Smart Wireless Sensing: Feature, Algorithm, and Dataset

智能无线感知：特征、算法、数据集

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个人简介

- 清华大学副教授、博士生导师
- 国家“万人计划”青年拔尖人才、北京市科技新星
- 国家优秀青年基金获得者
- 获得国家自然科学二等奖
- 研究方向：物联网、移动计算、大数据、边缘计算
- 发表CCF推荐A类论文 100 余篇，中英文专著 1 部，英文专著 2 部

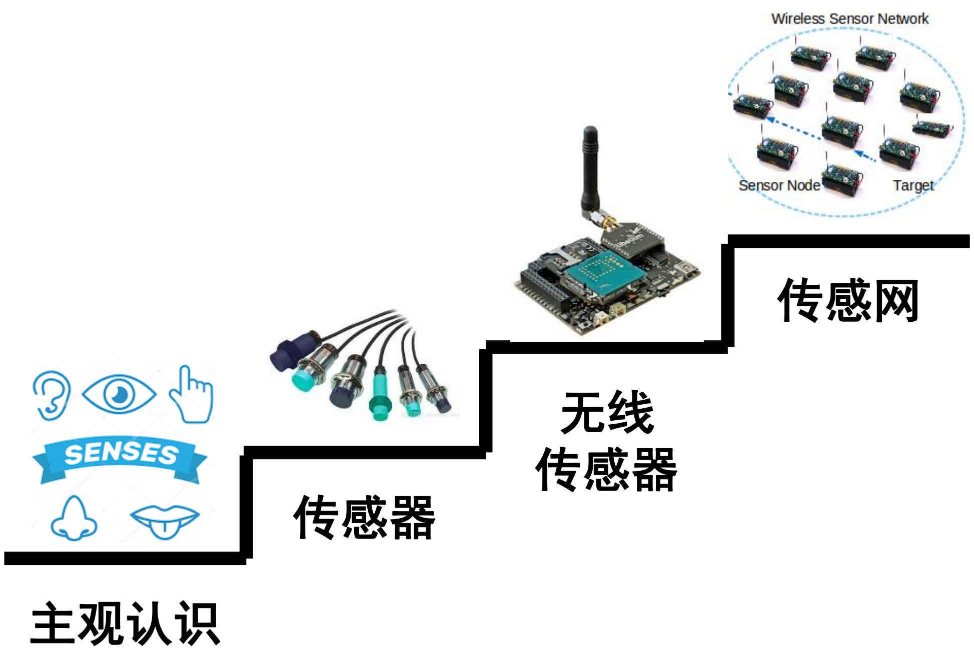
摘要

无线感知是一种利用泛在无线信号实现场景感知的技术。它通过分析接收信号特征，获得信号传播空间的特性，以实现场景（人+环境）感知。无线感知已成为过去几年来物联网领域的研究热点，许多新理论新方法新技术涌现。已有工作面临的挑战包括：1，人与环境信号特征的有效解耦；2，无线信号特征空间中对行为的精准建模；3，高质量数据集的采集。针对以上挑战，本讲座介绍清华大学杨铮研究团队的最新工作*Widar3.0*，通过提取运动目标速度谱特征以及建模人员行为的时空特性，实现环境无依赖的行为识别模型，有效提升了感知的准确性、鲁棒性、与普适性；并公开相关数据集，包括在75个不同环境下采集的26万次人员动作实例，总时长超过144小时。

Outline

- **Introduction**
- Feature
- Algorithm
- Dataset
- Opportunity

人类对物理世界的感知



范围越来越广

规模越来越大

问题暴露越多

部署和维护长期稳定运行的大规模传感网
的难度和成本越来越高

转换思路，突破定式

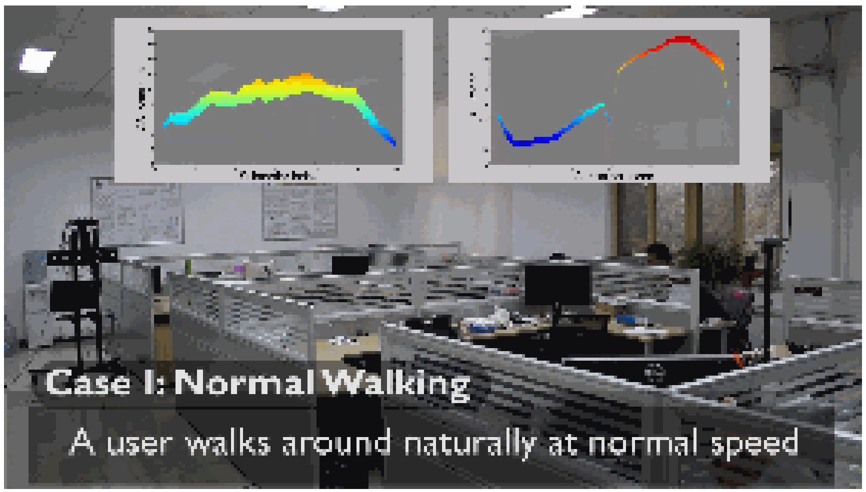
- 考虑不部署任何专用传感器是否也能感知到环境？
  - 已有方法：事先计划部署的专用传感器
  - 新思路：利用环境中泛在无线信号来实现感知

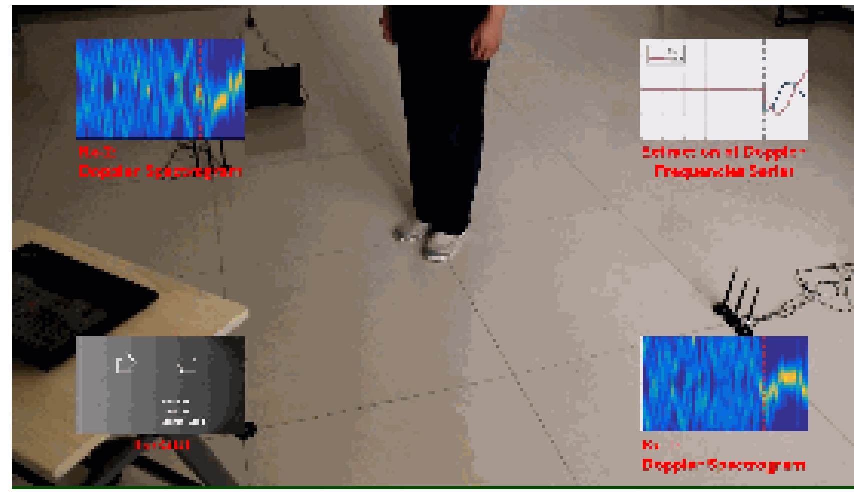
无需部署专用的传感器，也无需人员携带传感器

范围广、维护易、普适强、潜力大

非传感器感知

- **基本思想：无线信号不仅可以传输数据，还可以感知环境**
  信号发射机产生的无线电波经由直射、反射、散射等多条路径传播，在信号接收机处形成的多径叠加信号携带反映环境特征的信息。





