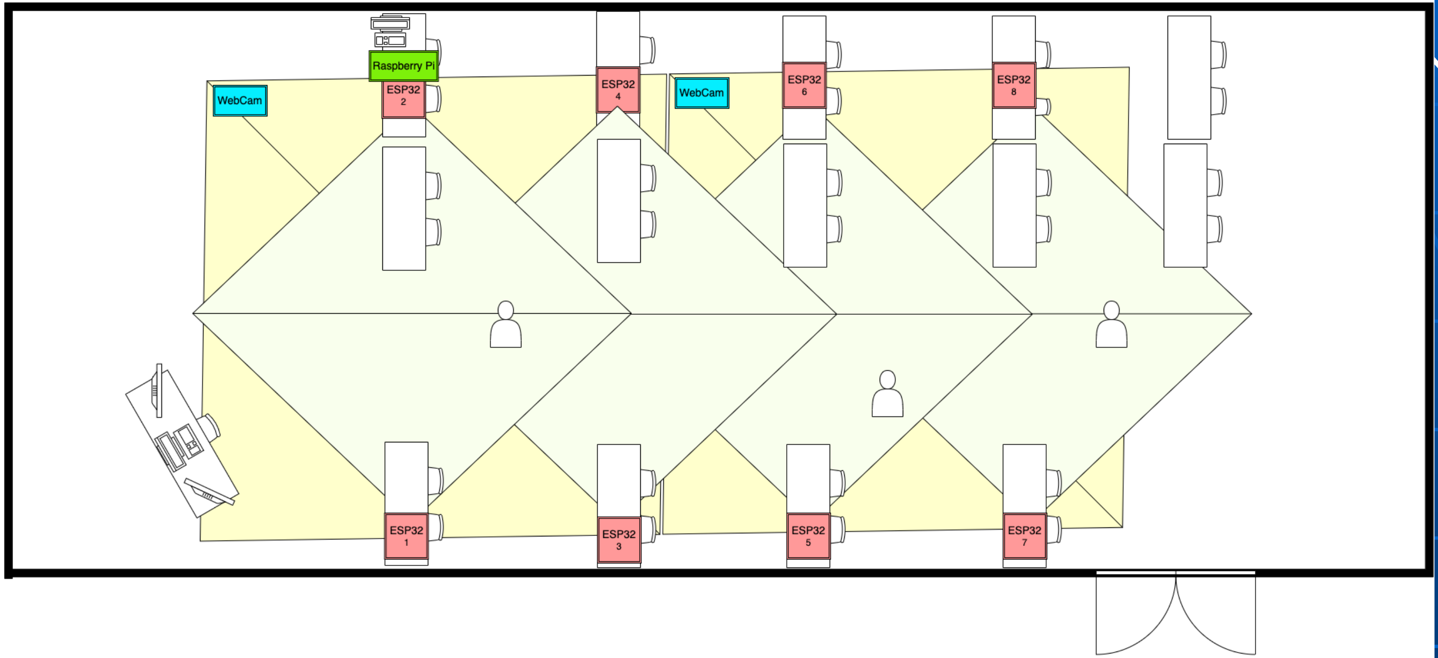
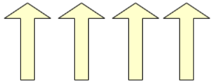


Figure 1.4: Conference Room ITIV/KIT as use case for Energy Efficiency.

Conference Room ITIV-KIT

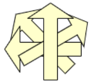


Conf 1



Link1-2, Link3-4, Link 5-6, Link 7-8

Conf 2
1 Frame/s, 10 ms, 4 L, A=2x2



Link1-8,Link3-6, Link 5-4, Link7-2

Conf 3
0,25 Frames/s, 10 ms, 14 L, A=11x2

BroadCast1 BroadCast3 BroadCast5 BroadCast7

MIMO CSI

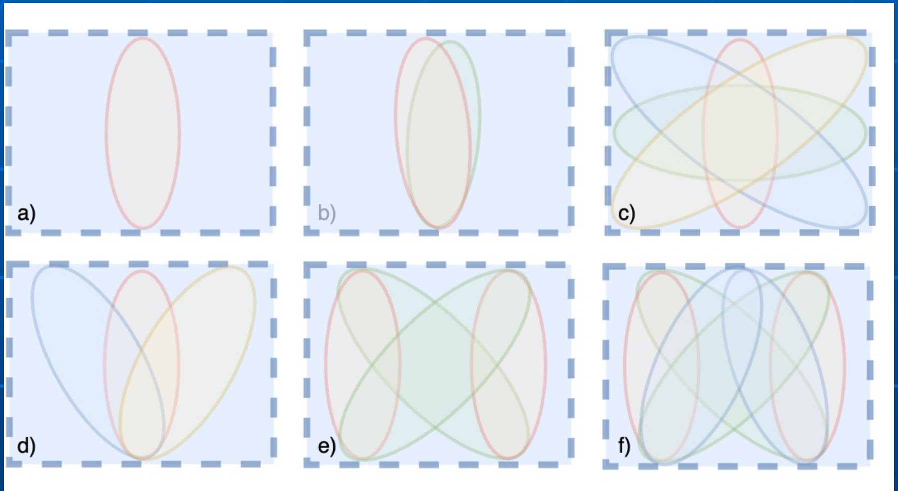
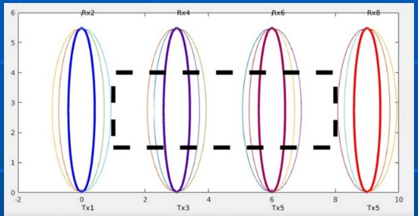


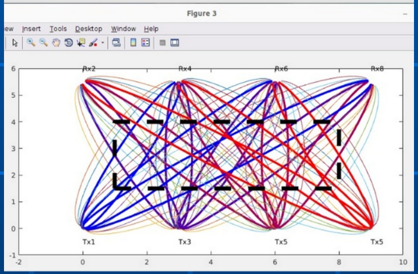
Fig. 5. *Sensor positioning to cover a given area of interest. a) Single link, e.g., [22]. b) Two links with small displacement. "Curtain" used to count passage, e.g., [23]. c) 4 links arrangement used by [9]. d) One Tx - Three Rx (each with 4 antenas) ([10]. e) S221 used in the present paper. f) Illustrates S231. (S261 mainly used in this work is shown in Fig.ure 6).*

