AI for Good
Machine Learning
in 5G Challenge

Understanding How People Move Using Modern Civilian Radar

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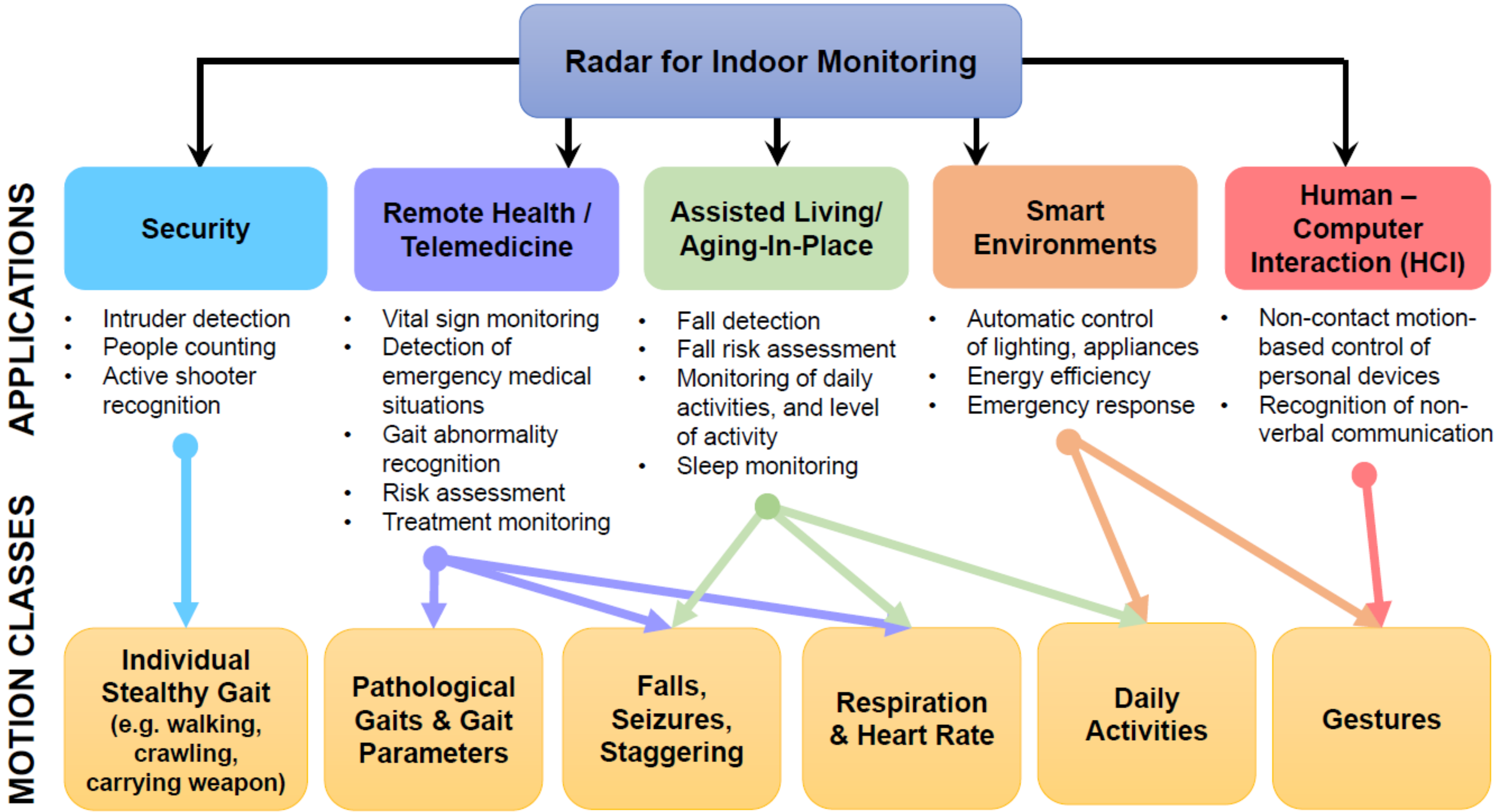
Applications of Human Ambient Intelligence (AmI)

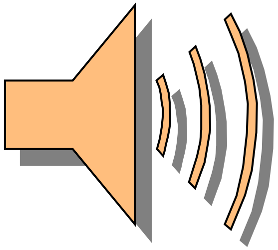


Why Radar for Human AmI?

