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Algorithmic Sensing in the Age of Artificial Intelligence

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AI. vs Co. Sensing

Sensing from Past to Today

- Sensing is closely related to communication: extracting information from signals
- Sensing techniques are crucial components for majority engineering problems in real life
- Advanced sensing techniques are a driving force behind the new intelligent systems:
  - intelligence is enabled by information,
  - information comes from both sensing

Path from conventional sensors to algorithmic sensing:

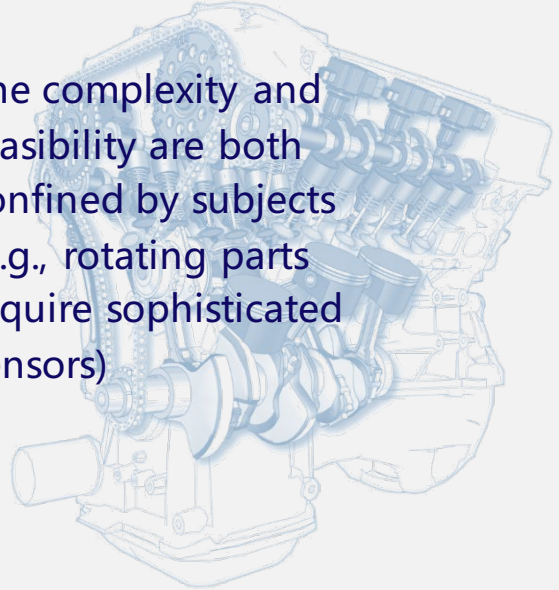
- **Conventional sensing** (sensor) performs physical (often energy) conversion

- **Algorithmic sensing** interprets the complicated information out of physical conversion

AI. vs Co. Sensing

Why Algorithmic?

- The outcome of (sensor) conversion can be complicated
- Certain conversion demands contacts, thus introducing uncontrollable errors
- The complexity and feasibility are both confined by subjects (e.g., rotating parts require sophisticated sensors)



Algorithmic sensing is complementary by its nature:

- It starts as signal processing but goes far beyond later
- It entails sensors with a consistent complexity and no need for adapting to subjects
- It may even repurpose commodity hardware beyond its designed purpose
- It allows software side **(intelligent algorithms)** to fine-tune the sensing performance, hence accommodate a wide range of sensing front-ends

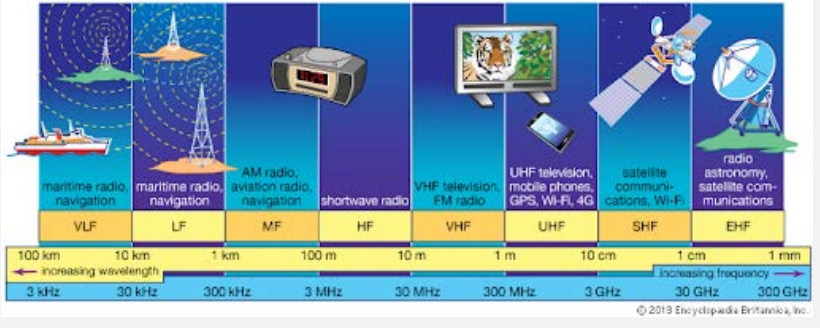
AI. vs Co. Sensing

Media for Algo. Sensing

- Algorithmic sensing requires media to conduct information; typically *light*, *acoustic*, and *electromagnetic field*
- Light sensing (infrared or visible light) directly concerns photography and computer vision
- Acoustic sensing (audio or ultrasound) is less energy efficient, but has a great potential in passive sensing

Electromagnetic field covers almost all spectra out of light and acoustics:

- The spectrum from kHz to THz is used by RF communication, hence the term: RF-sensing
- Far more energy efficient and interference resilient than acoustic sensing
- Superior to light sensing as it allows sensing to go beyond both line-of-sight and visual range.



Algorithmic RF Sensing

RF-Sensing Basics

- RF-sensing has a 100-year history since WW1, started in the form of RADAR: RAdio Detection And Ranging
- The analogy of RF vs light sensing: that of compound vs human eyes: a tradeoff between responsiveness and accuracy
- Mostly driven by military technologies, such as the Aegis Combat System of US Navy

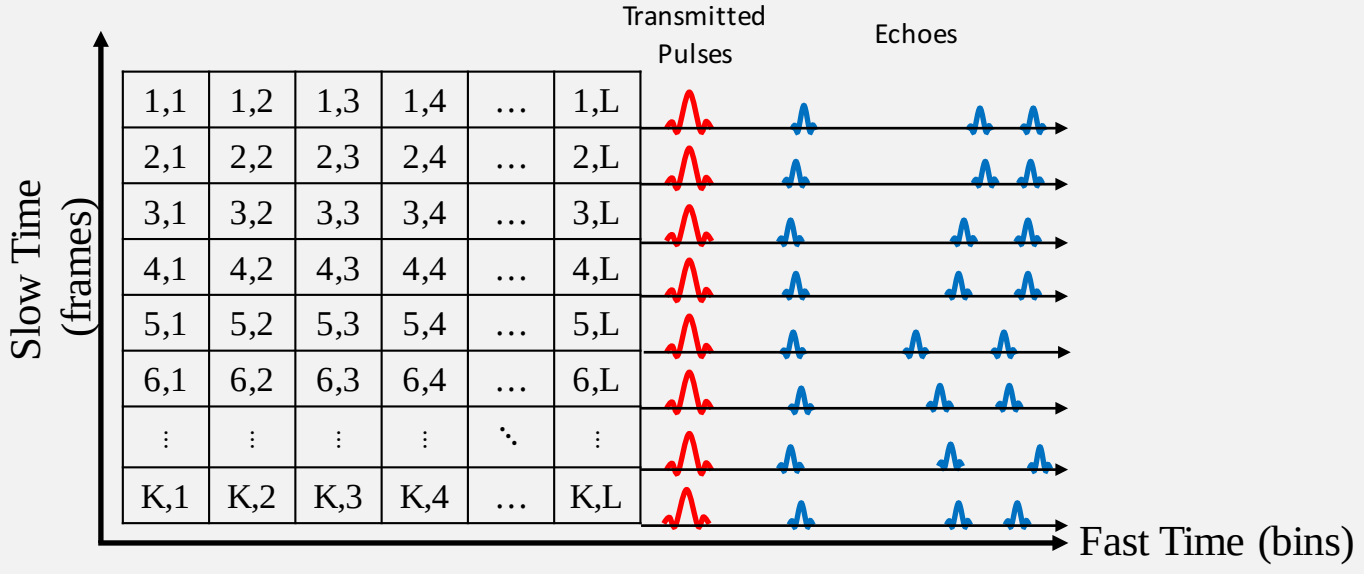
Mainstream RF-sensing has two dual (time vs frequency) modes:

- IR-UWB: Impulse Radio Ultra Wideband
- FMCW: Frequency-Modulated Continuous-Wave

Algorithmic RF Sensing

Principles of RF-Sensing

- A three-dimensional (3D) sensing system covering temporal, spatial and frequency domains: temporal further separated into fast- and slow-time, representing range and speed respectively.
- Sensing accuracy affected by both central frequency and bandwidth
- Taking the CIR (Channel Impulse Response) of IR-UWB as an example:

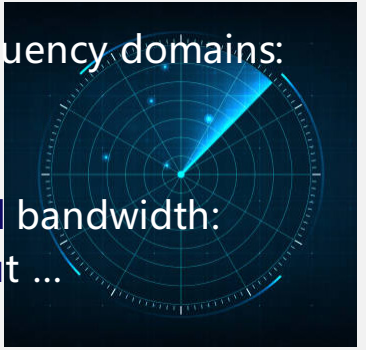


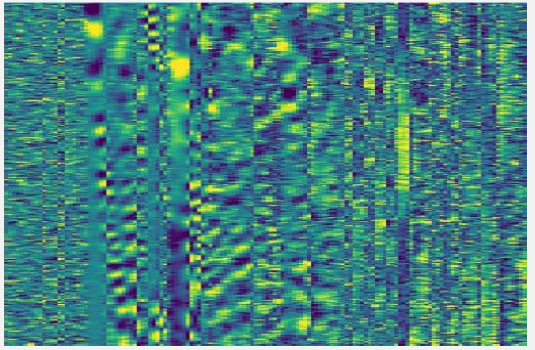
RF-Net: A Unified Meta-Learning Framework for RF-enabled One-Shot Human Activity Recognition, *ACM SenSys*, 2020

Algorithmic RF Sensing

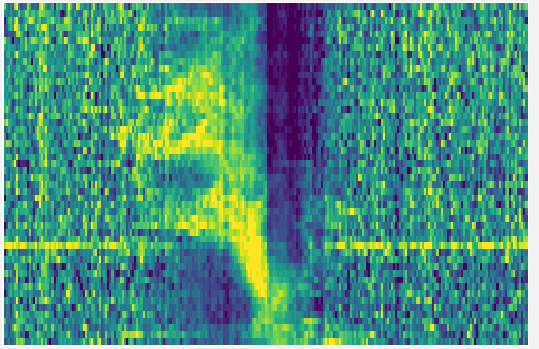
Principles of RF-Sensing

- A 3D sensing system covering temporal, spatial and frequency domains: modern near-field sensing vs traditional far-field one.
- Sensing accuracy affected by both central frequency and bandwidth: higher frequency and larger bandwidth are preferred, but …
- Human Activity Recognition (HAR) with two types of radars





IR-UWB: Walking



FMCW: Walking

RF-Net: A Unified Meta-Learning Framework for RF-enabled One-Shot Human Activity Recognition, *ACM SenSys*, 2020

Algorithmic RF Sensing

Principles of RF-Sensing

- A 3D sensing system covering temporal, spatial and frequency domains: spatial (2D) is provided by sophisticated antenna arrays (a.k.a., MIMO).
- Sensing accuracy affected by both central frequency and bandwidth
- Taking the CIR of IR-UWB again as an example:

slow time \ tx-rx pair							
		(N,1,1)	(N,1,2)	(N,1,3)	(N,1,4)	…	(N,1,K)
	(2,1,1)	(2,1,2)	(2,1,3)	(2,1,4)	…	(2,1,K)	(N,2,K)
(1,1,1)	(1,1,2)	(1,1,3)	(1,1,4)	…	(1,1,K)	(2,2,K)	(N,3,K)
(1,2,1)	(1,2,2)	(1,2,N)	(1,2,4)	…	(1,2,K)	(2,3,K)	(N,4,K)
(1,3,1)	(1,3,2)	(1,3,N)	(1,3,4)	…	(1,3,K)	(2,4,K)	…
(1,4,1)	(1,4,2)	(1,4,N)	(1,4,4)	…	(1,4,K)	…	(N,L,K)
…	…	…	…	…	…	(2,L,K)	
(1,L,1)	(1,L,2)	(1,L,3)	(1,L,4)	…	(1,L,K)		