4 links

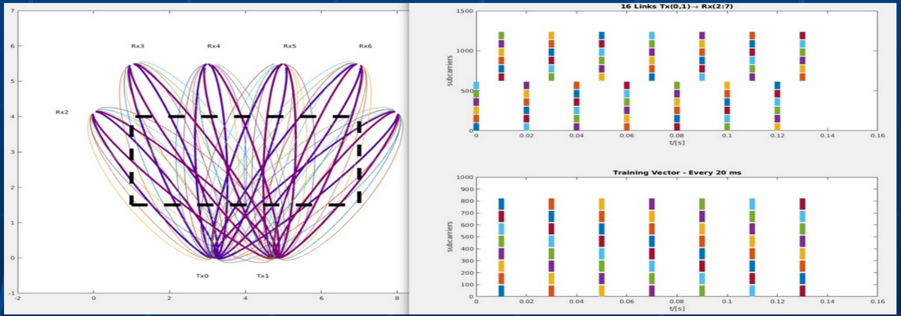
M1:M4



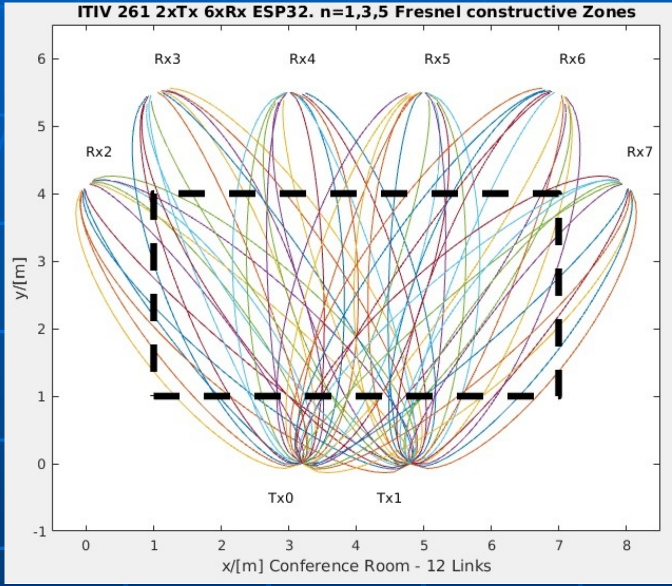
14 links
M1:M4

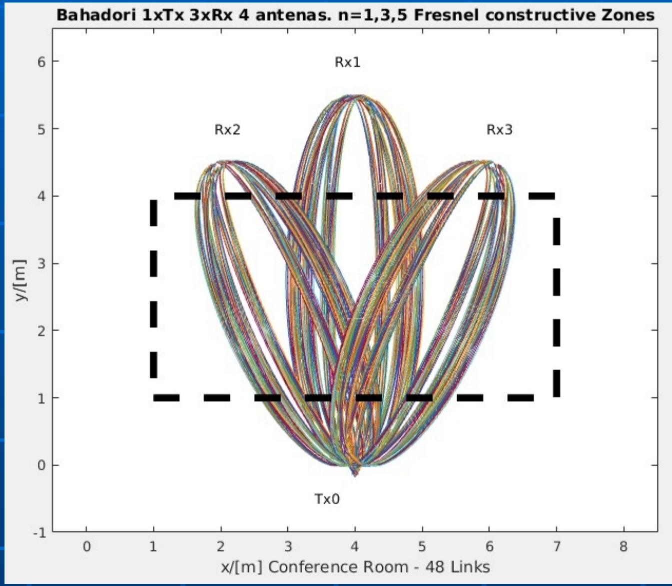


12 links
M1:M2



CSI261- HAR

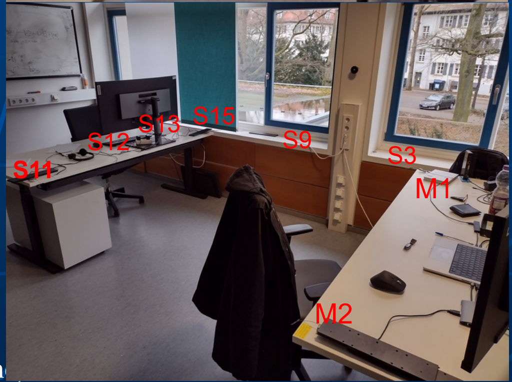




E1
GDH

E2
ITIV

E3
ITIV

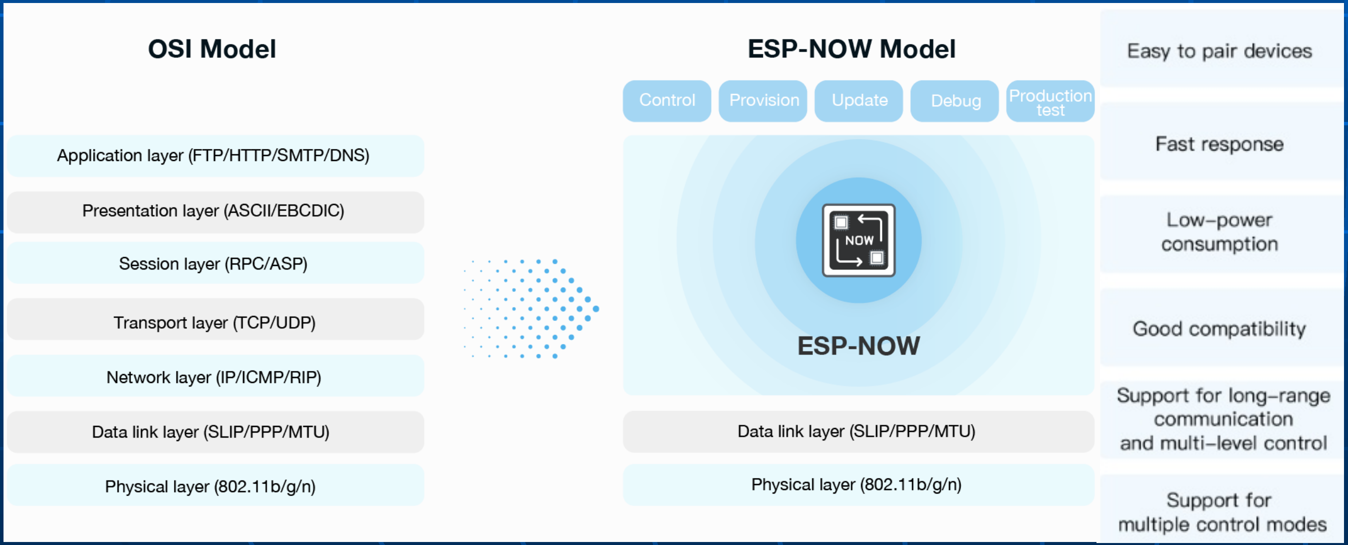


12 Links M1:M2 S3:S8
1 Antenna
52 subcarriers
34 x 264 => PCA 34 x 34 (Amp/Pha)
40 MHz
2x Tx ESP32 2.4GHz
6x Rx ESP32

48 Links. Tx0. Rx1:3
4 Antennas
242 subcarriers
=> PCA 242 x 242 (Amp)
80MHz BW
1x Tx Netgear R78006 STA
3x Tx Asus RT-AC86U WiFi routers

ESP-NOW (on 802.11 PHY)

Connectionless WiFi Communication Protocol



PCA Frame 34x34	Train	Test
Masters	2	2
Sensors	6	6
Amp/Phase	2	2
Carriers w/o Pilots	52	52
CSI Lines	17	17
Experiments	9	1
Frames/Exp.	47	42
Total Frames	423	42
Points/Carrier	7191	714
Points/Link	373932	37128
Total A/Ph points	8974368	891072
Total PCA points	1061208	117912

TABLE 2. PCA Images are 34x34. 423 Frames are used for training and 42 for testing in the different scenarios. A total of 1.061.208 points are used in the training. 117.912 for testing.