- There are a lot of sensors types…

Camera

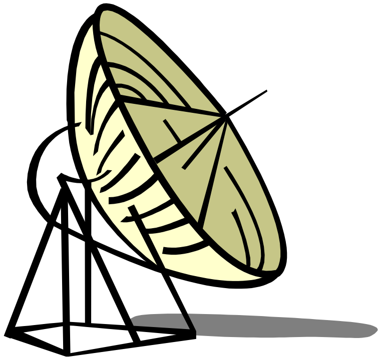
Acoustic



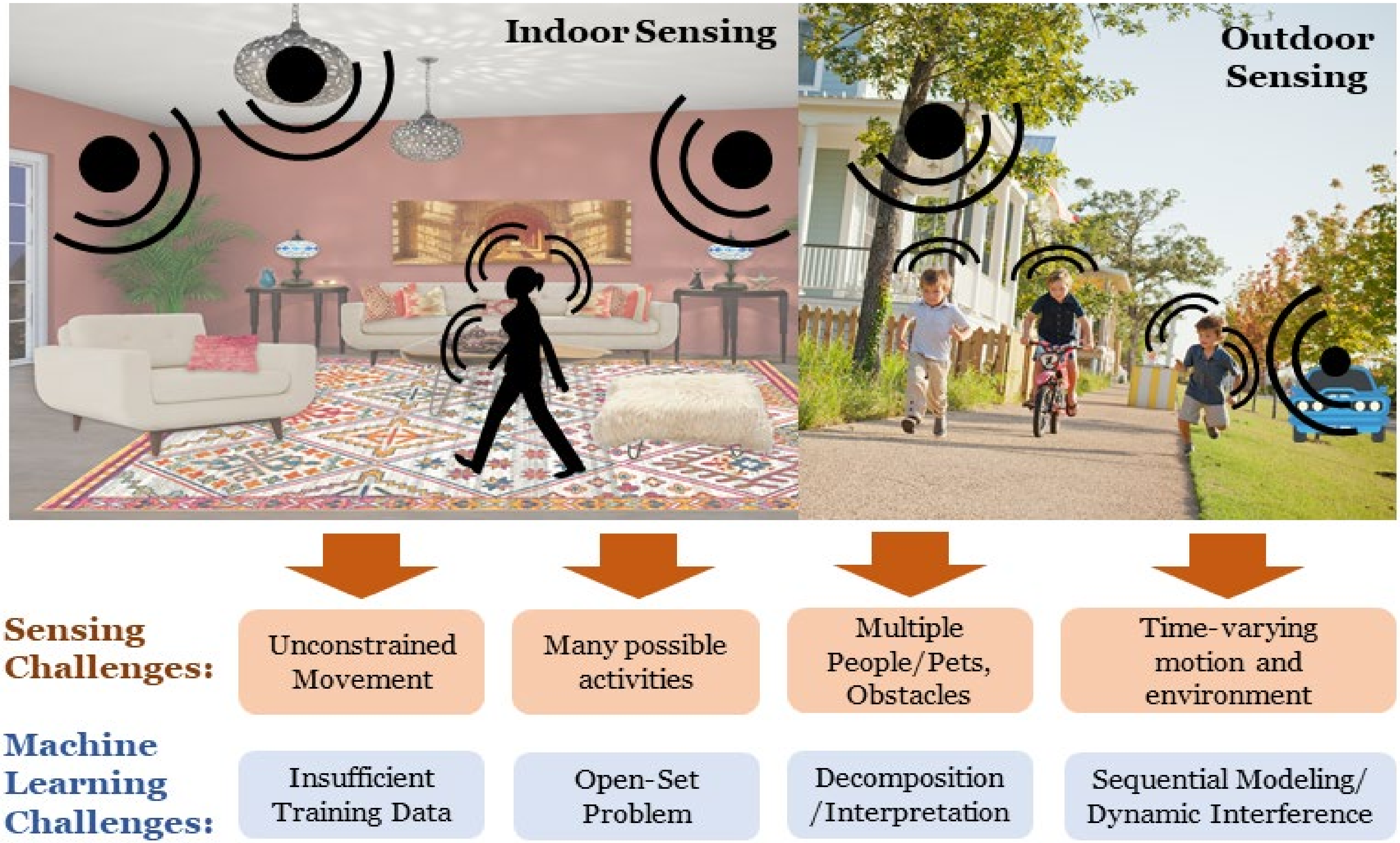
Infrared

Seismic/Vibration

- But, radar can sense
  - remotely (at a distance, non-contact)
  - through-walls, sub-surface
  - in the dark (no external light)
  - at wider range
  - and protects privacy