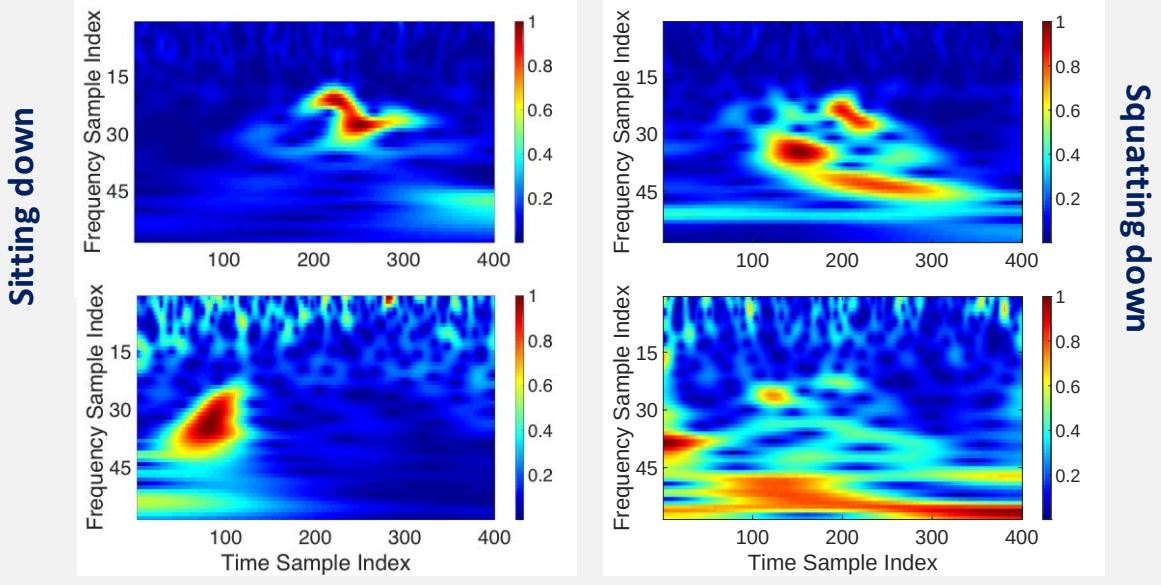
fast time

Enhancing RF Sensing with Deep Learning: A Layered Approach, *IEEE Comm. Mag.*, 2021

Algorithmic RF Sensing

Principles of RF-Sensing

- A 3D sensing system covering temporal, spatial and frequency domains: time-frequency analysis can be applied to both temporal sub-dimensions.
- Taking two IR-UWB frames as examples: similar activities are clearly distinguished, but lack of intuitive sense (thus need algorithms)



RF-Net: A Unified Meta-Learning Framework for RF-enabled One-Shot Human Activity Recognition, *ACM SenSys*, 2020

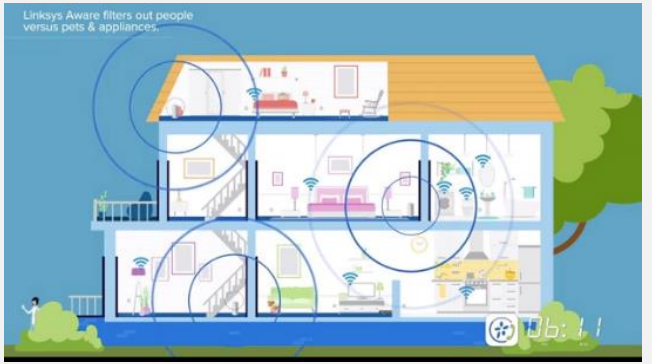
Algorithmic RF Sensing

Commercial RF-Sensing Developments

- Confined by the device complexity, commercial RF-sensing starts only in the current century
- Academia have boasted Wi-Fi as an alternative to radars in the first 15 years
- Commodity-grade RF-sensing equipment appears in the market only in the last 5 years or so

Wi-Fi sensing: where to go?

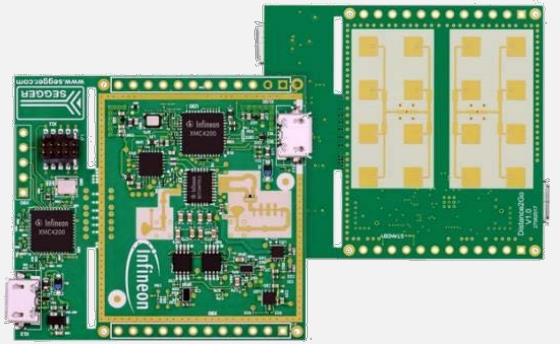
- 20 ~ 40MHz bandwidth cannot offer a sufficient sensing resolution: $\delta = \frac{\lambda f}{2B}$
- Wi-Fi is designed as a multistatic communication mechanism, so sensing can be seriously affected by this nature
- Integrated Sensing And Communication (ISAC) design is imperative



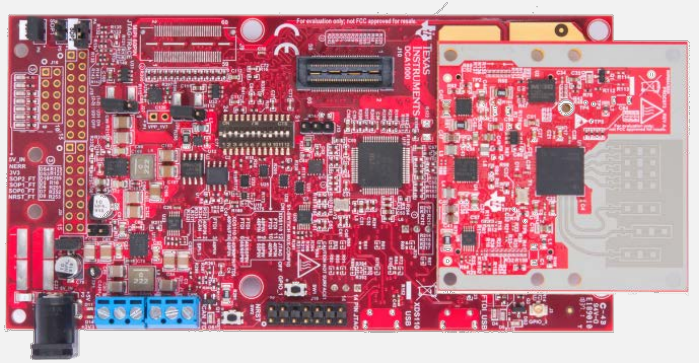
Algorithmic RF Sensing

Commercial RF-Sensing Developments

- Large-scale RF-sensing devices:
  - monopolized by major vendors (e.g., Qualcomm and Huawei) and,
  - too bulky to be adopted for individual users.