CSI261 acquisition

FreeRTOS CYCLE

– TDMA delta

- BroadCast M1 – S1:S5 enable CSI

- BroadCast M1 - S1:S6 collect CSI M1

- BroadCast M2 - S1:S6 collect CSI M2

- S1:S5 disable CSI

- S1 – send M1 CSI (M1, M2), save file.csv

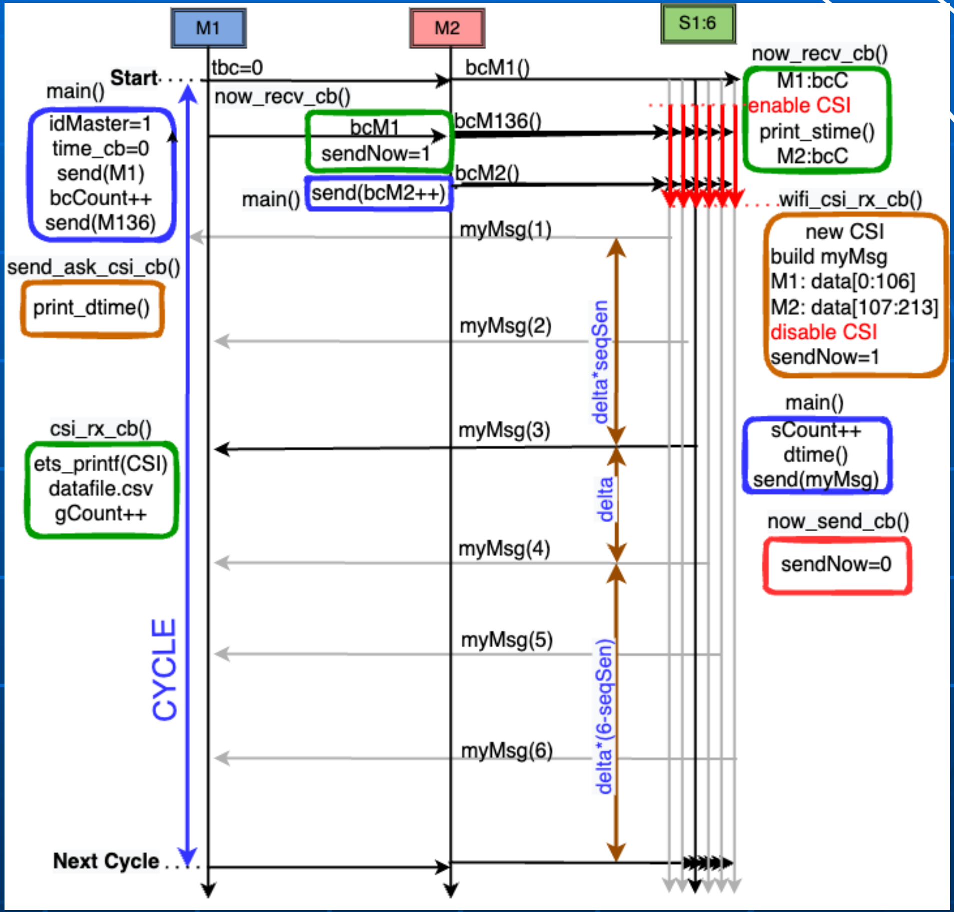
- S2 – send M1 CSI (M1, M2), save file.csv

- S3 – send M1 CSI (M1, M2), save file.csv

- S4 – send M1 CSI (M1, M2), save file.csv

- S5 – send M1 CSI (M1, M2), save file.csv

- S6 – send M1 CSI (M1, M2), save file.csv



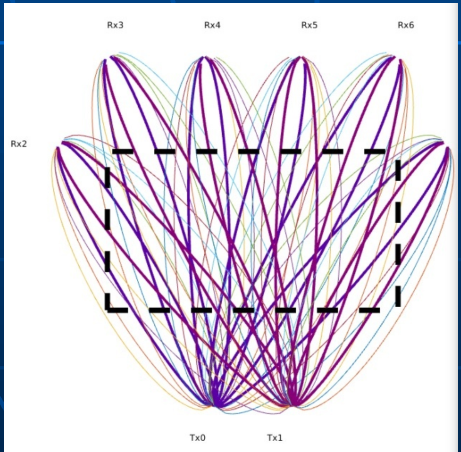
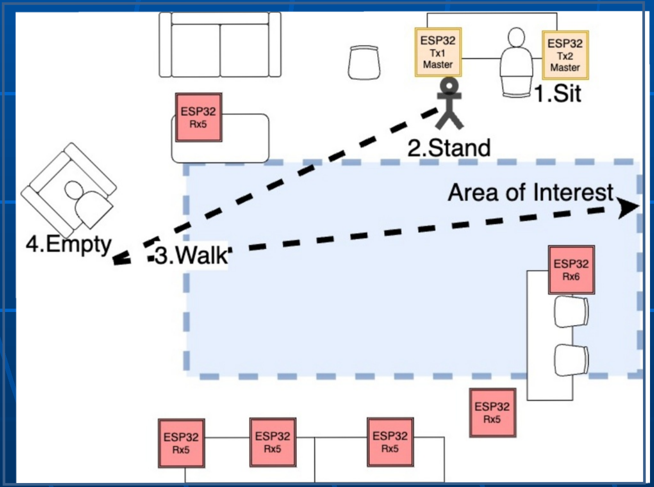


Fig. 9. Time flow of the CSI261 acquisition. M1 starts the process and collects the CSI signals. M2 fires short after receiving the broadcast from M1. A Time Division Multiple Access gives each sensor a preferred window to tranfer its data.to M1.

Csi261 – Fev2023

4 Fev 2023 GDH – test data - 6 experiments 8 min
5 Fev 2023 GDH – training data - 4 experiments 8 min



Csi261

Data Preparation

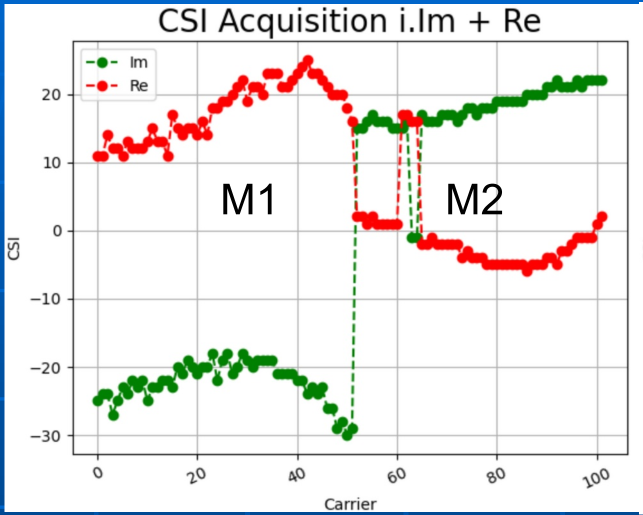
- CSI data: (signed) int8 (Im, Re)

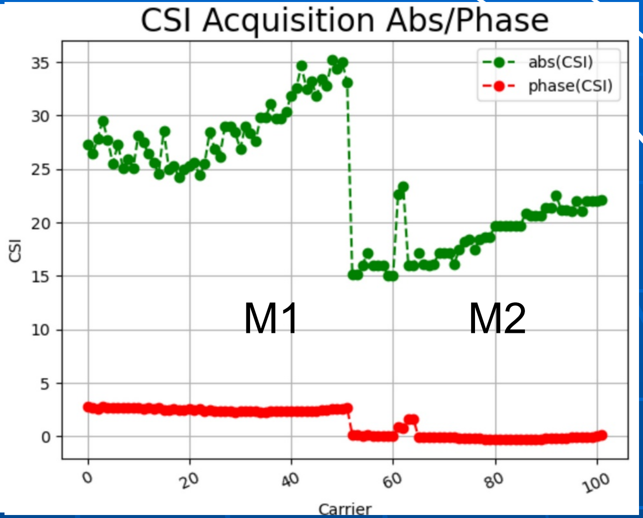
➢ data[0:216] x data[0:244]
244:len(myMsg)