非传感器感知是一种利用泛在无线信号实现场景感知的技术。它通过分析接收信号特征，获得信号传播空间的特性，以实现场景（人+环境）感知。

非传感器感知的应用

人员入侵检测

贵重资产保护

安防

睡眠监测

跌到检测

医疗

手势控制

沉浸式体感游戏

人机交互

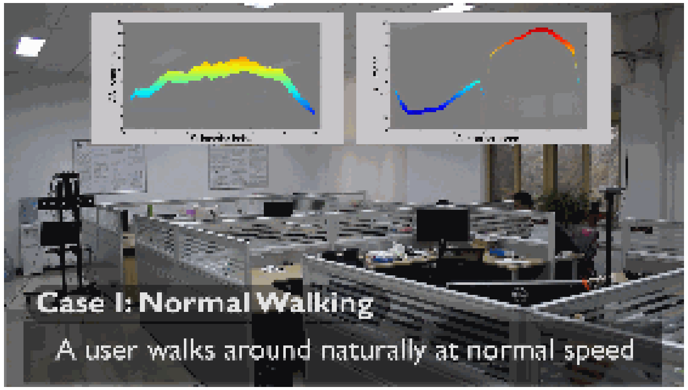
国外现状

发达国家将非传感器感知列为重点支持的方向，但目前尚缺乏系统深入的研究，总体水平仍处于初级阶段

国内外现状

应充分利用国内无线网络部署的规模优势，尽快形成我国在非传感器感知领域的世界领先地位

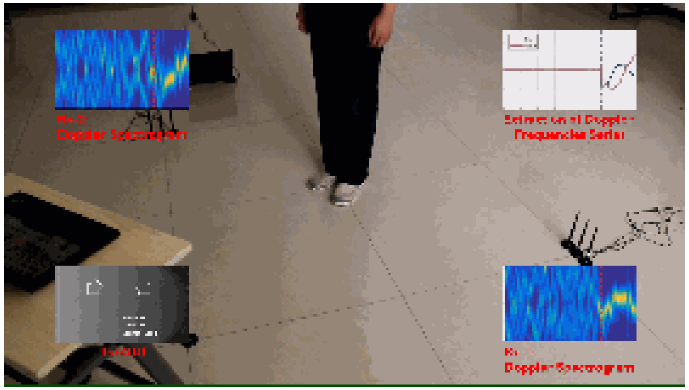
前期成果



被动式人员发现
IEEE ICPADS **最佳论文提名奖**

周期性运动位移
ACM MobiCom (A类) **亚毫米级**

人员定位与跟踪
ACM MobiHoc **亚米级**



人员行为识别
ACM CHI (A类) **最佳论文提名奖**

示范应用：面向安全保卫应用的精确人员感知

针对传统安防手段的局限性，将非传感器场景感知技术应用于安全保卫应用，部署长期稳定运行的大规模安防传感系统，并应用于高铁、机场、博物馆等应用场景。

- 某机场油库安防系统（已使用，合作单位：某机场）
- 高速铁路沿线异物入侵监测系统（合作单位：北京铁路局）

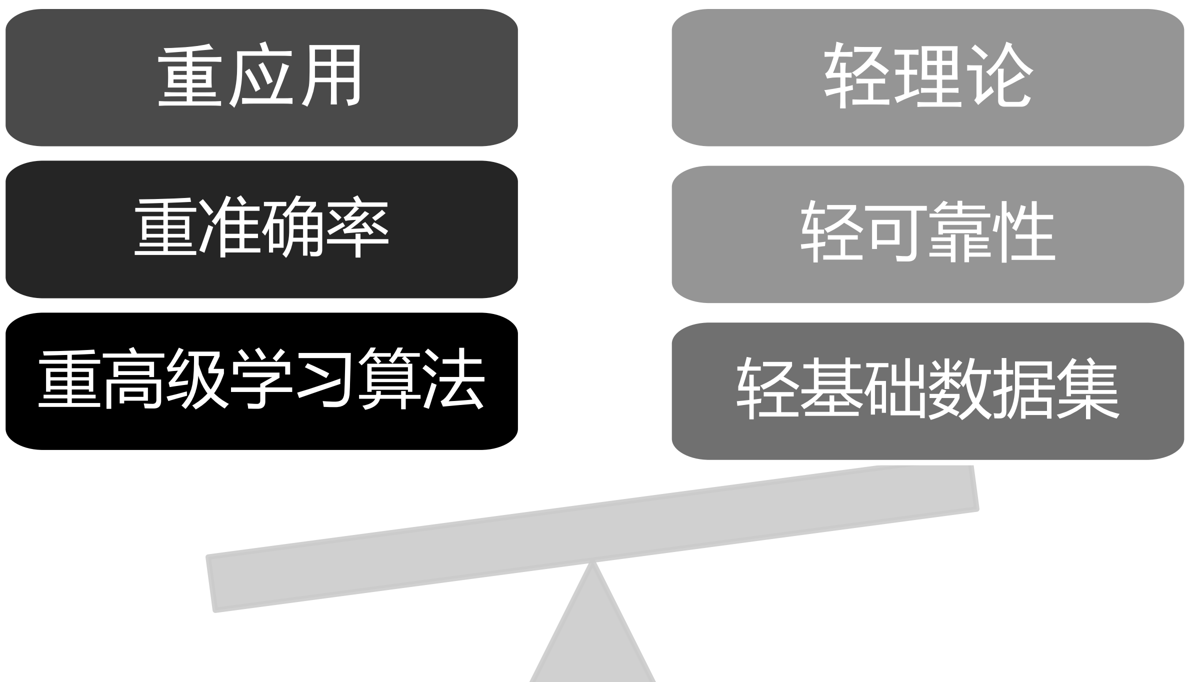
高铁周界安防

机场周界安防

博物馆区域安防

发展状况与面临的问题

- 发展状况：野蛮生长的时代，新应用层出不穷
- 面临的问题：“三重三轻”



非传感器感知的挑战

三大挑战

- **有效特征湮没**：信号特征非独立于背景环境，导致感知结果依赖于部署环境、普适性差、学习训练成本高
- **识别模型粗陋**：缺乏在无线信号特征空间对对人行为活动的精细时空建模，导致感知精度低、鲁棒性差
- **数据集缺失**：高质量公开数据集的缺失造成性能比较不客观、实验结果难复现、技术进步难积累

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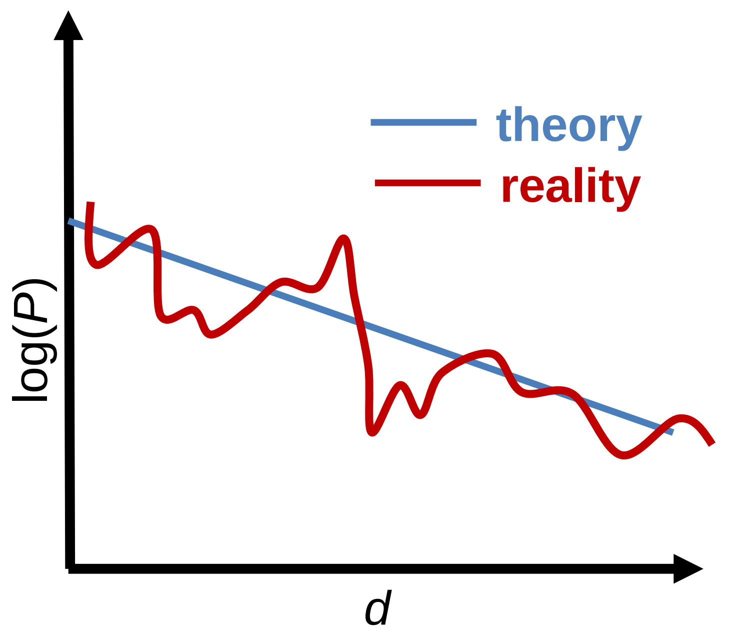
Detect Environment Dynamics

Signal Strength + **LED** = 

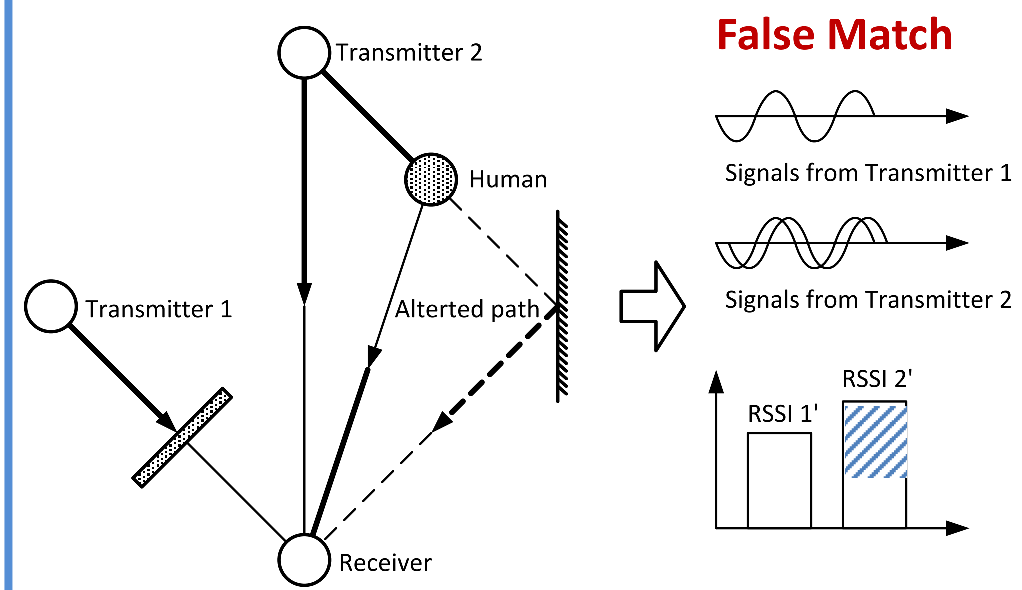
- Capture environment dynamics via the fluctuation of radio signal
  - **Received radio signal strength (RSSI)**
- Is RSSI a Good Signal Feature?
  - In theory, it is. However …
  - In practice, sensing ability of RSSI is greatly weakened by rich multipath effects

Multipath: Enemy!