- Small commodity-grade radars gain momentum in the past few years; typically including
  - TI 60 and 77GHz mmWave radars,
  - Infineon 24GHz mmWave radars, and
  - Novelda X4 IR-UWB.



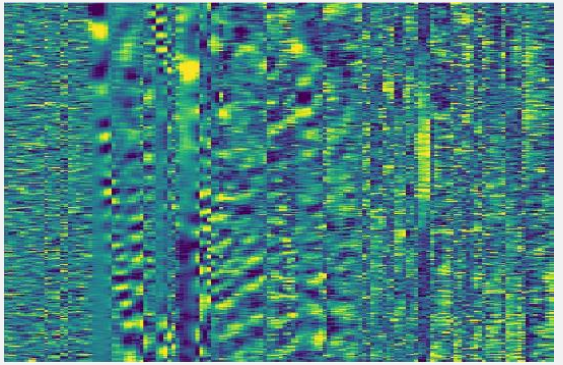
Deep Algorithmic Sensing

Relation with Computer Vision (CV)

- RF-sensing has 2D image representations, so modules for CV can be directly applicable, but …
- RF-sensing data can be extend to higher dimensions, including both depth and temporal dynamics
- They cannot be directly interpreted by human eyes, render offline labelling impossible, yet preserving privacy

Consequent requirements:

- More effective (deep learning) algorithms to conduct data analytics
- Training mechanisms demanding small data, as the difficulty of acquiring labelled data grows substantially

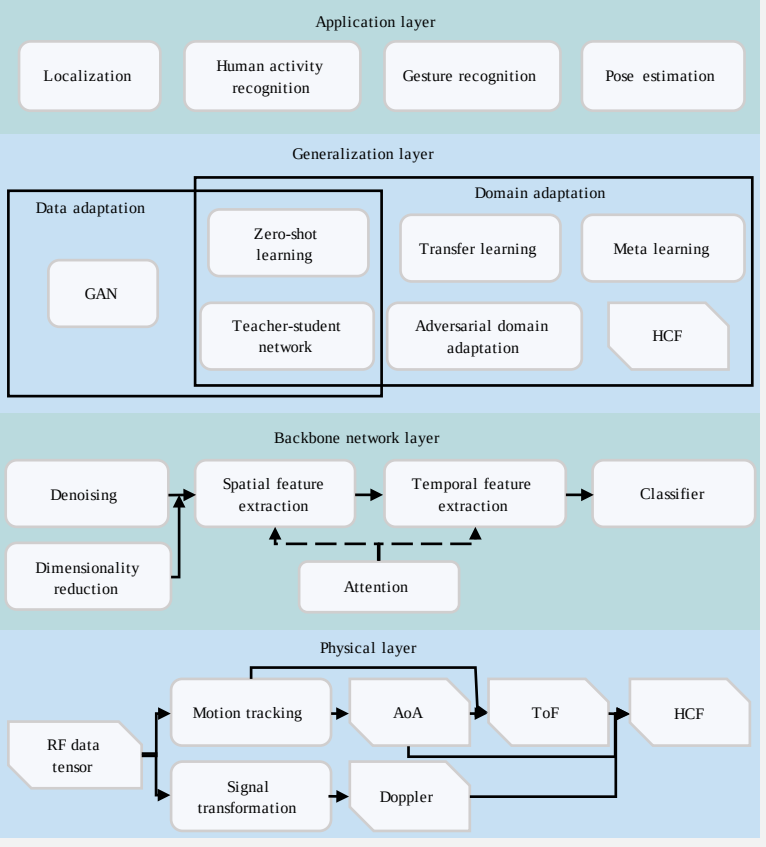


RF-Net: A Unified Meta-Learning Framework for RF-enabled One-Shot Human Activity Recognition, *ACM SenSys*, 2020

Deep Algorithmic Sensing

A Layered Design Principle

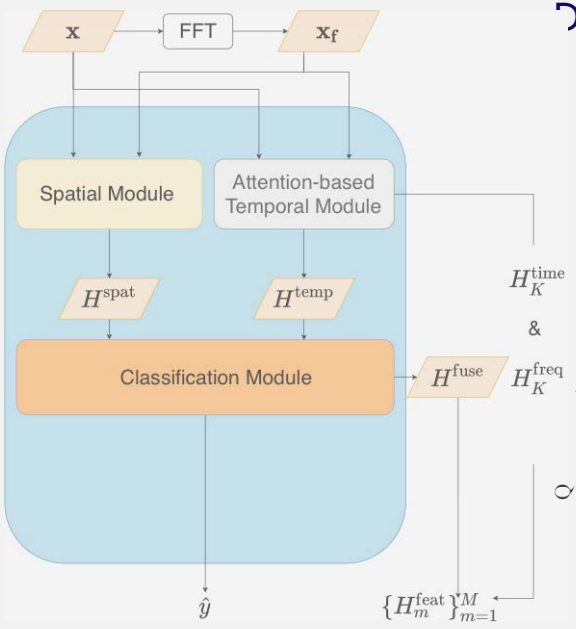
- RF data tensor: a unified data pre-processing framework for all types of RF-sensing
- Specialized backbone network design: an art more than science (still experience driven)
- Adaptable training mechanism, guided by conventional optimization principles



Enhancing RF Sensing with Deep Learning: A Layered Approach, *IEEE Comm. Mag.*, 2021