➢ (data[0:214])

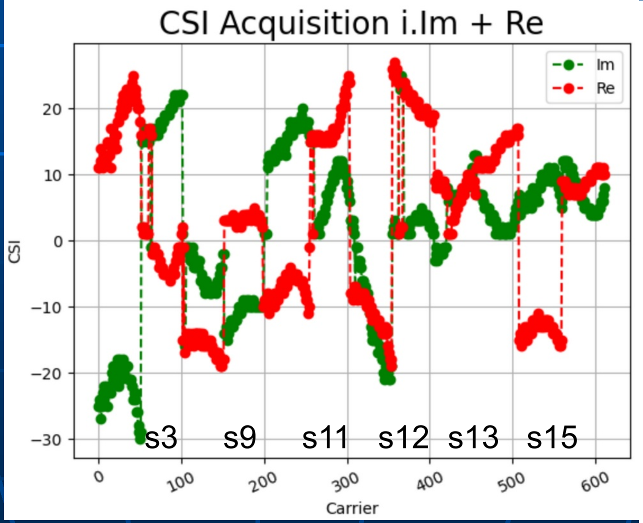
➢ Remove 0 "sub-carrier" guards

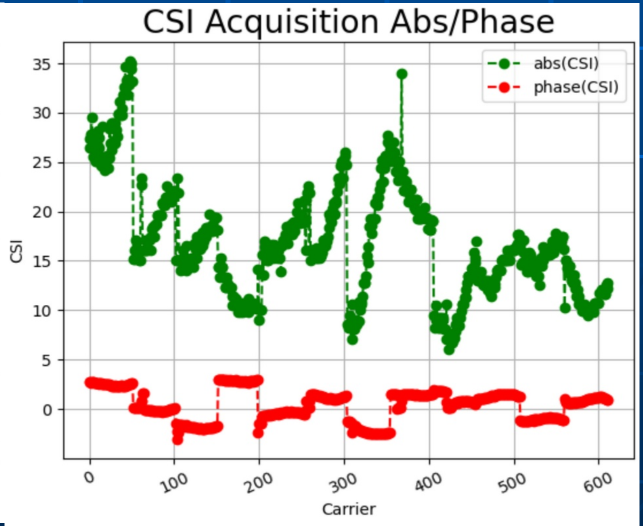
➢ Concatenate CSI-Lines





Si => {M1,M2} CSI Sensor Line





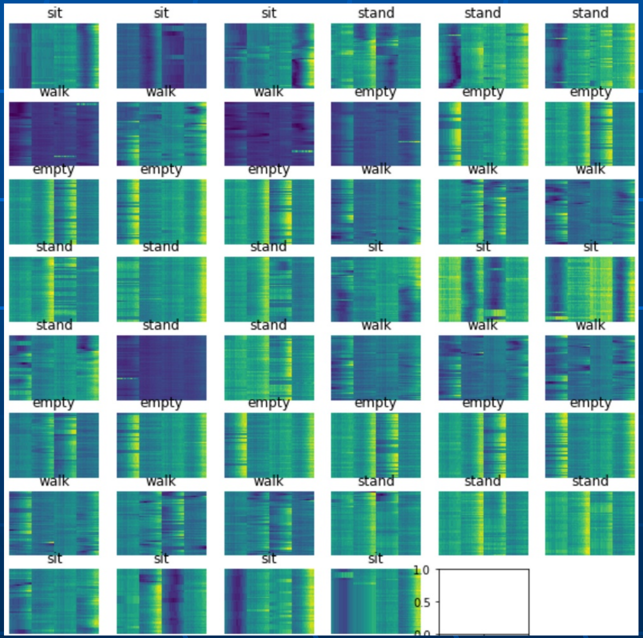
S1, S2, S3, S4, S5, S6 => {M1,M2} "Simultaneous" CSI MIMO Acquisition (12 Links)

Csi221 - Consistency – Camera/audio Activity Check

29janIIa221_5_10.csv

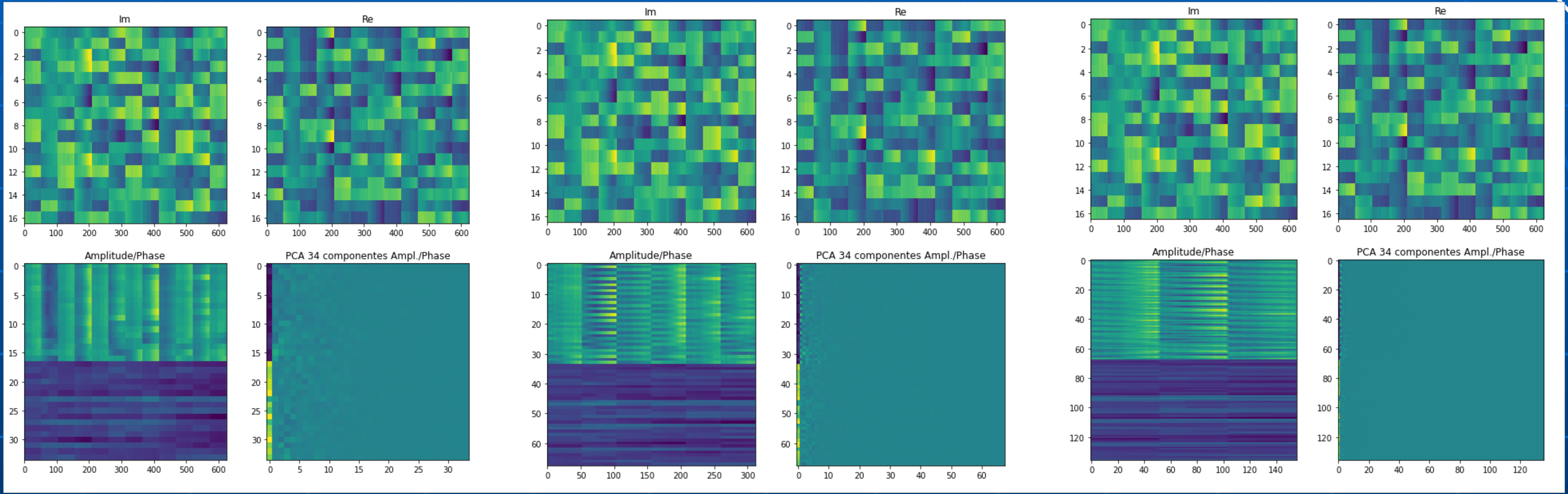
	Audio: prep.	sit	stand	walk	empty	walk	stand	sit	stand	walk	empty	walk	stand	sit.	end	close
29janIId221_5_10.csv	0:00	0:52	1:21	1:51	2:20	3:21	3:50	4:21	4:51	5:61	5:51	6:50	7:21	7:51	8:21	8:51
29janIId221_5_10.csv.	0:00	0:11	0:43	1:12	1:41	2:42	3:12	3:42	4:12	4:42	5:12	6:12	6:42	7:13	7:43	8:18
29janIIe221_5_10.csv	0:00	0:15	0:48	1:19	1:49	2:51	3:17	3:48	4:18	4:48	5:18	6:18	6:49	7:18	7:48	8:22