- Impacts of Multipath Effects:
  - Bound Accuracy of Ranging
  - Induce False Match in Fingerprinting

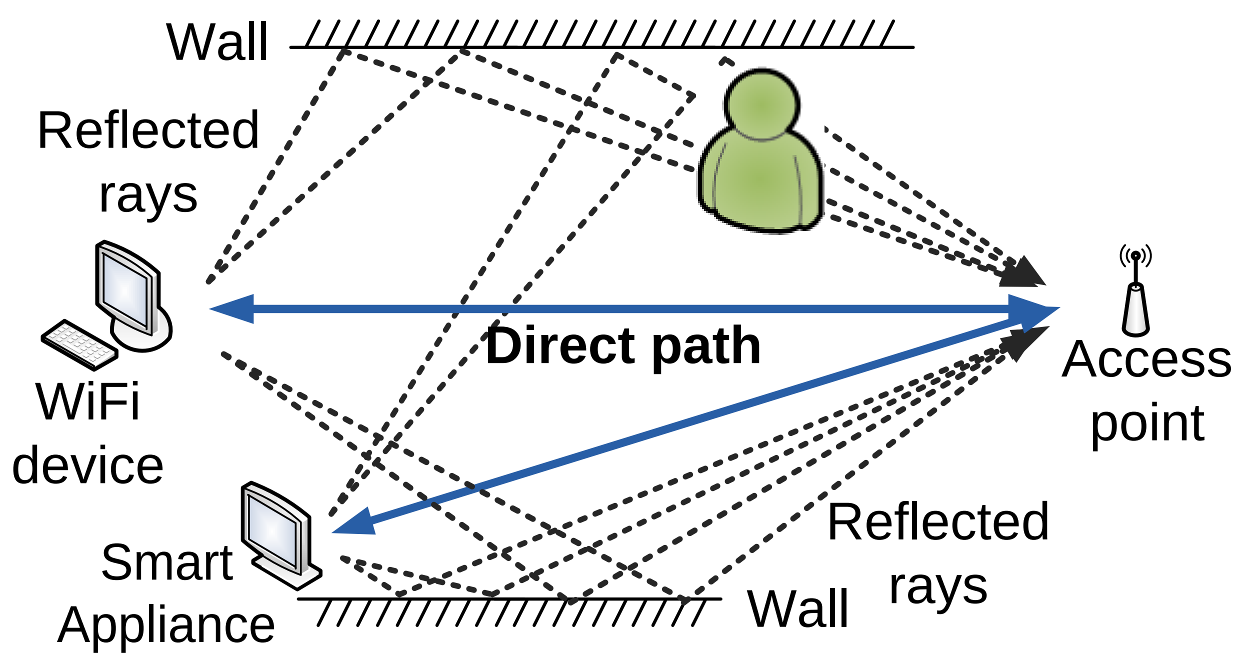


RSSI-based Ranging



RSSI-based Fingerprinting

Multipath: Friend?!

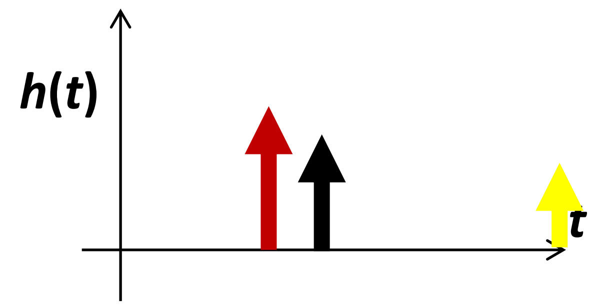


Multipath Propagation Conveys Rich Environment Information

Characterizing Multipath: From RSSI to CSI

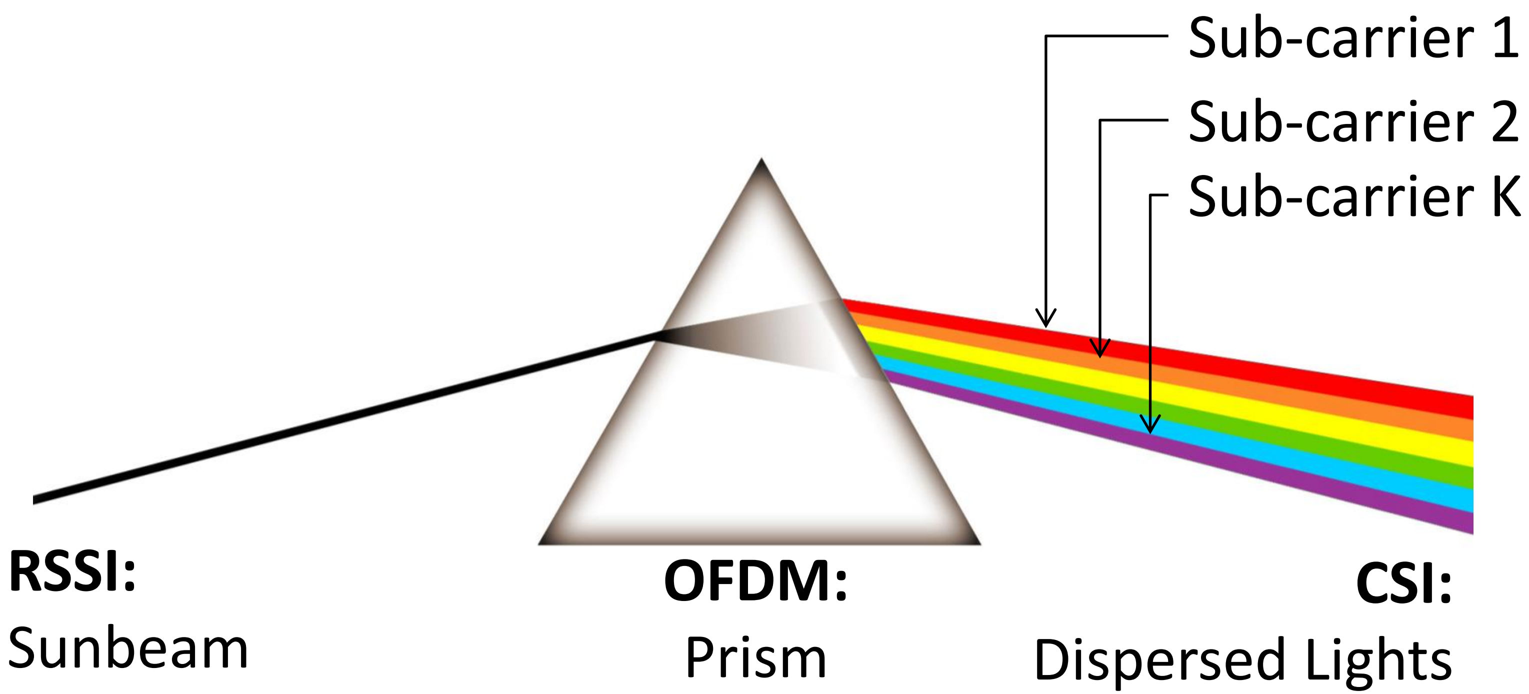
- Channel Impulse Response (CIR)
  - a set of attenuated, delayed impulse functions, depicting multipath

$$h(\tau)=\sum_{i=0}^{N-1} a_i \exp(-j\theta_i)\delta(\tau-\tau_i)$$



- Deriving Channel Response
  - VNA / SDR for precise measurement
  - Channel State Information (CSI): sampled version of channel response with OFDM at sub-carrier level
  - CSI on a single sub-carrier k: $H(f_k)=\|H(f_k)\|e^{j\sin(\angle H)}$

Channel State Information



- Analogously, CSI is to RSS what a rainbow is to a sunbeam.
  - CSI separates signals of different wavelengths via OFDM
  - RSS only provides a single-valued amplitude of superposed paths.

CSI vs. RSSI

Category	RSSI	CSI
Layering	MAC layer	PHY layer
Time Resolution	Packet level	Multipath clusters
Frequency Resolution	N/A	Sub-carrier level
Stability	Low	High for CFR structure
Ubiquity	Handy access	Commercial Wi-Fi

CSI, the fine-grained channel response accessible on commodity WiFi devices, acts as an essential upgrade of RSSI.

Noisy Phase

Raw CSI phase is useless because Tx/Rx are not synchronized, introducing a random phase shift.