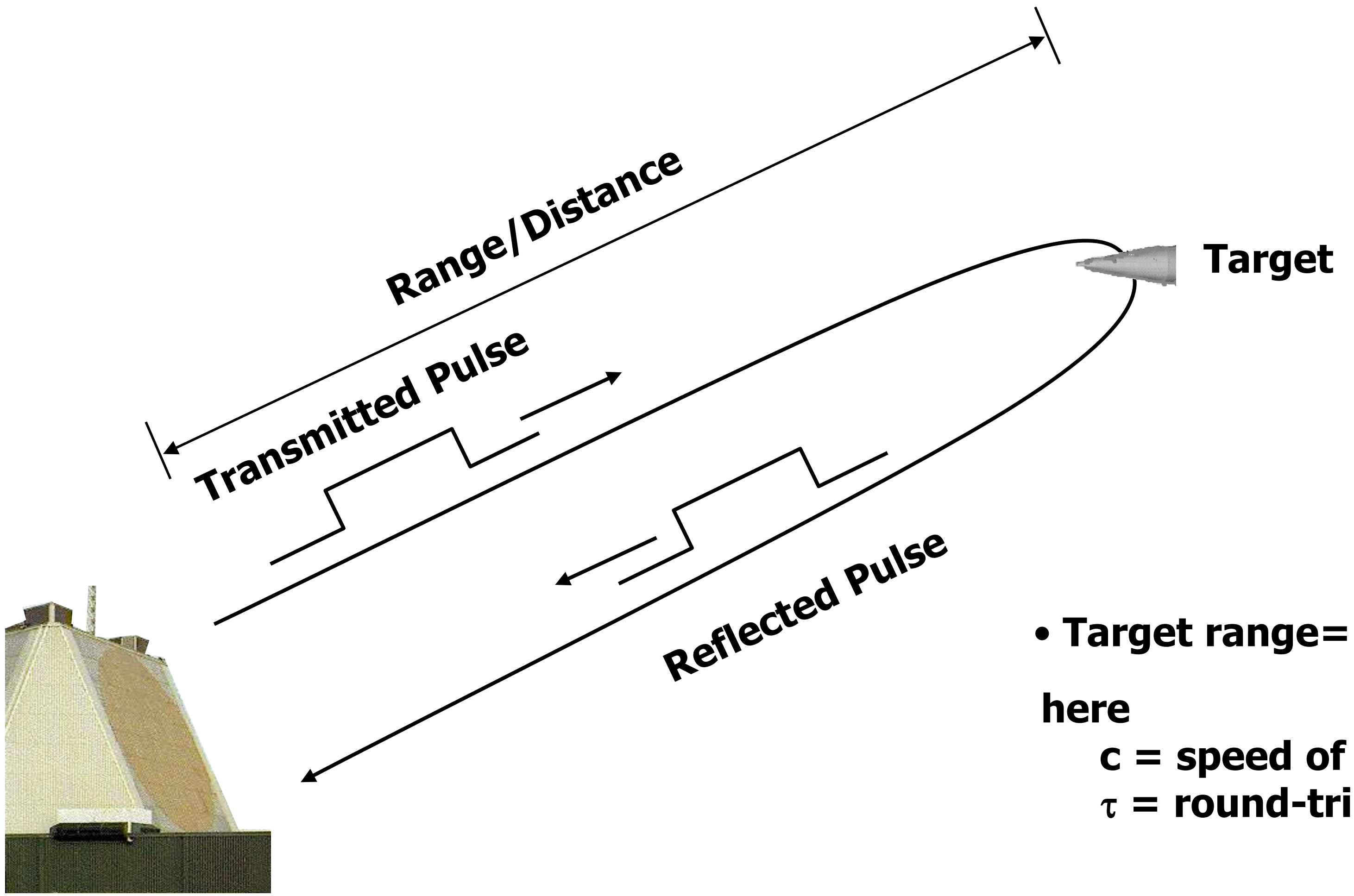
Challenges to AmI



Overview

- ❖ Radar Measurements and Pre-Processing
- ❖ Radar Data Representations
- ❖ Micro-Doppler Signature Based Classification
- ❖ Approaches for Training Under Low Sample Support
  - Transfer learning, unsupervised pre-training
  - Training with synthetic data generated by models or GANs
- ❖ Physics-Aware Machine Learning
- ❖ Cross-Frequency Training Challenge
  - Dataset and Recent Results

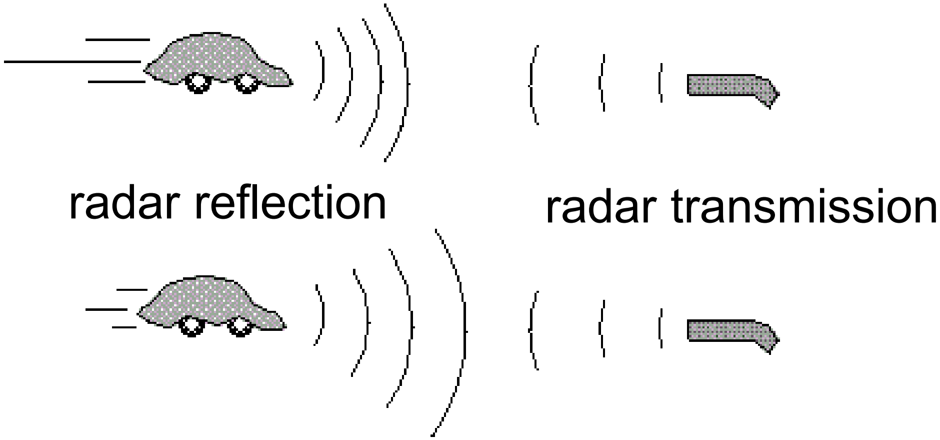
Range Measurements



- Target range= $\frac{c\tau}{2}$

here
- c = speed of light
- τ = round-trip travel time

Velocity Measurement



Received signal's frequency related to radial velocity of target….