$E_{border} < 1$ s



VID_20230129_114023391.mp4

Csi261 – Fev2023



34x34 600 ep Training acc: 0.2743 Testing acc: 0.3461

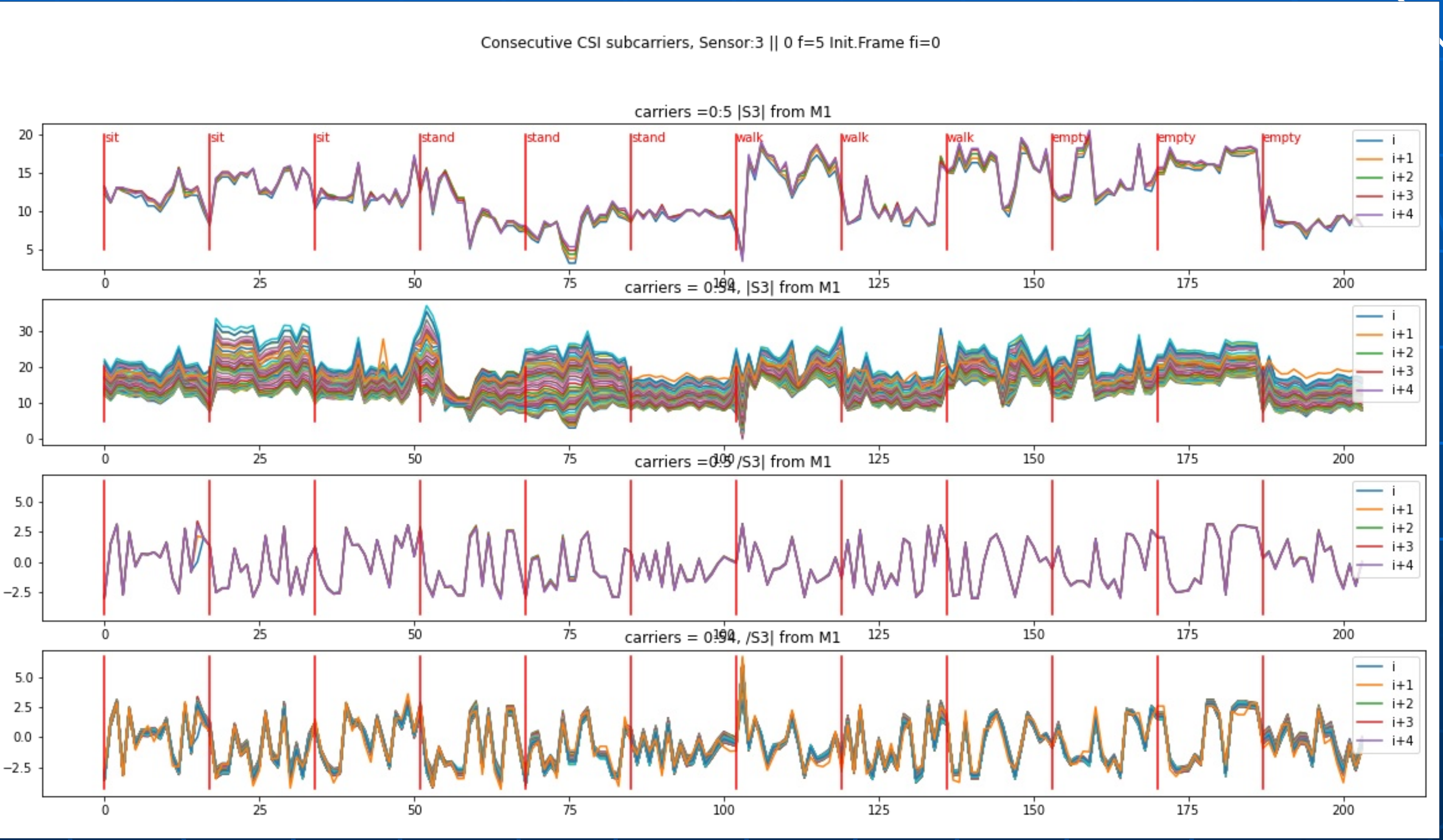
68x68 600 ep Training acc: 0.08849 Testing acc: 0.11538

136x136 600 ep Training acc: 0.27876 Testing acc: 0.30357

```
CF: [[0.  0.66666667 0.  0.33333333]
     [0.  0.625 0.  0.375 ]
     [0.  0.875 0.  0.125 ]
     [0.  0.42857143 0.  0.57142857]]
```

34x34 600 ep plus 2 x Conv2d(64,64) Training acc: 0.08407
(226,26) 6ex images 5fev 34x34 1600 ep plus 2 x Conv2d(64,64) Training acc: 0.26991
(168,) 4ex images 4fev
Testing acc: 0.30769

Csi261 – Fev2023



CSI-HAR261 A. Bauchspiess

Csi261
– Fev2023

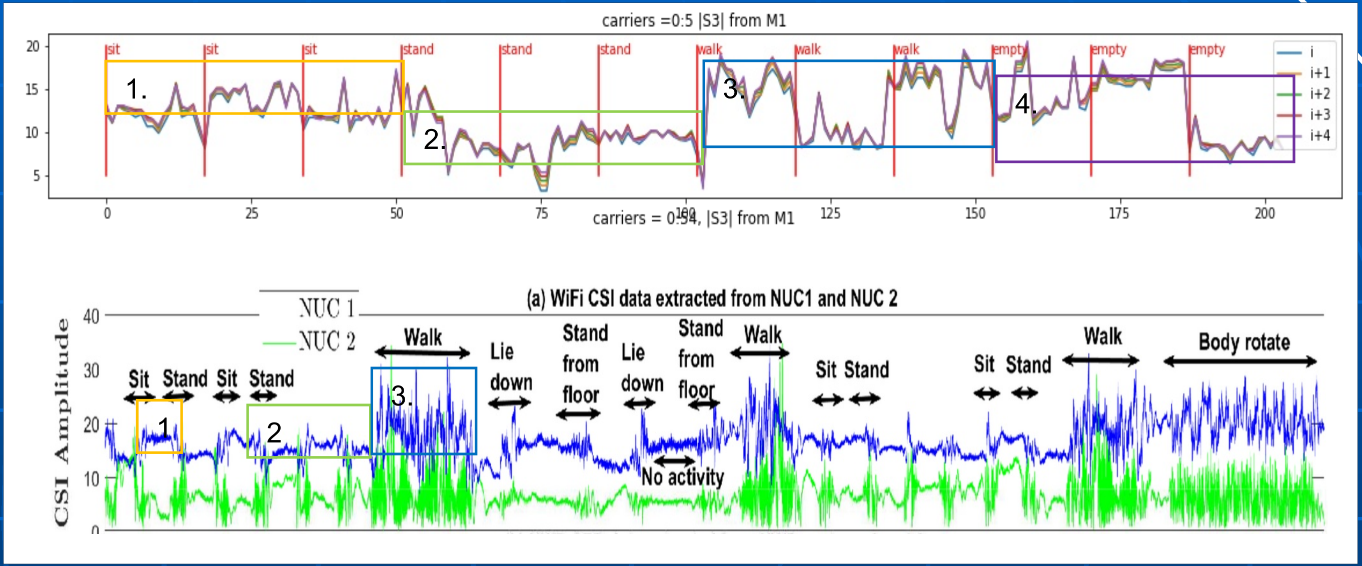
"Expert" Knowledge:

1- "sit" has higher CSI

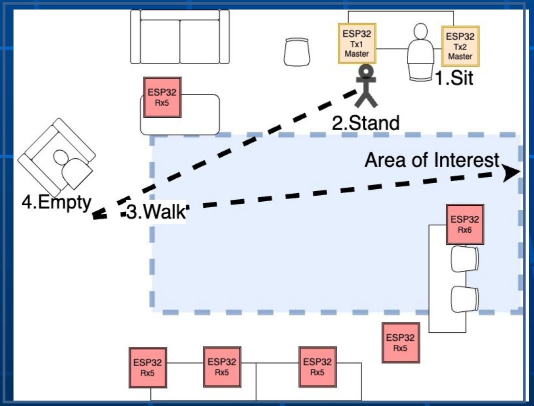
2- "stand" has lower CSI

3- "walking" has higher CSI variance

4 - "empty" has the highest CSI - "free sight"



OPERAnet: A Multimodal Activity Recognition Dataset Acquired from Radio Frequency and Vision-based Sensors
Mohammud J. Bocus et al. 8 Oct2021 arXiv



CSI-HAR261 A. Bauchspiess

Cross Domain Diversity: Environment (ITIV, GDH), Location (L1,L2,L4), Person (Pa,Pe,Pi), Sensor Net (221,261), Bundle (B123, B333).

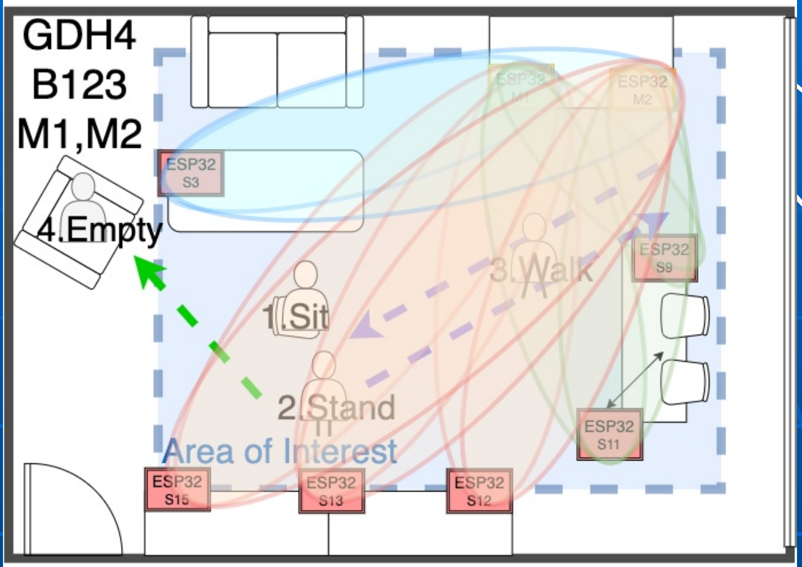
Bundles & Majority Vote Ensembles

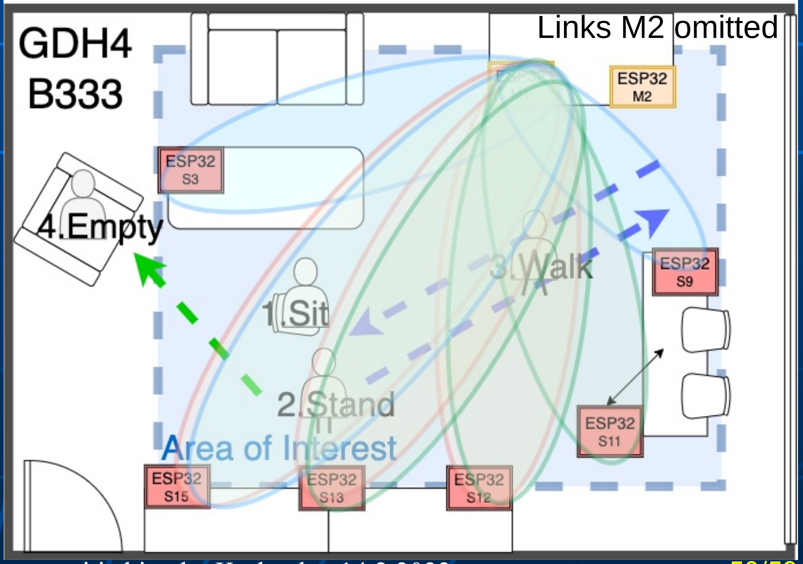
B11: (Bundles – aggregated links)
Modelo CNN1: (S3-M1,M2)
Modelo CNN1: (S9-M1,M2)

B123:
Modelo CNN1: (S3-M1,M2) - 2 CSI links
Modelo CNN2: (S9:S12-M1,M2) - 4 CSI links
Modelo CNN3: (S12:S13:S15-M1,M2) - 6 CSI links

B333: Overlapped (inspired by Malvar's Wavelets)
Modelo CNN1: (S3:S9:S15-M1,M2) - 6 links
Modelo CNN2: (S11:S12:S13-M1,M2) - 6 links, Modelo CNN2
Modelo CNN3: (S12:S13:S15-M1,M2) - 6 links, Modelo CNN3