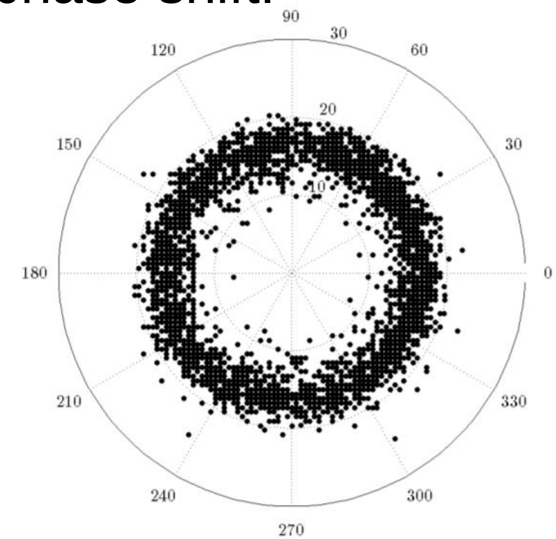
Measured Phase

$$\boxed{\hat{\phi}_i} = \boxed{\phi_i} - \boxed{2\pi \frac{k_i}{N}\delta + \beta + Z}$$

Real Phase

Phase Shift

Phase relation for ith subcarrier



Raw phase distribution of ith subcarrier

Phase Sanitization

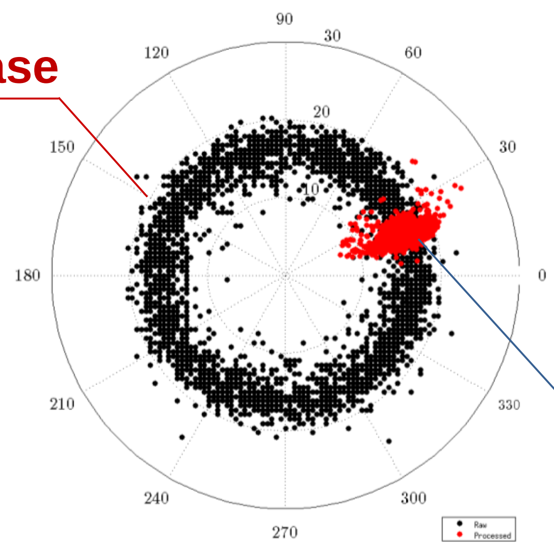
- **Solution:** extract accurate phase-related information from raw CSI by dealing with asynchronous sender and receiver, asynchronous antennas, and noises.

$$\tilde{\phi}_i = \hat{\phi}_i - ak_i - b = \underbrace{\phi_i - \frac{\phi_n - \phi_1}{k_n - k_1}k_i - \frac{1}{n}\sum_{j=1}^{n}\phi_j}$$

Linear combination of real phases $\{\phi_i\}_{i=1}^{n}$

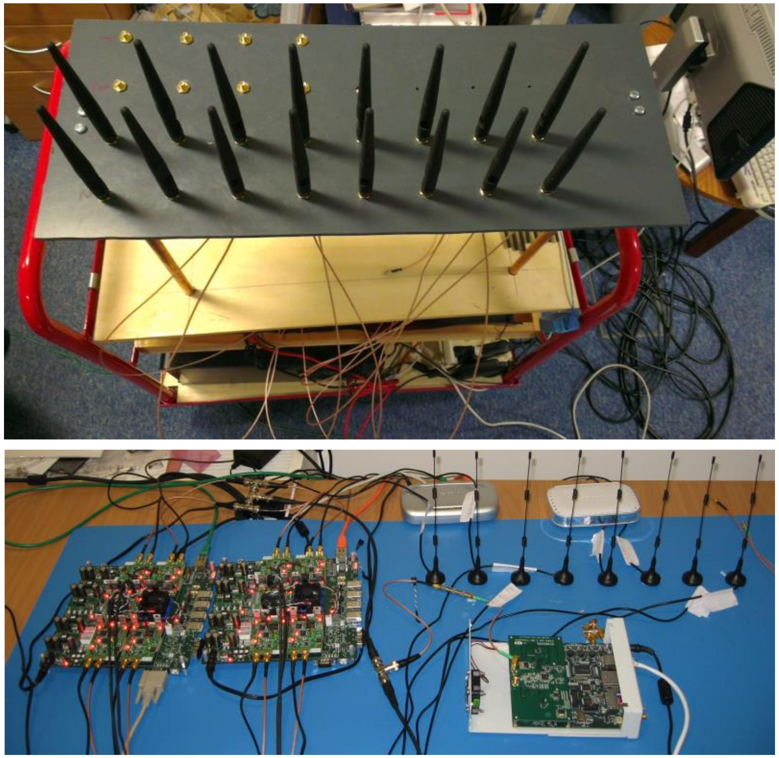
- Stable
- Sufficient to use

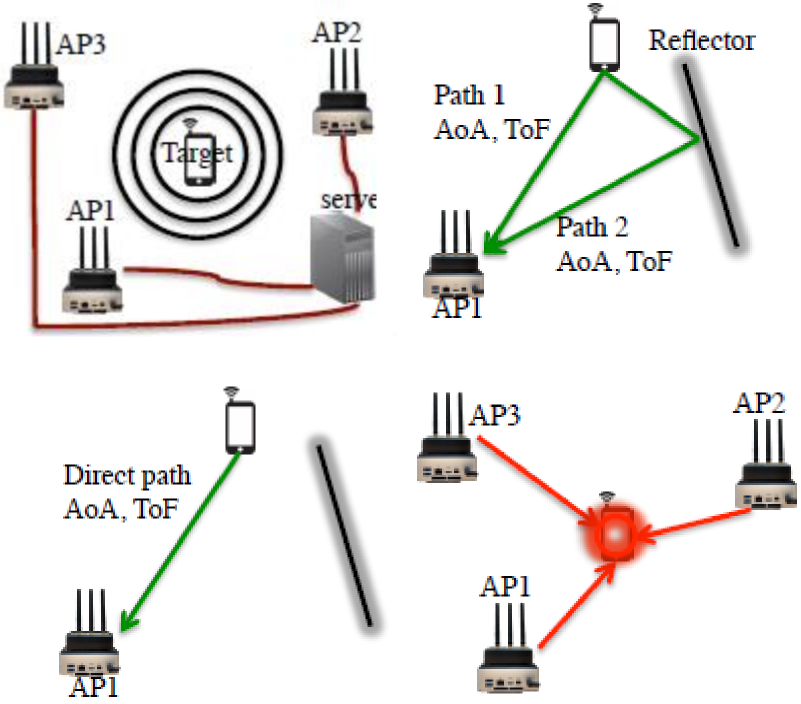
Raw Phase



Sanitized Phase

AoA&ToF





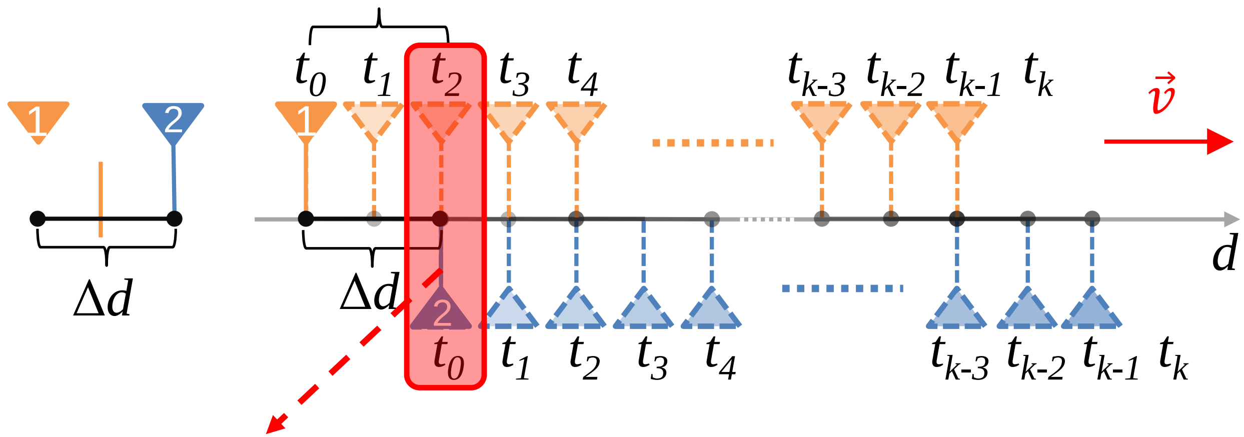
ArrayTrack (NSDI '13)

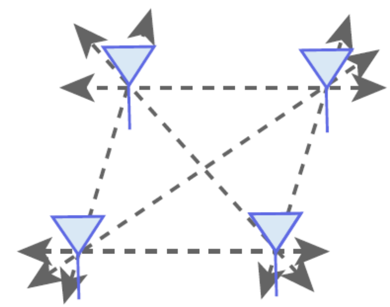
Combines the algorithms for AoA based direction estimation and suppressing the NLOS reflections.