$$\Delta f = \frac{2 f_o v \cos\theta}{c}$$

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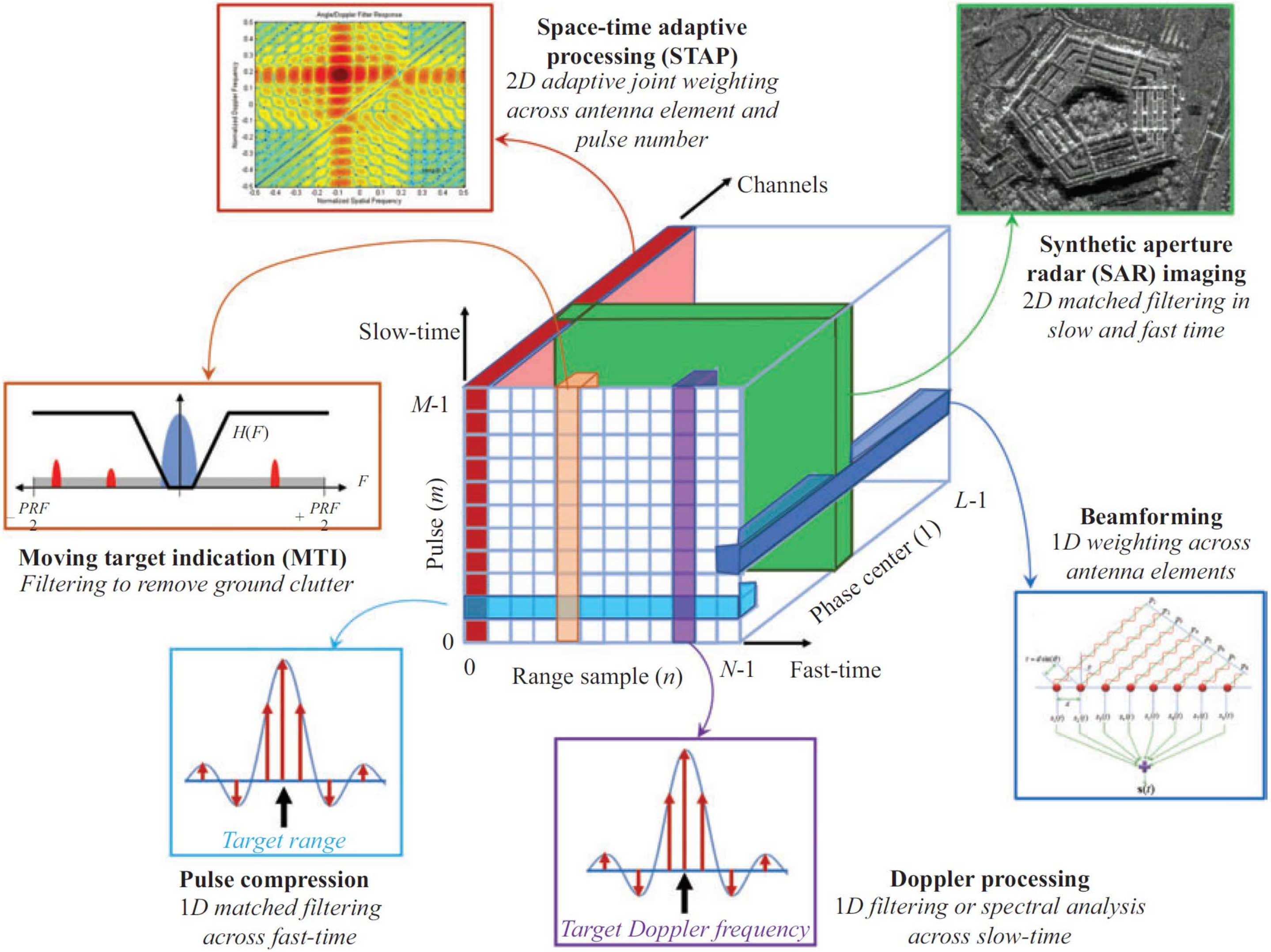
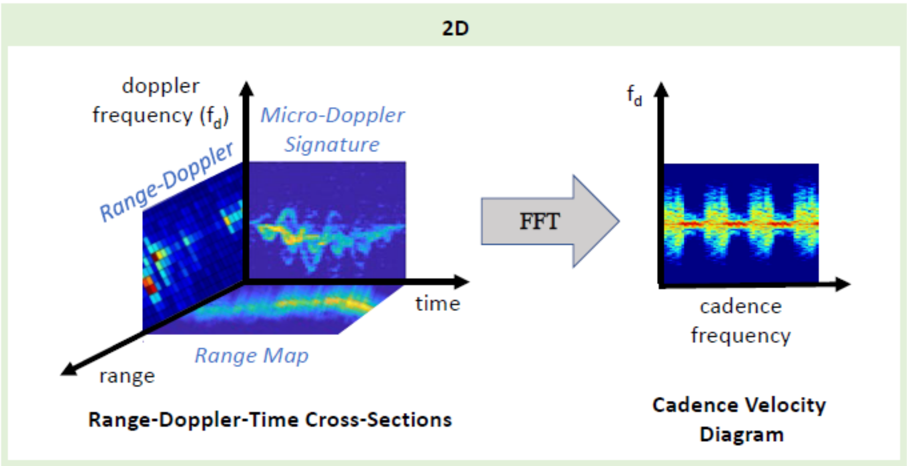
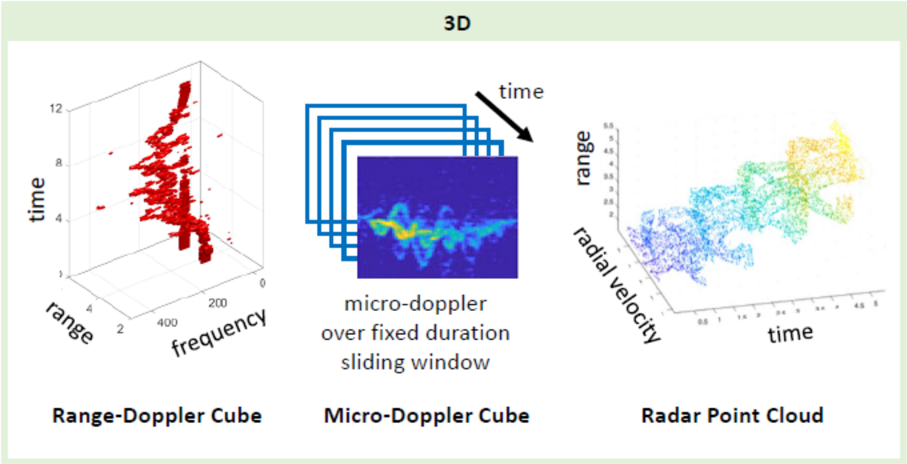
RF Data Representations



