Algorithmic Sensing in the Age of Artificial Intelligence

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Al. 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
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
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.

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

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

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
- 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:

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**Algorithmic RF Sensing**

**Principles of RF-Sensing**

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*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
- 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:

<table>
<thead>
<tr>
<th>Slow time</th>
<th>Fast time</th>
</tr>
</thead>
<tbody>
<tr>
<td>tx-rx pair</td>
<td></td>
</tr>
<tr>
<td>(N,1,1)</td>
<td>(N,1,2)</td>
</tr>
<tr>
<td>(1,1,1)</td>
<td>(1,1,2)</td>
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<td>(1,2,1)</td>
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<td>(1,3,1)</td>
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<td>(1,4,1)</td>
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<td>...</td>
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</tr>
<tr>
<td>(1,L,1)</td>
<td>(1,L,2)</td>
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</tbody>
</table>
• 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)
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
• 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.
• 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
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

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
• 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

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
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
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

- 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

Our Research Philosophy

WiRUSH: http://en.wirush.ai/
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 MobCom, 2021
• Indoor vital signs and activity (e.g., falling) monitoring is very useful for elder and child cares

• In-vehicle vital signs and activity monitoring (V²iFi) can promote a healthy and safe driving habit

• How is conduct them at the same time remains an open problem then
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

MoVi-Fi creatively exploits deep contrastive learning to perform blind signal source separation, extracting vital signs waveform out of other concurrent interferences.

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.

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
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.

• Though not identifiable by human eyes, RF-sensing data can be fully understood by deep learning models, with almost perfect 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.
• 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.
Q & A

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