SpotFi (Sigcomm '15)

Incorporates super-resolution AoA algorithms and robust direct path identification to indoor location.

Moving Distance & Direction





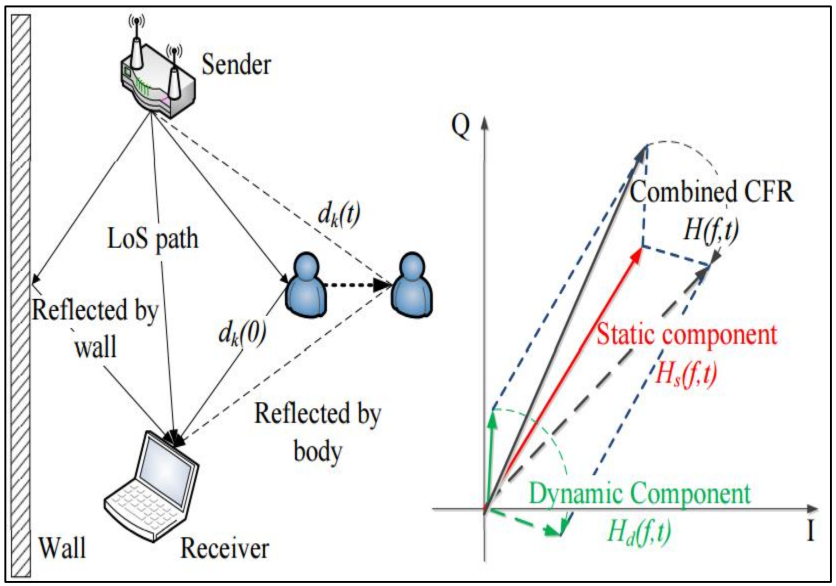
Aligned virtual antennas

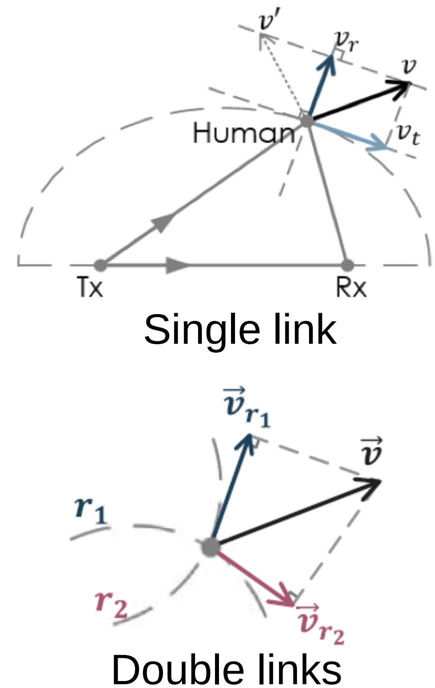
Quadrangle: 12 directions

RIM (SIGCOMM '19)

Turns COTS WiFi radio into precise IMU that measures multiple motion parameters, including moving distance, heading direction, rotating angle, etc.

Doppler Frequency Shift (DFS)





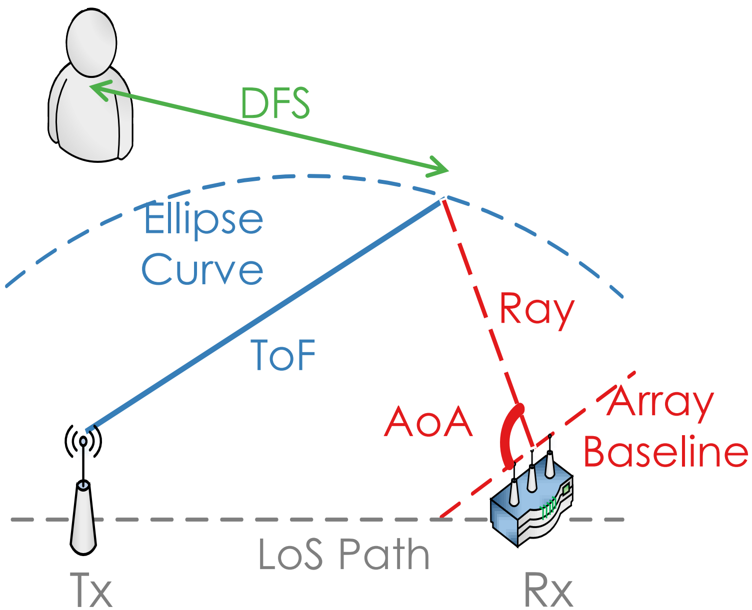
CARM (Mobicom '15)

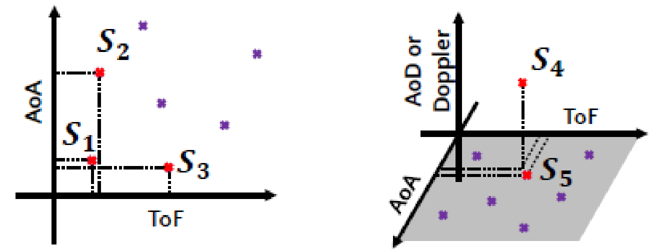
Calculates power distribution of Doppler Frequency Shifts components as learning features of HMM model.

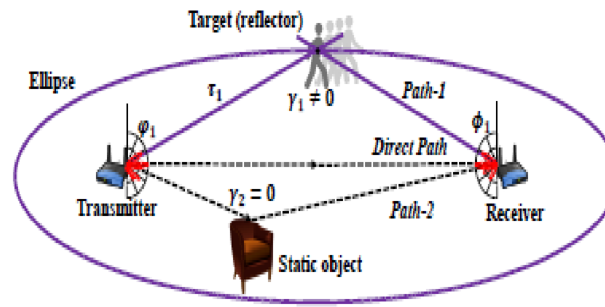
Widar (MobiHoc '17)

Models the relation among person's walking velocity, location and DFS, and pinpoints the person passively.

Combining multiple features







Widar2.0 (MobiSys '18)

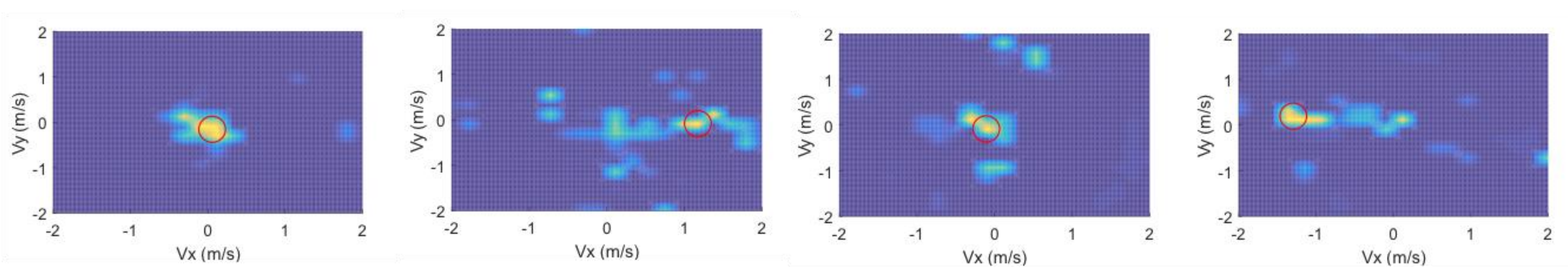
Passive human tracking system with a single commercial Wi-Fi link, endowing passive tracking with ubiquity as well as accuracy.

mD-Track (Mobicom '19)

Incorporates information from four dimensions to advance the accuracy of passive wireless sensing in a multipath environment.

Environment-unrelated feature

- In Widar3.0 (MobiSys 2019), we propose a new feature BVP: ***B**ody-coordinate **V**elocity **P**rofile*
  - Same gestures may exhibit different velocity distributions in the global coordinate system.
  - Transformation can be achieved with the knowledge of locations of devices, and location and orientation information of the user.