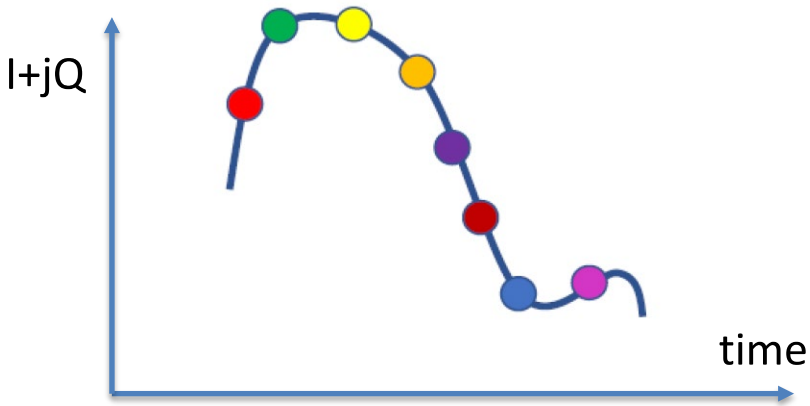
DNN Design for RF Applications

Input Representations





Sequential Models

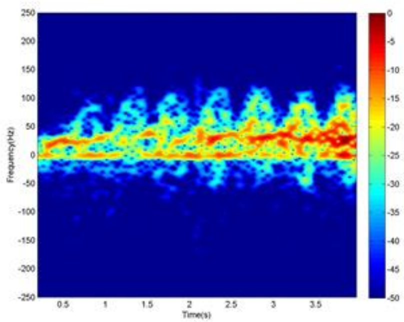


RF engineers have drawn on

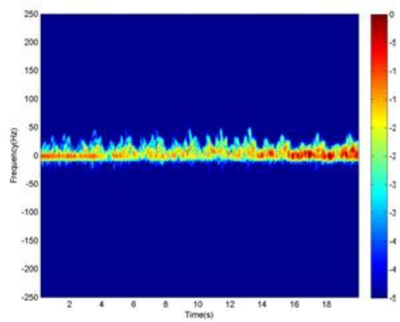
- *Computer vision for*
  → 2D/3D images/videos
- *Speech processing for*
  → 1D time-series

Micro-Doppler Signature Classification

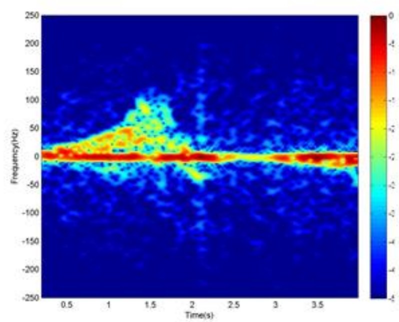
Walking



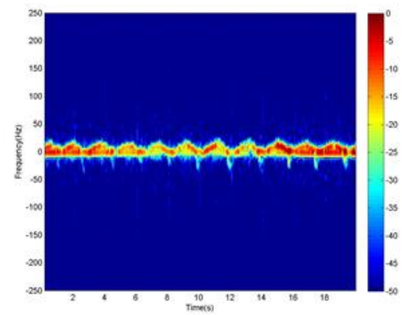
Limping



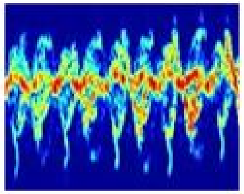
Falling



Wheelchair Use



INPUT



- Raw I/Q data
- Spectrogram

CLASSIFICATION PROCESS

FEATURE EXTRACTION

- Physical
- Speech-Inspired
- Transform-Based

FEATURE SELECTION

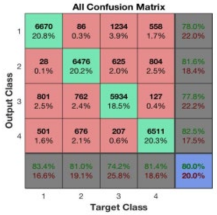
- Dimension Reduction
- Filters
- Wrappers