Ensembles: e.g. avg{CNN1, CNN2}, maj{CNN1, CNN2, CNN3}





X-HAR

X-Environment: GDH, ITIV

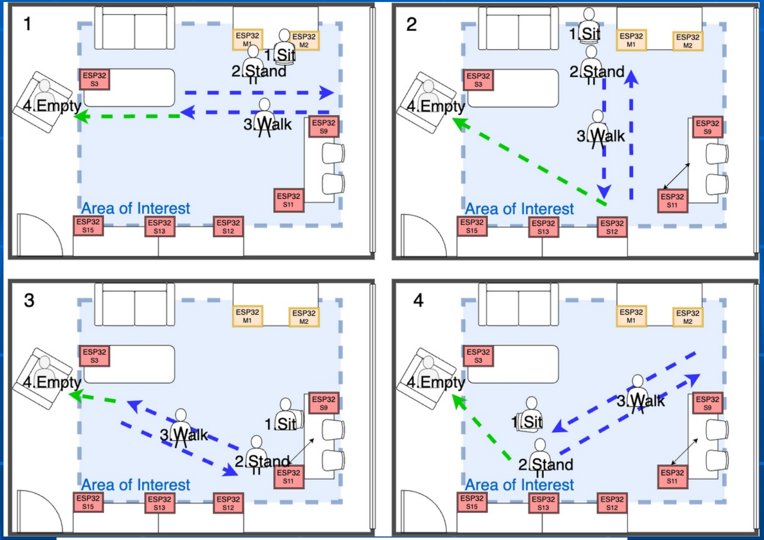
X-Sensing: 221, 261

X-Location: GDH1, GDH2, GDH3, GDH4

X-Person: a, e, j

X-Bundle: e.g. 321, 222, 431

E1 Environment GDH – **Cross Locations**

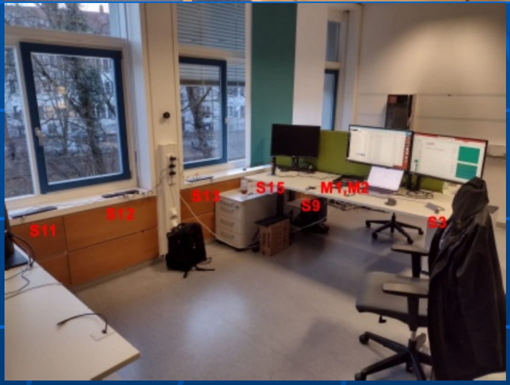


t\Fr.	0	10s	20s	30s	40s	50s	60s
	0. Sit	Sit	Sit	Stand	Stand	Stand	
	1. Walk	Walk	Walk	Empty	Empty	Empty	
	2. Empty	Empty	Empty	Walk	Walk	Walk	
	3.Stand	Stand	Stand	Sit	Sit	Sit	
	4. Stand	Stand	Stand	Walk	Walk	Walk	
	5. Empty	Empty	Empty	Empty	Empty	Empty	
	6. Walk	Walk	Walk	Stand	Stand	Stand	
	7. Sit	Sit	Sit	Sit	Sit	Sit	

Activities during the 8 min data acquisition routines
48 Frames of 10 sec. 17 CSI lines per Frame
12 Sit, 12 Empty, 12 Stand, 12 Stand (Balanced Activities)

E1 - CSI261
GDH
Cross-Location

E2 - CSI261
ITIV
Cross-Room



E3 - 221
ITIV
Cross-Sensing

CNN - Non-linear Feature Mapping $f(\theta)$

```
pmodel1, model2, model3 = ProtoNet(
  (encoder): Sequential(
    (0): Sequential(
      (0): Conv2d(1, 32, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
      (1): BatchNorm2d(32, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      (2): ReLU()
      (3): MaxPool2d(kernel_size=2, stride=2, padding=0, dilation=1, ceil_mode=False)
    )
    (1): Sequential(
      (0): Conv2d(32, 32, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
      (1): BatchNorm2d(32, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      (2): ReLU()
      (3): MaxPool2d(kernel_size=2, stride=2, padding=0, dilation=1, ceil_mode=False)
    )
    (2): Sequential(
      (0): Conv2d(32, 32, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
      (1): BatchNorm2d(32, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      (2): ReLU()
      (3): MaxPool2d(kernel_size=2, stride=2, padding=0, dilation=1, ceil_mode=False)
    )
    (3): Sequential(
      (0): Conv2d(32, 32, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
      (1): BatchNorm2d(32, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      (2): ReLU()
      (3): MaxPool2d(kernel_size=2, stride=2, padding=0, dilation=1, ceil_mode=False)
    )
    (4): Sequential(
      (0): Conv2d(32, 64, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
      (1): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      (2): ReLU()
      (3): MaxPool2d(kernel_size=2, stride=2, padding=0, dilation=1, ceil_mode=False)
    )
    (5): Flatten()
  )
)
```

CSI261 Few Shot Results

Table 3.2: Test accuracy of Bundled CSI.

S261 GDH-a				
Loc-Run	B321	B222	B411	B333
2-i	0.611	0.522	0.573	**0.620**
2-ii	0.498	0.528	0.516	0.576
2-iii	0.545	0.588	0.618	0.610
avg	0.551	0.546	0.569	**0.609**
σ	0.057	0.036	0.051	0.023
3-i	0.526	0.569	0.537	0.639
3-ii	0.593	0.594	0.491	0.588
3-iii	0.623	0.598	0.539	**0.681**
avg	0.580	0.587	0.522	**0.636**
stdev	0.050	0.016	0.027	0.046
4-i	0.523	0.608	0.566	0.560
4-ii	0.580	0.508	0.577	0.545
4-iii	0.564	0.585	**0.656**	0.558
avg	0.556	0.567	**0.599**	0.554
σ	0.029	0.052	0.049	0.008

S261 GDH-e				
4-i	0.536	0.585	0.509	0.655
4-ii	0.494	0.607	0.608	0.615
4-iii	0.606	0.668	**0.675**	0.595
avg	0.545	0.620	0.597	**0.626**
σ	0.056	0.043	0.083	0.031

S261 ITIV-a				
Loc-Run	B321	B222	B411	B333
1-i	0.323	0.361	0.285	0.375
1-ii	0.328	0.358	0.318	**0.433**
1-iii	0.392	0.366	0.303	0.378
avg	0.348	0.361	0.302	**0.395**
σ	0.038	0.004	0.016	0.033
2-i	0.576	0.585	0.566	0.545
2-ii	0.580	0.584	0.602	0.602
2-iii	**0.645**	0.5658	0.6108	0.6133
avg	**0.600**	0.578	0.593	0.587
σ	0.039	0.011	0.024	0.037

S261 ITIV-i				
1-i	0.294	0.323	0.359	0.342
1-ii	0.244	**0.408**	0.388	0.326
1-iii	0.254	0.353	0.293	0.372
avg	0.264	**0.361**	0.347	0.347
sigma	0.026	0.043	0.048	0.023

S221 ITIIV-a				
1-i	0.411	0.350	0.314	0.409
1-ii	0.378	0.390	0.194	**0.468**
1-iii	0.309	0.381	0.281	0.376
avg	0.366	0.374	0.263	**0.418**
σ	0.052	0.021	0.062	0.047

CSI261 Few Shot (n,s,q) Results

Acc. over all	0.652	Over All Comparison over BundleS3_KIT Few-Shot Training				ITIV-KIT 2023, March 3rd	
Bundle	Loc\Run	3a	4a	4e	ITIV	ITIV_IT	ITIV_AB	ITIV_2AB
n4s5q3	BestAvgEnv.	0.526	0.551	0.519	0.562	0.581	0.454	0.505
	BestBund	432	333	332	332	333	332	332
n4s1q3	BestAvgEnv.	0.370	0.369	0.377	0.367	0.409	0.317	0.355
	BestBund	432	411	333	332	432	411	333
n4s1q1	BestAvgEnv.	0.593	0.559	0.604	0.371	0.393	0.387	0.570
	BestBund	432	321	432	432	333	121	432
n4s1q5	BestAvgEnv.	0.387	0.385	0.377	0.381	0.393	0.344	0.358
	BestBund	432	411	333	332	333	432	332
n4s5q1	BestAvgEnv.	0.625	0.627	0.652	0.505	0.400	0.444	0.635
	BestBund	321	321	411	332	332	432	432
n4s5q5	BestAvgEnv.	0.546	0.485	0.527	0.584	0.569	0.429	0.485
	BestBund	432	321	332	332	411	411	332
Majority vote	BestAll Bund	432	321	332	332	333	432	332
	Max Env.	0.625	0.627	0.652	0.584	0.581	0.454	0.635
	Avg Env.	0.532	0.518	0.536	0.478	0.470	0.406	0.510

Automation Transfer

Rooms in a typical building share many WiFi channel simmilarities.