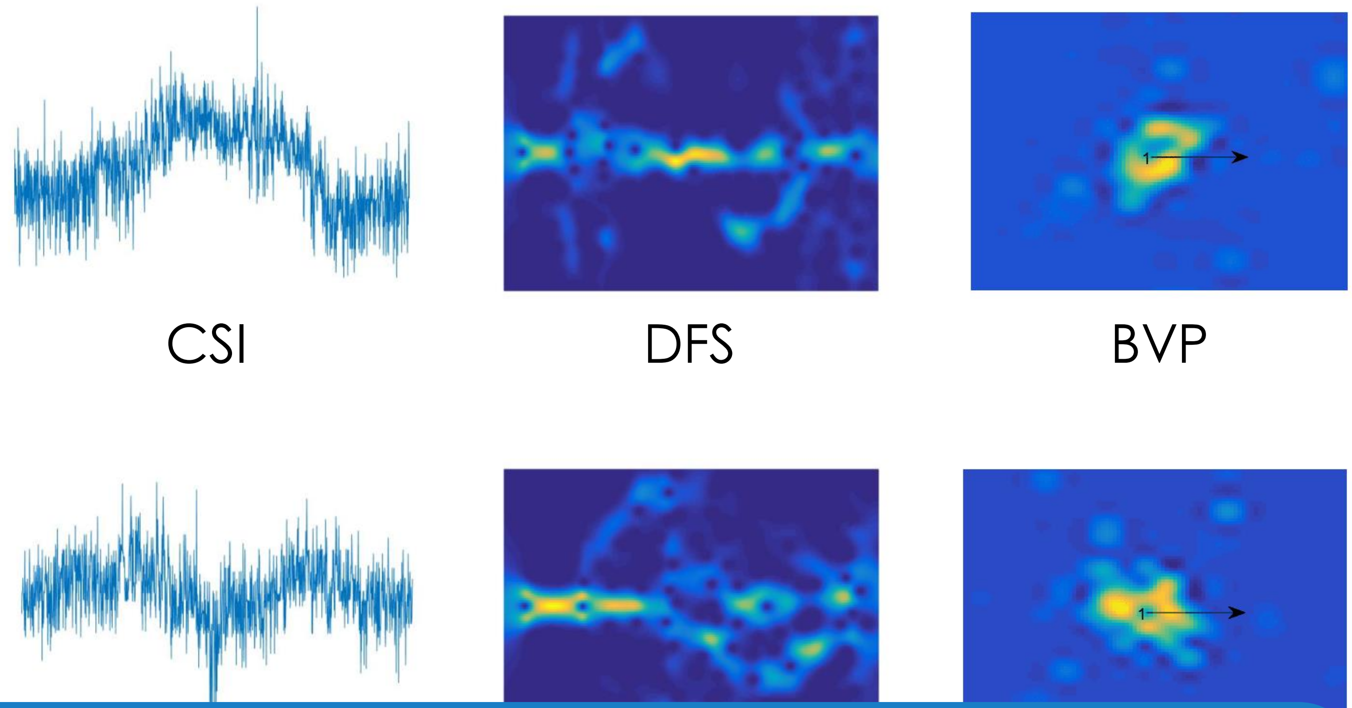
Stage 1: Start | Stage 2: Push | Stage 3: Stop | Stage 4: Pull

Comparison of Signal Features

- Investigate raw CSI, DFS, BVP
  - example gesture: Pushing and Pulling
  - two domains

Comparison of Signal Features

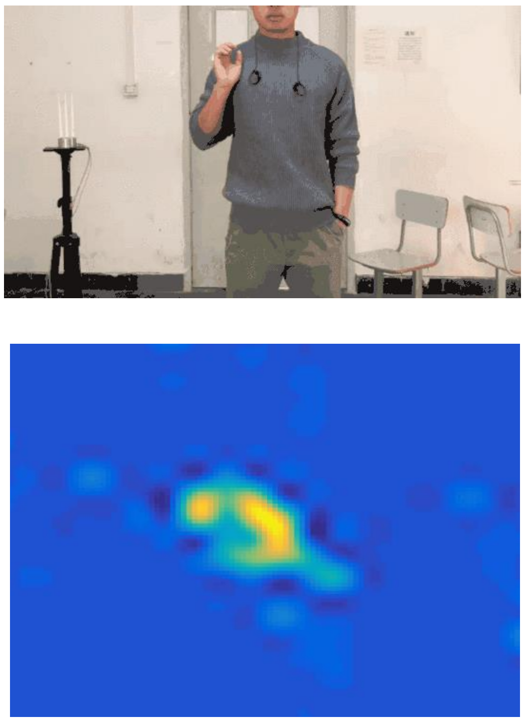
Domain-1
orientation #1
location #1
environment #1



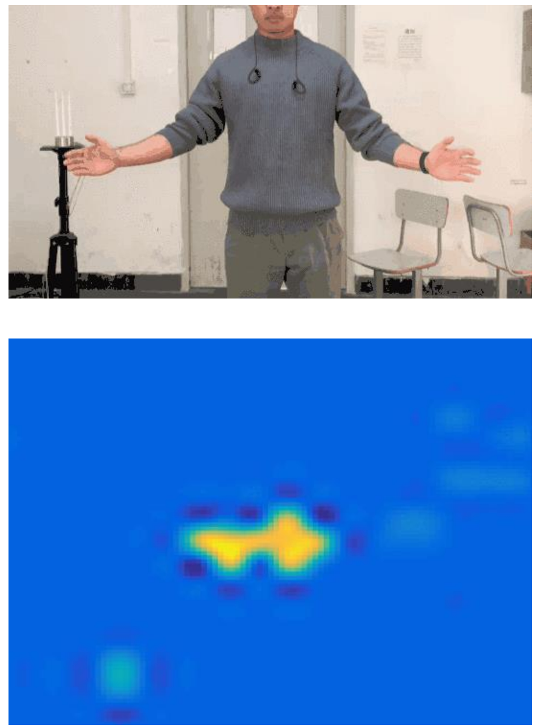
Domain-2
orientation #2
location #2
environment #2

CSI and DFS of same gestures are probable to vary across different domains, but BVP stays consistent!

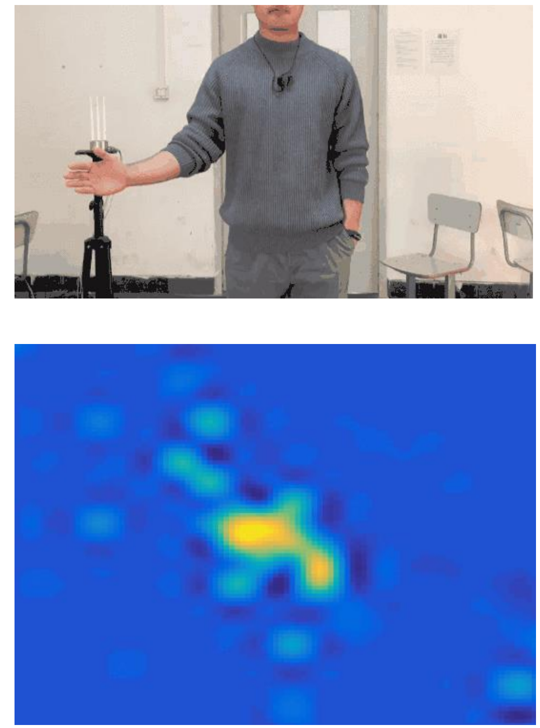
BVP Examples



Pushing & Pulling



Clapping



Sliding

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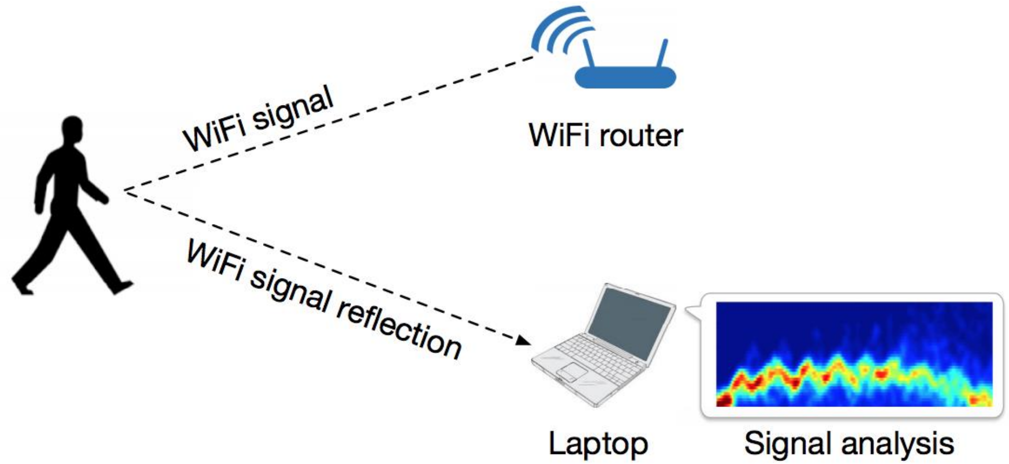
Machine Learning Based Algorithms

- Support Vector Machine (SVM)
- Decision Trees
- K-Nearest Neighbors (KNN)
- Hidden Markov Model (HMM)
- ……