CLASSIFICATION

- SVM
- kNN
- Bayesian

...and more

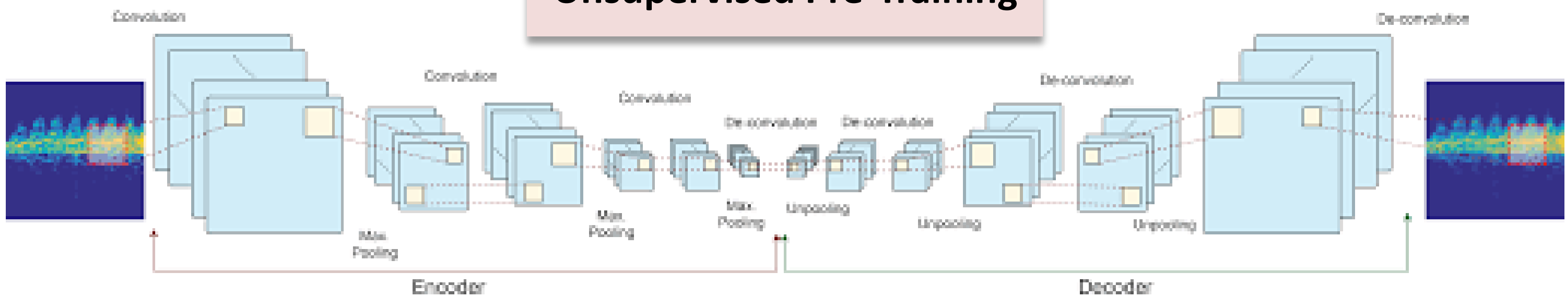
OUTPUT



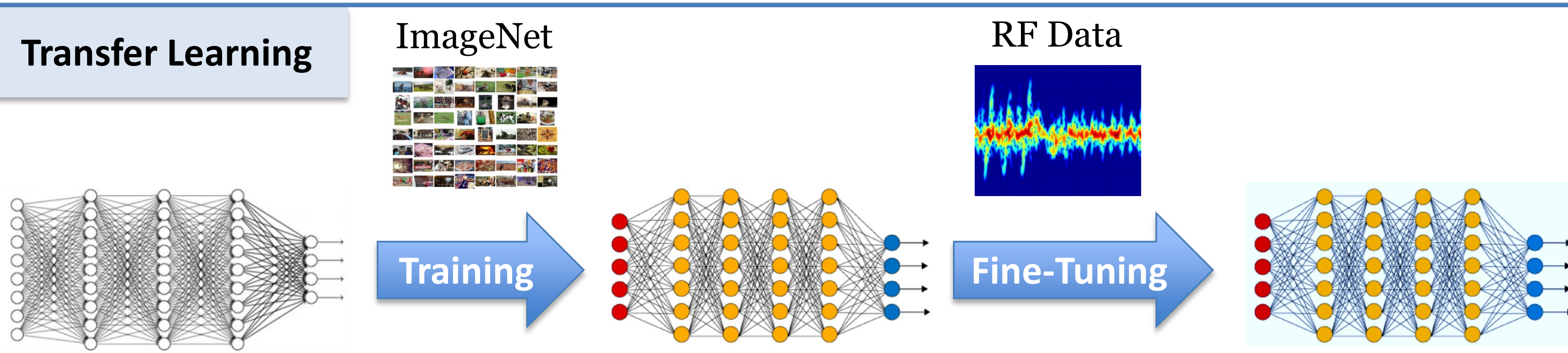
- Confusion matrix

Approaches for Training under Low Sample Support

Unsupervised Pre-Training



Transfer Learning



Randomly Initialized DNN

DNN Pre-Trained on Data from Domain A

DNN Fine-Tuned on Data from Domain B

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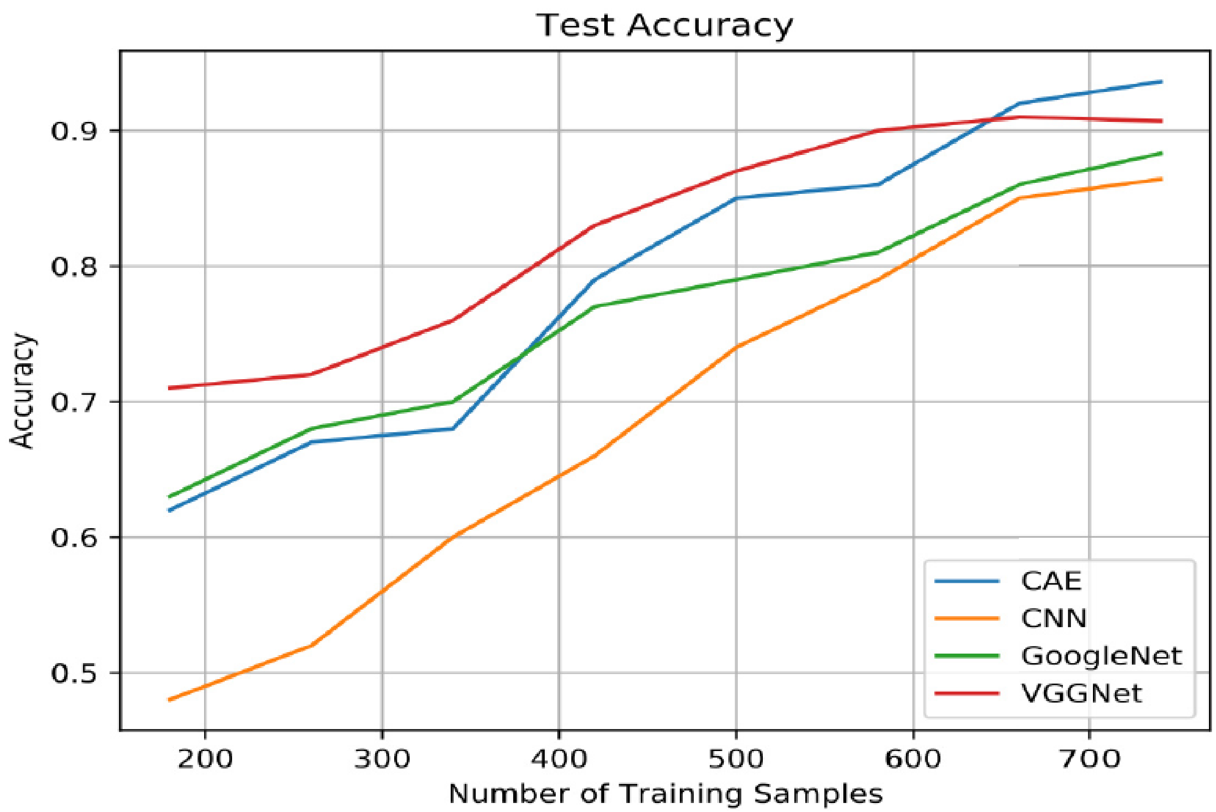
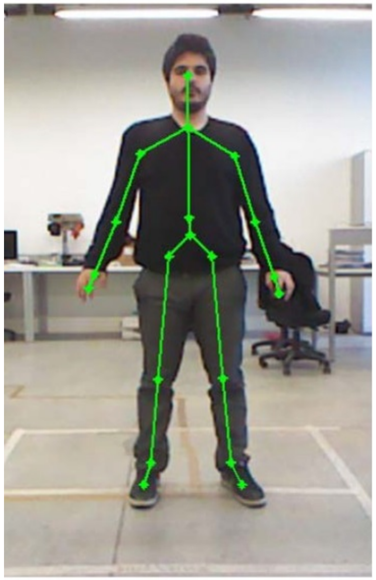
Comparison of Unsupervised Pre-Training with Transfer Learning



M.S. Seyfioglu, S.Z. Gurbuz, "Deep Neural Network Initialization Methods for Micro-Doppler Classification With Low Training Sample Support, IEEE Geoscience and Remote Sensing Letters, Dec. 2017.

Physics-Aware Pre-Training: Synthetic Data Generated from Motion Capture (MOCAP) Data

- Kinect sensor has RGB and infrared cameras
- Skeleton tracking to emulate radar range measurements



$$s_h(n,t) = \sum_{i=1}^{K} a_{t,i} rect\left(\frac{\hat{t} - t_{d,i}}{\tau}\right) e^{j[-2\pi f_c t_{d,i} + \pi\gamma(\hat{t} - t_{d,i})^2]}$$

$$a_{t,i} = \frac{G\lambda\sqrt{P_t \sigma_i}\sigma_n}{(4\pi)^{1.5} R_i^2 \sqrt{L_s}\sqrt{L_a}\sqrt{T_{sys}}}$$