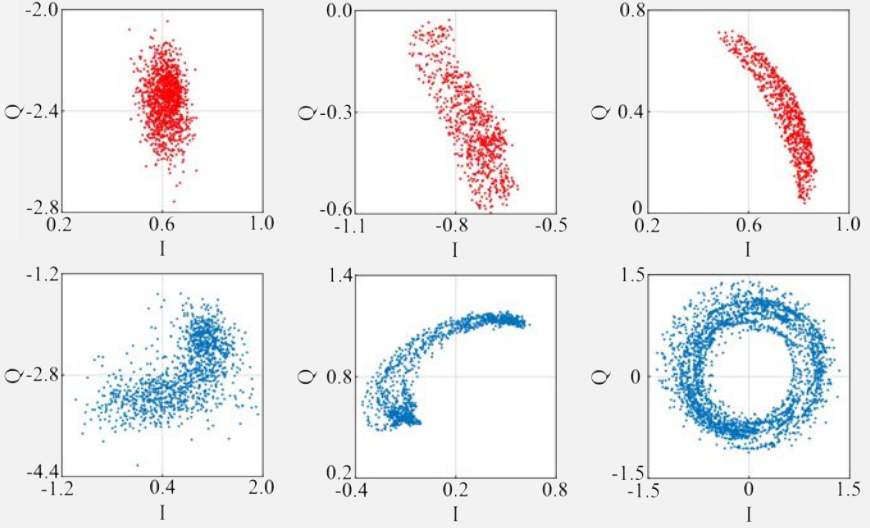
Deep Algorithmic Sensing

Specialized Backbone Design



Dual-path inputs can be preferred

- Pre-separating time and frequency to reduce network complexity
- I/Q complex input stream has to be separated into two streams



(a) Wi-Fi. (b) IR-UWB. (c) FMCW.

Can We Obtain Fine-grained Heartbeat Waveform via Contact-free RF-sensing? *IEEE INFOCOM*, 2022

RF-Net: A Unified Meta-Learning Framework for RF-enabled One-Shot Human Activity Recognition, *ACM SenSys*, 2020

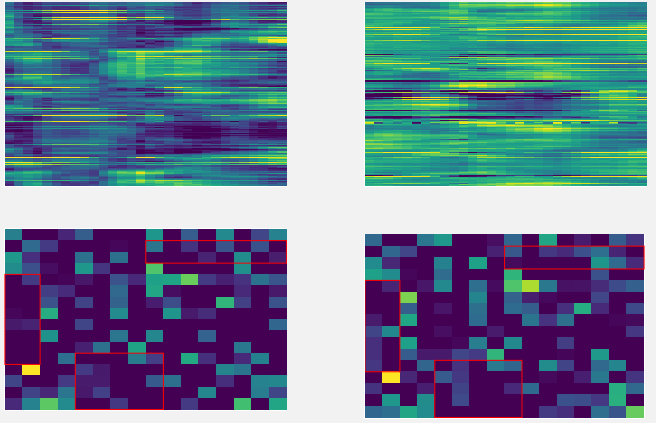
Deep Algorithmic Sensing

Cross-domain Sensing

- Similar to CV, RF-sensing can also be interfered by environments (background), albeit to a much less extent
- Segmentation based on semantics is not applicable anymore
- Cross-domain (environment) analytics is necessary given the scarcity of training data

Common methods for cross-domain learning :

- Transfer Learning
- Domain Adaptation
- Meta-Learning based Few-shot Learning



Enhancing RF Sensing with Deep Learning: A Layered Approach, *IEEE Comm. Mag.*, 2021

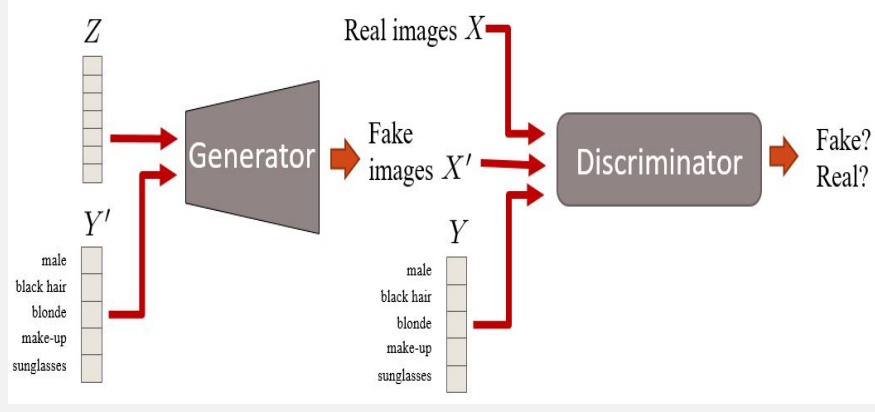
Deep Algorithmic Sensing

Adversarial Learning for Signal Separation

- Generative Adversarial Networks (GANs) have generated a hype due to its ability in "creating out of nothing"
- Assisted by certain priors, conditional-GAN (cGAN) may offer the ability of picking out "a needle in a haystack"
- Under certain conditions, cGAN and variational inference (VAE) can break the curse of low SNR

RF-sensing mostly operate under low SNR :

- Motion robust vital sign monitoring
- Multi-person HAR
- Separating multiple acoustic signal sources