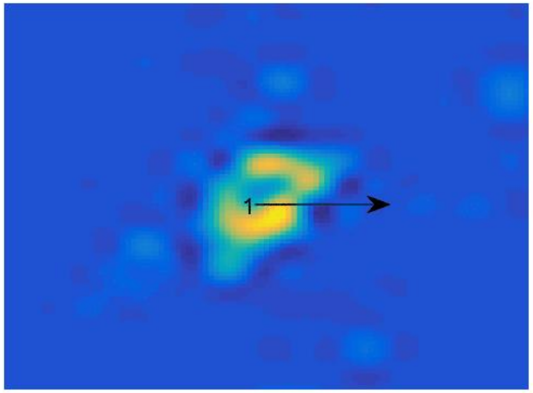


CARM (Wang, et al. MobiCom'15), WiFiU (Wang, et al. UbiComp'16)

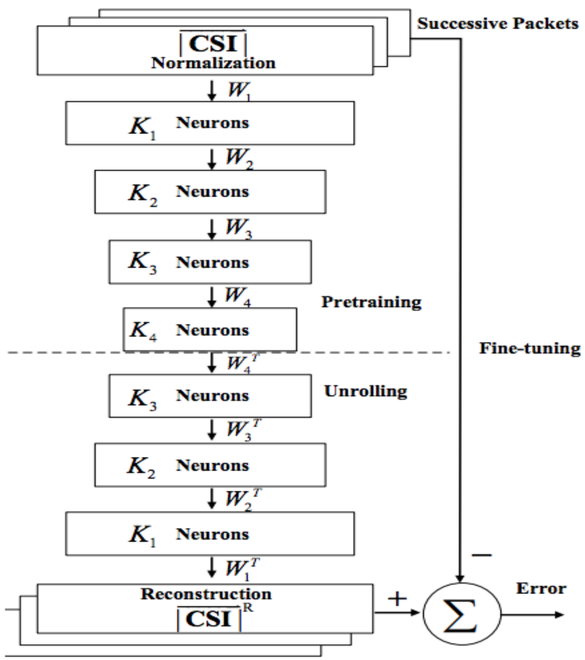
Deep Learning Based Algorithms

- Deep learning has achieved great success in the field of computer vision, and has produced many accurate and reliable recognition models, which can be directly applied in wireless sensing.

- However, existing works ignore the difference between visual perception and wireless sensing at the signal level, and there is still a lack of finer spatio-temporal modeling of behavioral activities in wireless signal space.

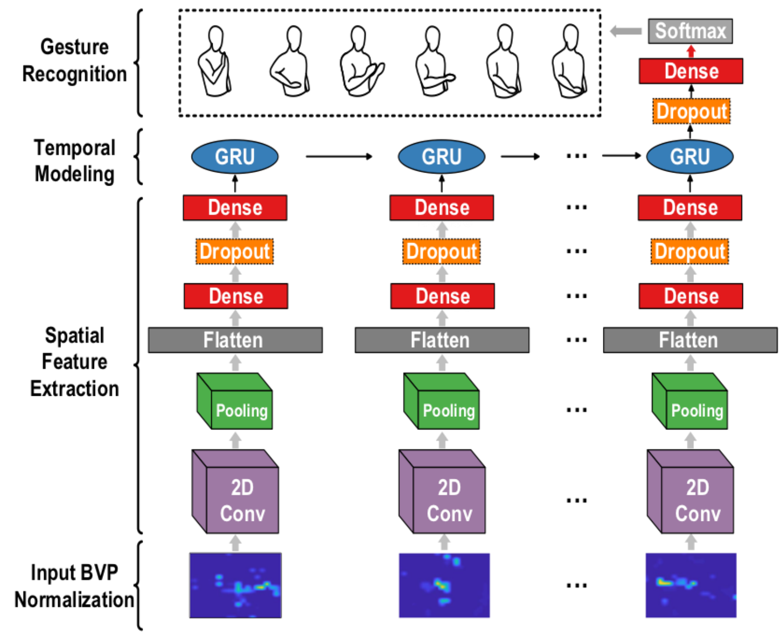


Deep Learning Based Algorithms



DeepFi (Wang, et al. TVT'17)

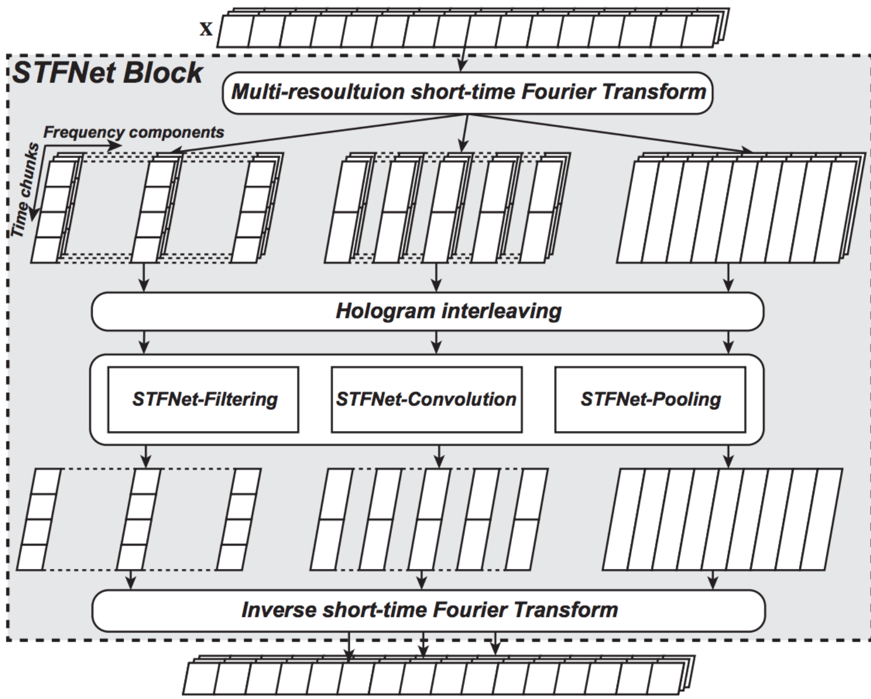
A stack of RBMs are adopted for fingerprinting-based indoor localization with CSI measurements as input.



Widar3.0 (Zheng, et al. MobiSys'19)

CNN and RNN are adopted to extract spatial features and model temporal dynamics of the input feature, BVP.

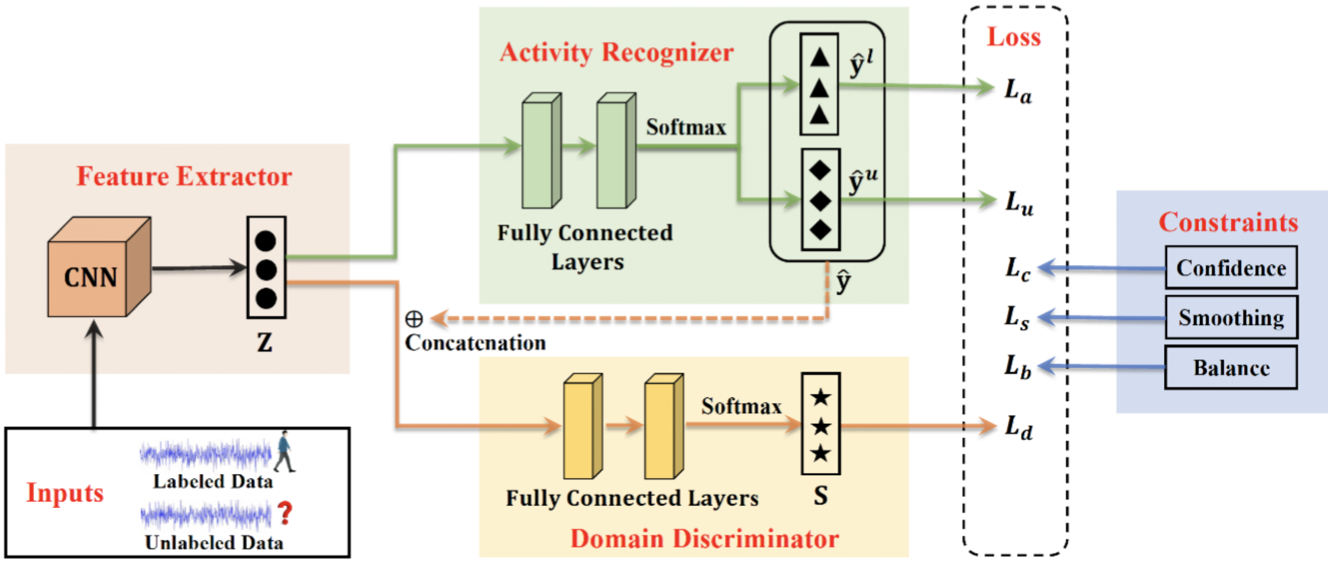
Feature Network



STFNet (Yao, et al. WWW'19)

STFNet enables time-frequency analysis in the model level to learn features directly in the frequency domain, and unveil the possibilities of incorporating domain-specific modeling and transformation techniques into neural network design.