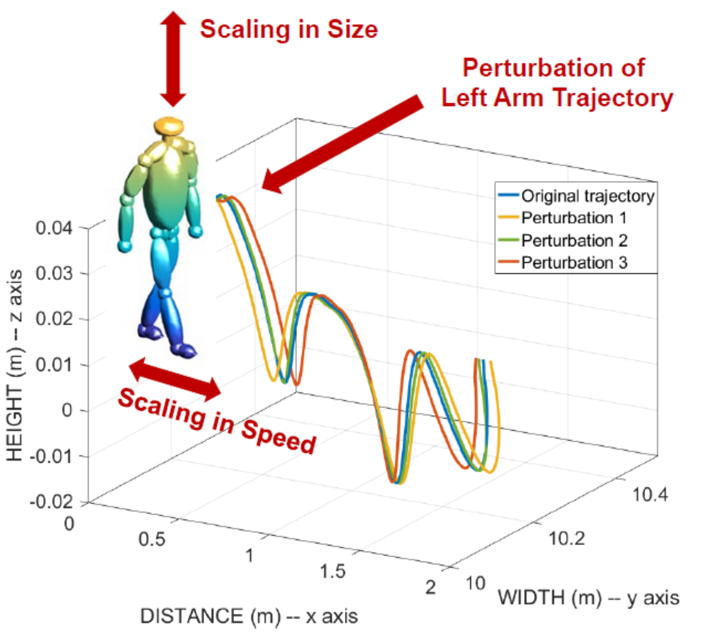
G :	antenna gain	λ :	wavelength
L_a :	atmospheric losses	L_s :	system losses
P_t :	transmitted signal power	T_{sys} :	system temperature
σ_n :	noise standard deviation	σ_i :	RCS of each body part

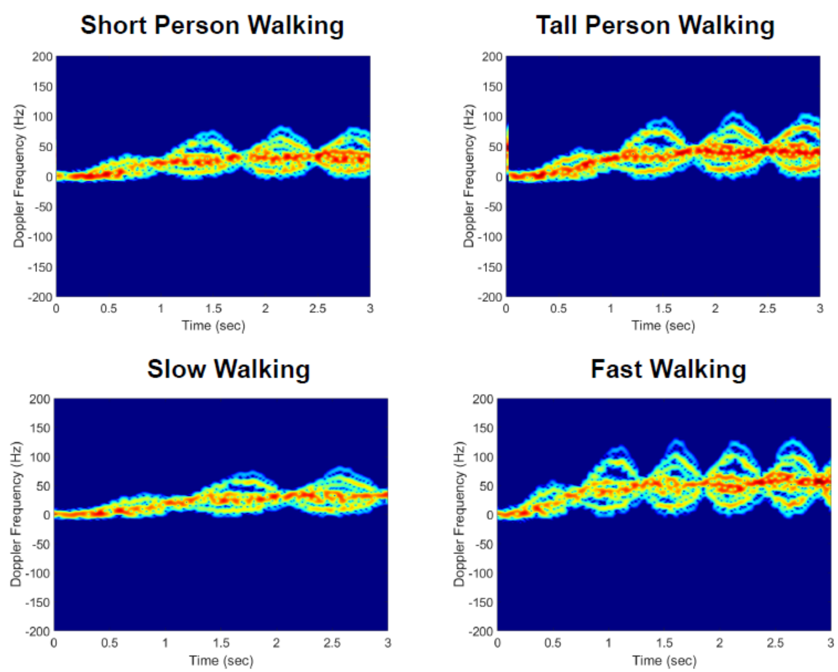
B.Erol, C. Karabacak, **S.Z. Gürbüz**, “A Kinect-Based Human Micro-Doppler Simulator,” IEEE Aerospace and Systems Magazine, vol. 30, no. 5, May 2015.

Diversified MOCAP

Data augmentation techniques for computer vision [scaling, rotation, translation]
→ Generate physically impossible variants of RF data

Physics-Aware Solution: Transform Underlying Skeleton
55 MOCAP Measurements → 32,000 mD Samples





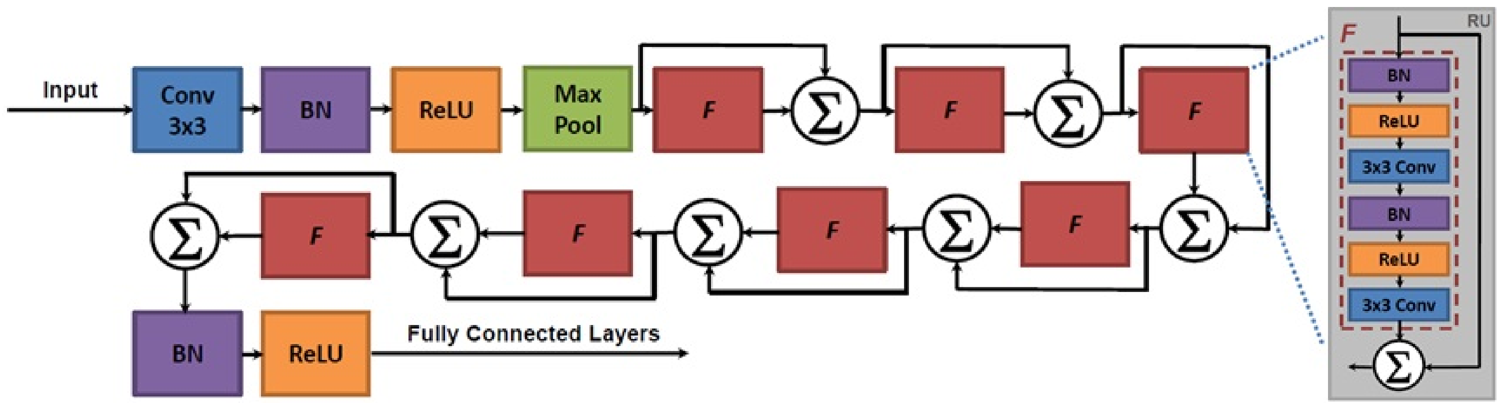
B.Erol, S.Z. Gürbüz, M.G. Amin, "DNN Transfer Learning from Diversified Micro-Doppler for Motion Classification," IEEE Trans. Aerospace and Electronic Systems, vol. 55, no. 5, October 2019.