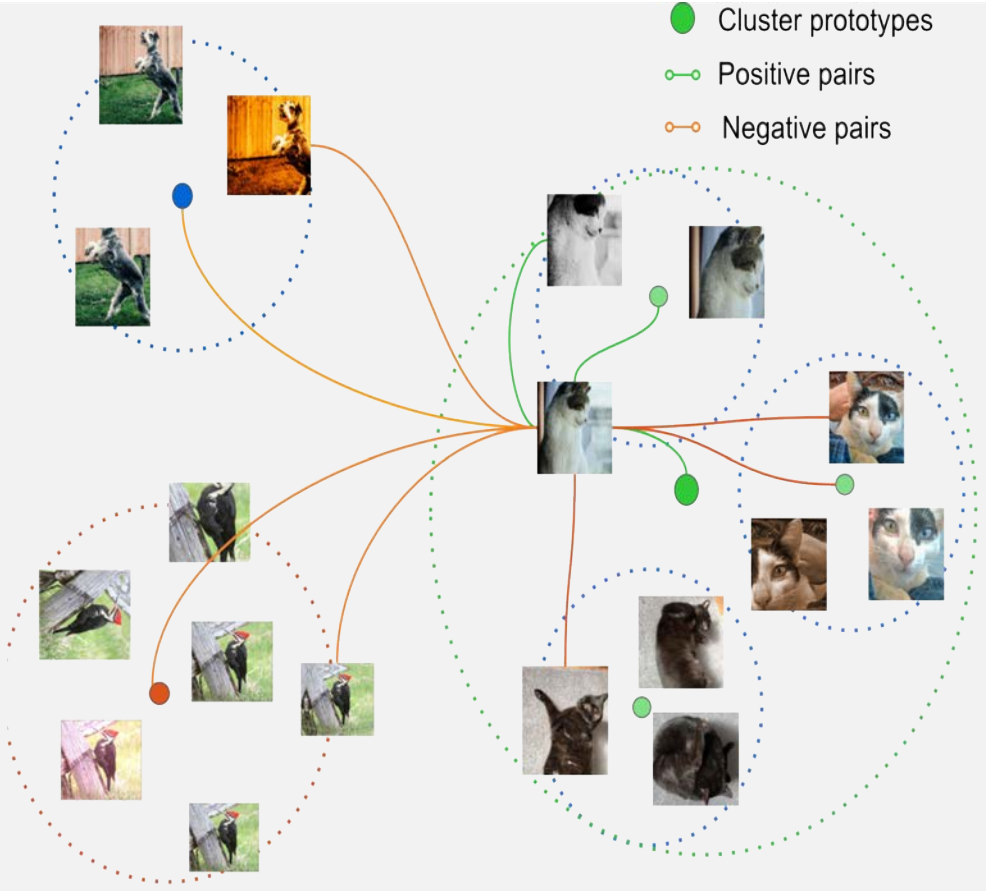
Enhancing RF Sensing with Deep Learning: A Layered Approach, *IEEE Comm. Mag.*, 2021

Deep Algorithmic Sensing

Contrastive Learning Primer

Mimicking human's way of learning :

- Learning by comparison or contrasting
- Self-supervising: no need for labelling
- Data augmentation is the trick



Different from clustering in that training is conducted by a GAN discriminator

MoVi-Fi: Motion-robust Vital Signs Waveform Recovery via Deep Interpreted RF Sensing, *ACM MobiCom*, 2021

Application Prototypes

Our Research Philosophy

- Relying on SG-CN joint research platforms
- Integrating research, education, and industry, and to bring deep RF-sensing into education/commercial applications
- User-oriented design and developments to offer community services
- Light-weight sensing device for edge-based pervasive deployments

Concrete products and solutions:

- Composite contact-free sensing gateway: connecting deep RF-sensing to IoT edges
- Open RF-sensing platforms, suitable for both industry and academia for flexible customization

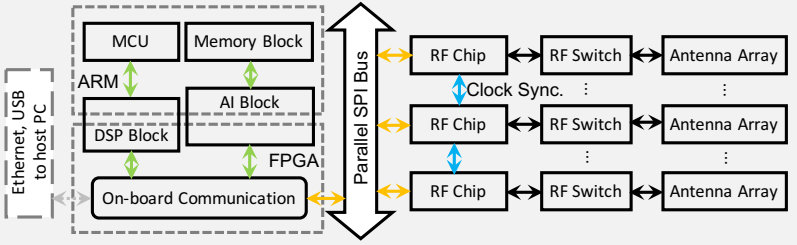
Application Prototypes

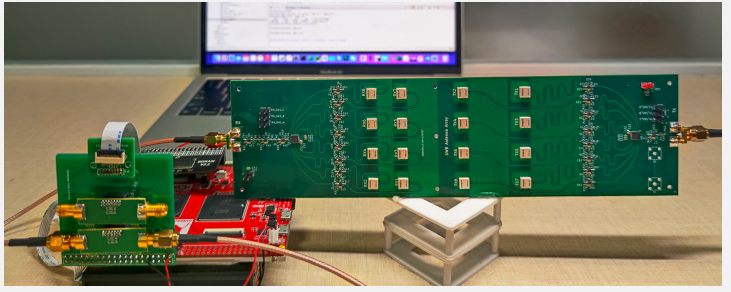
Octopus Platform

- Compact edge sensing for wide deployment
- Open platform enabling application customization
- UWB front-end with fine-grained and robust resolution
- Modularized MIMO array for scalability
- Heterogeneous/reconfigurable computing hardware facilitates application developments

Product demonstration :

- World's first open algorithmic sensing platform : Walabot and MIT only deliver closed source products
- Compatible with other front-end, such as FMCW and acoustic transceivers



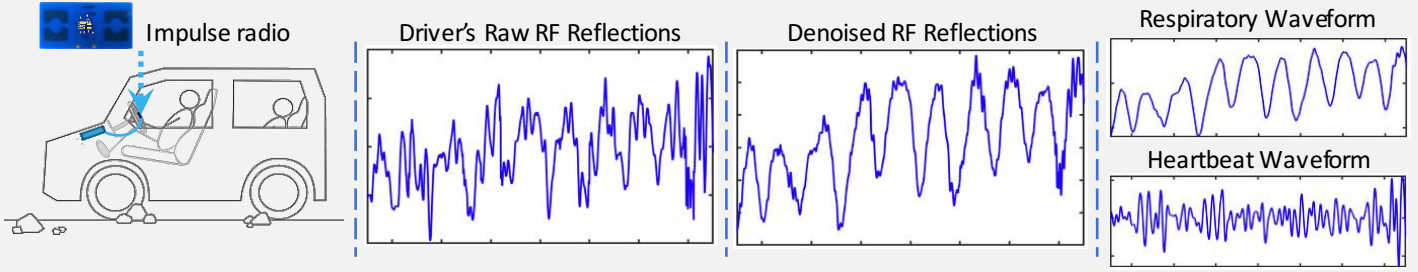


Octopus: A Practical and Versatile Wideband MIMO Sensing Platform, *ACM MobiCom*, 2021