Adversarial Learning



EI (Jiang, et al. MobiCom'18)

Domain discriminator is incorporated into the model for unsupervised domain adversarial training to fully make use of unlabeled data to remove the domain-specific uniqueness of activities.

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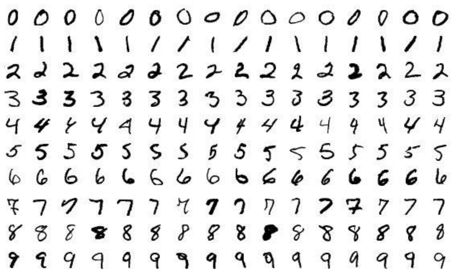
Why Dataset is Important

- The promotion of high-quality public datasets to research is enormous.
  - foundation for the success of deep learning algorithms.
  - Example: ImageNet, Mnsit, COCO, etc.
- Advantages:
  - enabling collaboration and competition on the same platform.
  - making experiment re-production easier, performance comparison more objective, collaboration more effective, and technological progress easier to accumulate.



Datasets

- Existing datasets for wireless sensing
  - Dataset 1 (U Toronto and Stanford, 2017)
    - ~4GB raw Wi-Fi measurements (CSI)
    - 6 persons; 6 activities: Lie down, Fall, Walk, Run, Sit down, Stand up
    - https://github.com/ermongroup/Wifi_Activity_Recognition
  - Dataset 2 (College of William and Mary, 2018)
    - ~6GB raw Wi-Fi measurements (CSI)
    - 276 sign words in the lab and home environments
    - https://github.com/yongsen/SignFi
  - Dataset 3 (Tsinghua U, 2018)
    - Widar 1.0/2.0 for passive localization and tracking
    - 1 person 80 traces in the classroom, office and corridor
    - http://tns.thss.tsinghua.edu.cn/wifiradar
- All suffer from ***small-scale data, limited scenario***

Widar3.0 Dataset

- Hand gesture dataset, which consists of raw Wi-Fi readings (CSI) and other sophisticated features (e.g., DFS and BVP) of 258K instances, duration of 8,620 minutes, from 75 domains.
- The dataset and Widar series of works can be found in http://tns.thss.tsinghua.edu.cn/widar3.0
- Other Download Source： 1， BaiduYun (password: 4m47)； 2， FTP: widarftp:widar2019@166.111.80.127:40121

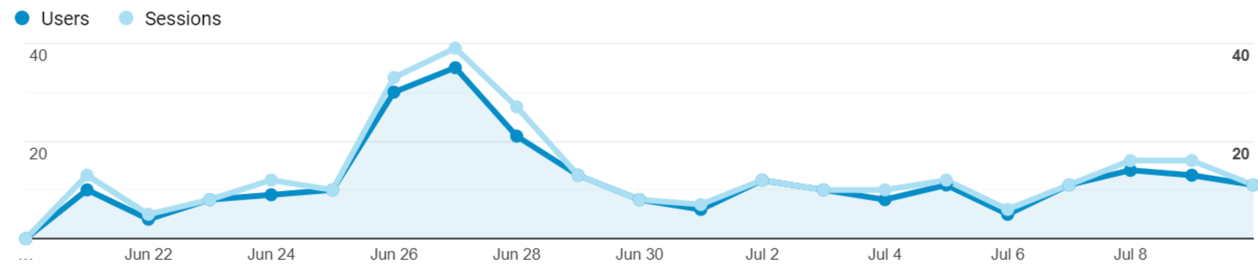
Widar3.0 User Profiles

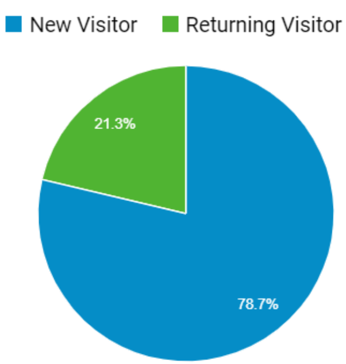
Users
194

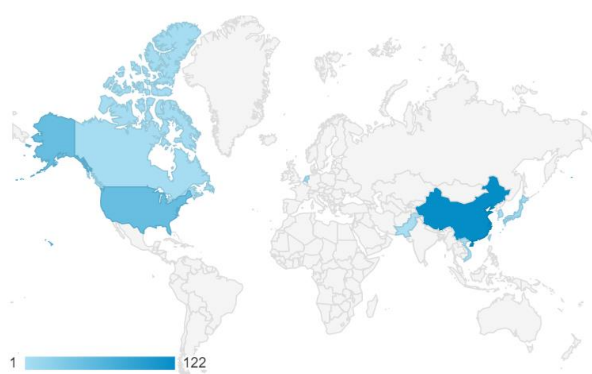
Sessions
279

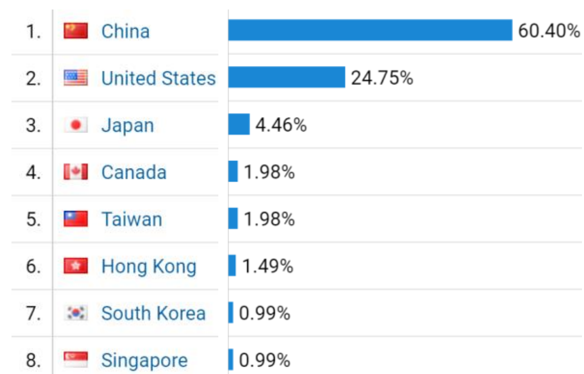
Pageviews
343

Avg. Session Duration
00:00:47









WiFi雷达实验平台

- “WiFi雷达”实验平台包括微型工控机、TNS-CSI Tool、Visual CSI软件等
- 可实时显示无线信道状态信息（振幅与相位），并能同步存储观测数据，方便使用者观察和分析环境变化对信道状态的影响。
- WiFi雷达主页：http://tns.thss.tsinghua.edu.cn/wifiradar/

Outline

- Introduction
- Feature
- Algorithm
- Dataset
- **Opportunity**

机遇

有效去除**跨协议、跨网络、跨设备**的射频干扰，提升感知鲁棒性，应对未来更复杂的电磁环境

提取并融合**环境无依赖**的信号特征，从方法上保证了感知效果不依赖于特定环境和人员，**普适性强、学习训练成本低**

在**无线信号空间**建立人员行为的时空模型，实现定位精度达到**分米级**，提高人员发现准确率与活动识别准确率。

实现毫米波相控阵列的波束扫描，突破传统Wi-Fi全向感知的局限，实现**多目标、高鲁棒性**的场景感知

Look ahead

以前在电视剧中总能看到这样的场景，当几个人做坏事或者密谋做坏事的时候，一般会选择一个密室，关好门拉上窗帘，有经验的还会检查桌子下面是否有窃听器，完事后还要仪式性地念叨一句“天知地知，你知我知”。

今后，别忘了还要把**Wi-Fi** 关掉。

《WiFi雷达：从RSSI到CSI》，《中国计算机学会通讯》，2014年11月

Look ahead

人类对物理世界的感知进入了**泛在智能**的新阶段，物联网与人工智能技术共同推动人类社会从万物互联走向万物智联的**AIoT**时代。

作为物联网与人工智能的交叉领域，**智能无线感知**正反映了这一趋势，成为当前学术界研究的热点。

其实，早在两千多年前，荀子就讨论了感知与智能的关系，在《荀子·正名篇》中郑重写下了"**知之在人者谓之知，知有所合者谓之智**"。但是，荀子他老人家肯定没能预料到知和智一旦结合起来，是一个怎样的泛在智能的时代。两千多年后的我们，有能力预料吗？

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- WiFi Radar Homepage： http://tns.thss.tsinghua.edu.cn/wifiradar/
- Dataset: http://tns.thss.tsinghua.edu.cn/widar3.0

我的微信

Thanks!

Q&A

研究趋势

- 研究大势：人类对物理世界的感知进入了**泛在智能**的新阶段
- 最有价值、最迫切需要解决的问题
  - 无线感知：利用泛在信号实现智能环境感知
  - 无源感知：捕获泛在无线信号能量，实现无需供电的感知
- 国内相关团队
  - 北邮马华东教授
  - 上交王新兵教授
  - 中科大李向阳教授