- Occupancy and Activities estimation
  => **Few Shot Automation Transfer**

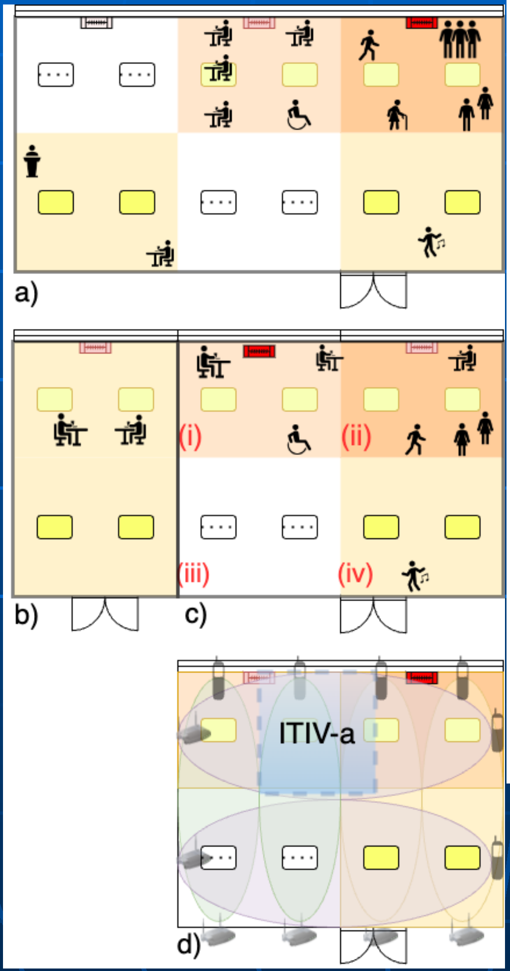


Fig. 3. Environment diversity in the ITIV-KIT building. a) Conference Room, b) Small researcher office, c) Large researcher office. Area of Interest ITIV-a is depicted in d) with minimal zonal WiFi coverage.

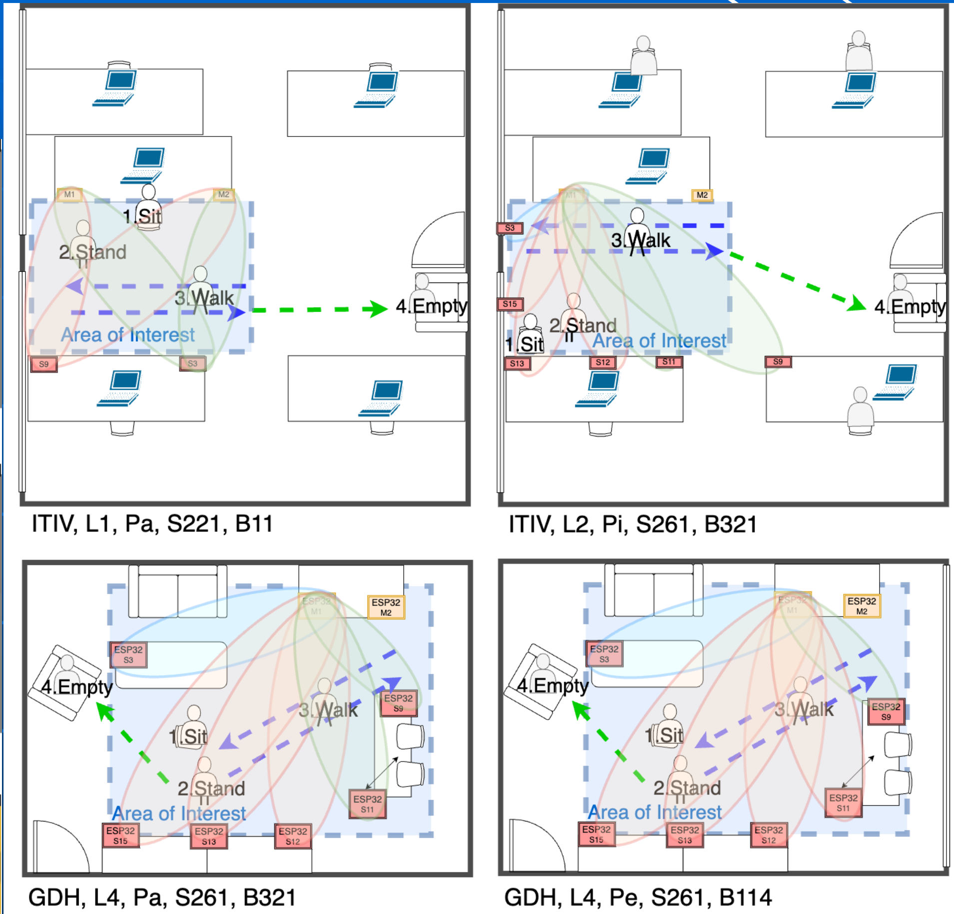


Fig. 7. Cross Domain Diversity: Environment (ITIV, GDH), Location (L1,L2,L4), Person (Pa,Pe,Pi), Sensor Net (221,261), Bundle (B11,B221, B321, B114).

Conclusions
Challenges & Perspectives

Open Questions

- WiFi is strongly dependent
    - on the person, attitude, cloth, metabolic rate etc.
    - change in furniture, chair position, computers, equipment
    > Multipath, Occlusion

Transfer Learning - Retraining of the ANNs still necessary?

- For Climatization

The exact position of the occupants is often not needed!

AI Opportunities

- *Deep Learning*
- *Reinforcement Learning*
- *Explanation Components*

"They shouldn't allow humans to drive!"

Learn to Drive:

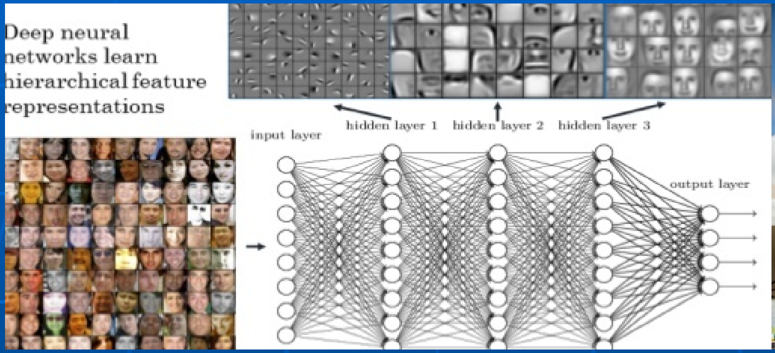
Self-Driving Car: >>1000 h

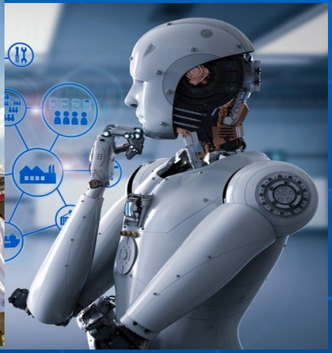
Human ~ 20 h

Challanges

- *AI with emotions*
- *AI consciosness*
- *ethics in AI*
- *non-human intelligence*
- *AGI (General, Strong AI)*

Super-human in one task != Intelligent!!





Thank You!

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