Application Prototypes

Contact-free Vital Signs and Activity Monitoring

- Indoor vital signs and activity (e.g., falling) monitoring is very useful for elder and child cares
- In-vehicle vital signs and activity monitoring (V^2iFi) can promote a healthy and safe driving habit
- How is conduct them at the same time remains an open problem then



V2iFi: in-Vehicle Vital Sign Monitoring via Compact RF Sensing, *ACM UbiComp*, 2020

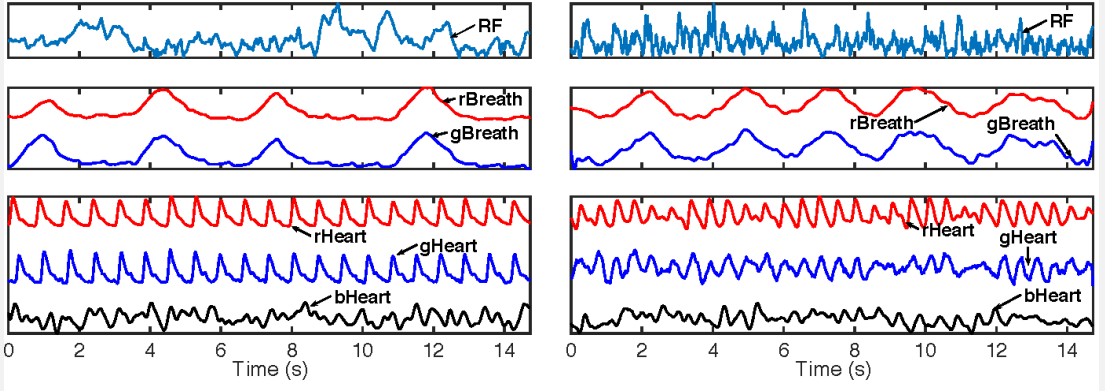
Application Prototypes

High-end Motion-robust Monitoring

- Body movements are inevitable
- Sensing has to be robust to such interferences
- **MoVi-Fi** creatively exploits deep contrastive learning to perform blind signal source separation, extracting vital signs waveform out of other concurrent interferences

Deep Contrastive Learning (DCL) works :

- Blind source separation often assumes linear signal mixture
- The mixture in RF signal space between body movements, respirations, and heart beats can be highly nonlinear
- The self-supervision ability of DCL makes nonlinear blind source separation possible, but sophisticated data augmentation is necessary



(a) Waveform recovery from typewriting. (b) Waveform recovery from walking-on-treadmill.

MoVi-Fi: Motion-robust Vital Signs Waveform Recovery via Deep Interpreted RF Sensing, *ACM MobiCom*, 2021

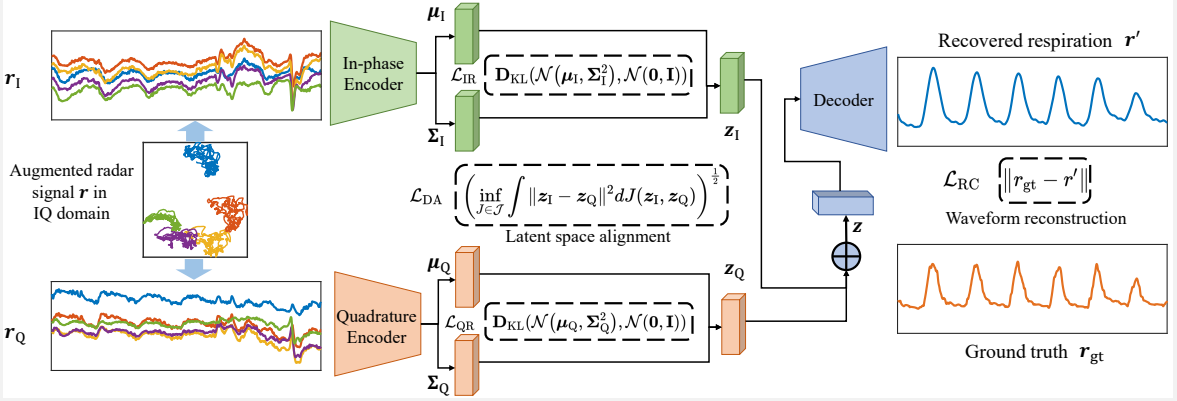
Application Prototypes

Low-end Motion-robust Monitoring

- The cost for MoVi-Fi can be high, so an alternative is needed
- **MoRe-Fi**, a single-radar contact-free respiration monitoring system, is first of its kind: it creatively employ the principles of variational inference, and enable the encoder-decoder model to extract target signals

Signal extraction based on complex input :

- Information is better represented by complex signal with I/Q components.
- Direct extraction based on prior information can be more efficient than blind separation.
- The "translation" capability of encoder-decoder model, together with generalizability of variational inference makes it possible to achieve robust non-linear extraction.

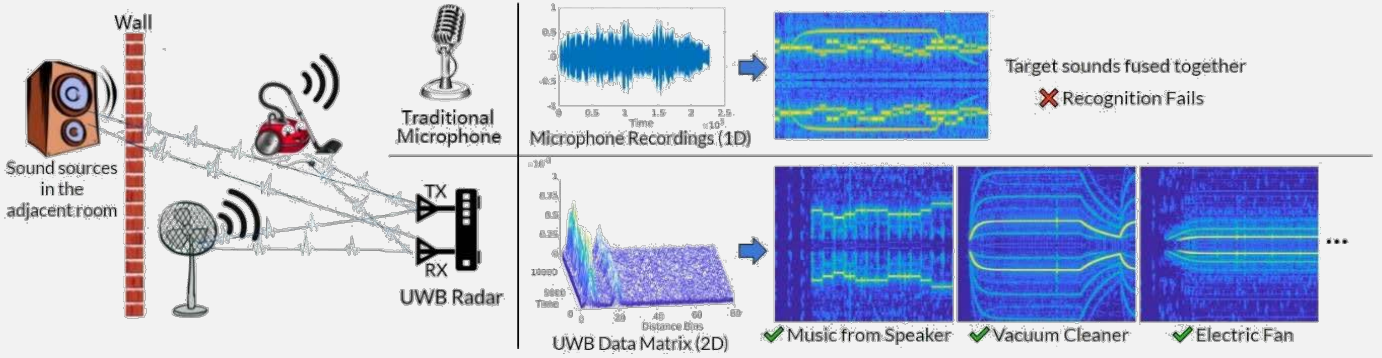


MoRe-Fi: Motion-robust and Fine-grained Respiration Monitoring via Deep-Learning UWB Radar, *ACM SenSys*, 2021

Application Prototypes

Acoustic Signal Source Separation

- Event/action inference driven by acoustic source separation has been widely adopted in practice, such as noise source discovery and removal
- Conventional methods based on mixed audio can hardly be effective, as signals are mixed during the propagation
- RF-sensing directly senses the vibrations of the acoustic sources, thus naturally offers spatial separation ability



UWHear: Through-wall Extraction and Separation of Audio Vibrations Using Wireless Signals, *ACM SenSys*, 2020

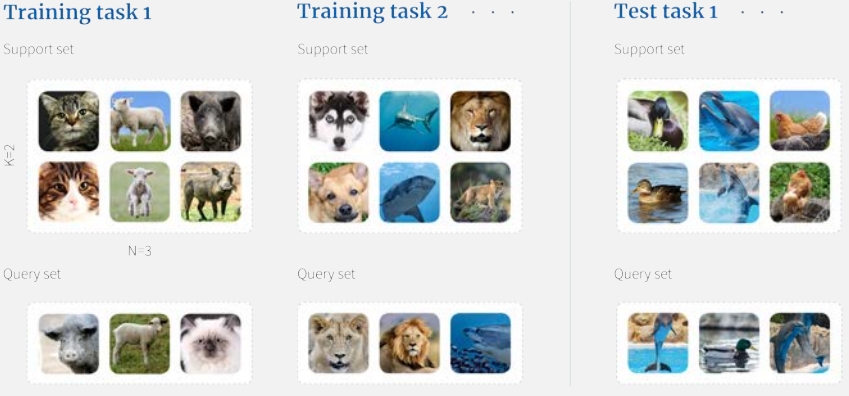
Application Prototypes

Cross-Domain HAR

- Though not identifiable by human eyes, RF-sensing data can be fully understood by deep learning models, with almost prefect feature extractions
- The complexity of RF analytics is far lower than CV analytics. Also, it goes beyond LoS and horizon, without incurring privacy infringements
- Yet the lack of training data calls for few-shot learning

We adopt Meta-learning to realize "Learning to learn" :

- Mimicking human learning style
- Partitioning datasets into multiple smaller sets and using them to implement a repetitive deep representation learning procedure
- When facing a new domain (environment), kNN is used to directly compare features for classification without further training.



RF-Net: A Unified Meta-Learning Framework for RF-enabled One-Shot Human Activity Recognition, *ACM SenSys*, 2020

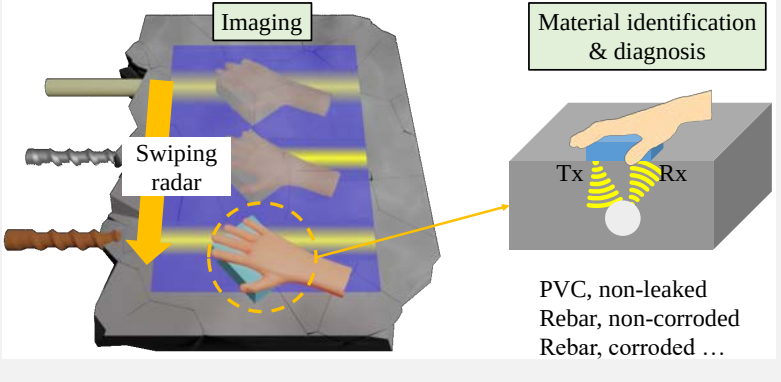
Application Prototypes

Seeing into Walls

- The internal structures of concrete walls can be corroded over time
- The problem is more severe in tropical countries (e.g., Singapore), especially for subway tunnels
- **SiWa**, the first-generation microwave non-destructive wall detection radar employs deep domain adaptation to detect water seepage and rebar corrosion in a calibration-free manner

Lessons learned from this system :

- Longer wavelengths are beneficial to penetrating solid structures, but they may cause diffractive interference
- The microwave band from 7 to 8GHz is probably the most effective for penetrating into walls.
- The so-called "through-wall" proposals are inapplicable: they simply bypass walls.



SiWa: See into Walls via Deep UWB Radar, *ACM MobiCom*, 2021

Q & A

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