Performance Comparisons

DivNet-15:

15-layer residual neural network pre-trained with 32k diversified MOCAP

Fine-tuned with just 474 real RF samples



MOTION CLASSES

1 Walking
2 Wheelchair
3 Limping
4 Cane
5 Walker
6 Falling
7 Crutches
8 Creeping
9 Crawling
10 Jogging
11 Sitting
12 Falling off Chair

- Data-driven feature learning with DNNs
- Non-DNN classification with data-driven feature engineering
- Conventional classification with handcrafted features

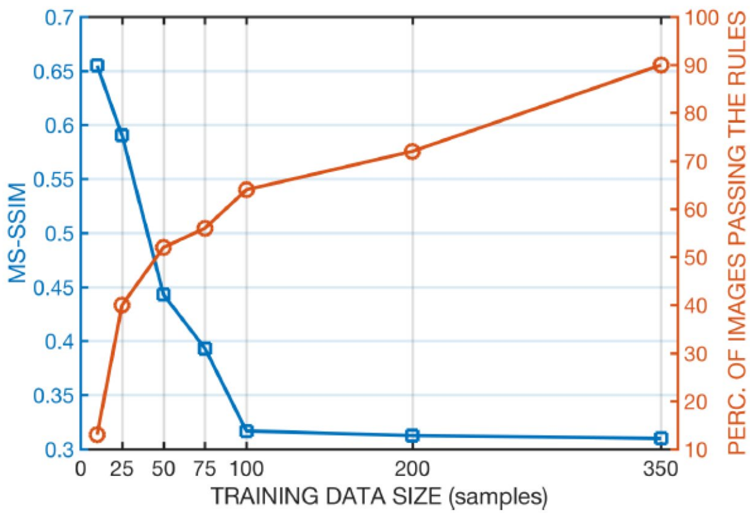
Increasing Accuracy →

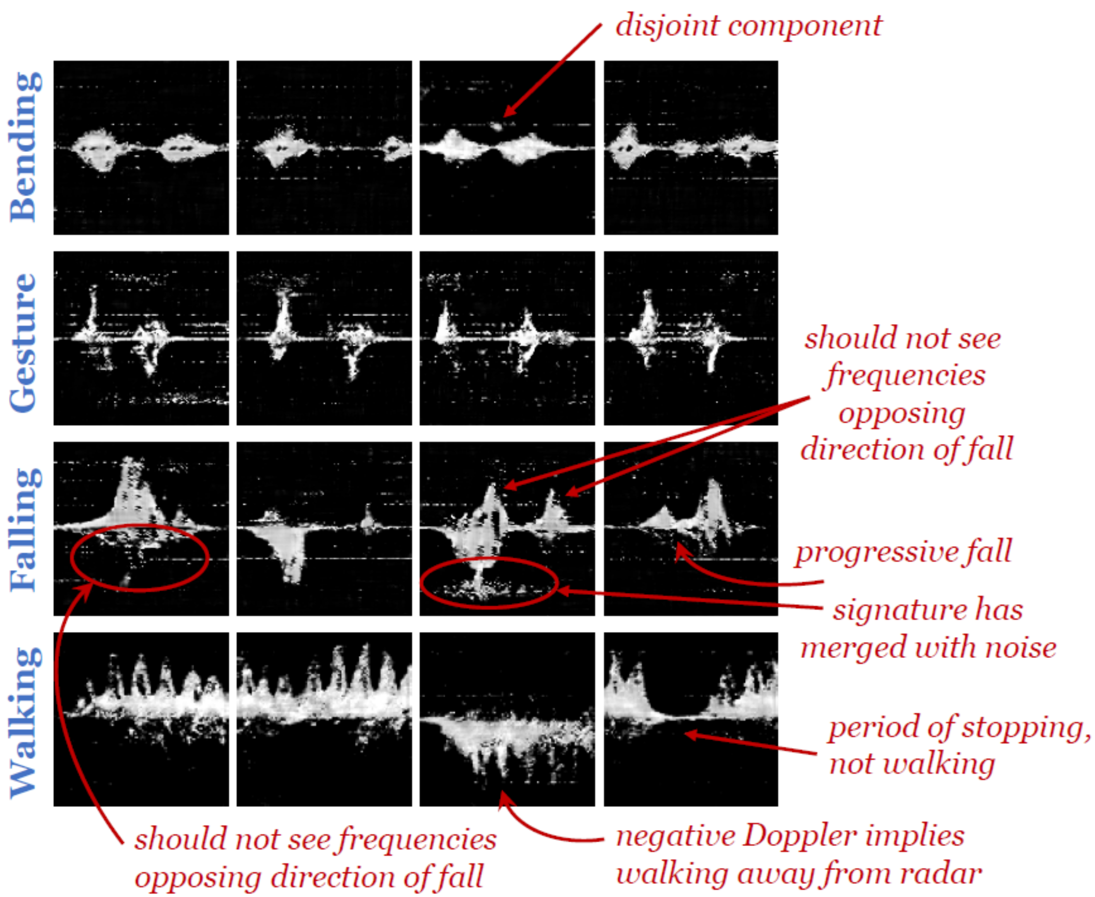
mSVM-50	AE	2D-PCA	CNN	VGGnet	GA-FWCC	CAE	DivNet-15
76.9%	84.1%	88.7%	90.1%	90.8%	94.1%	94.2%	95.1%

S. Z. Gurbuz and M. G. Amin, "Radar-Based Human-Motion Recognition With Deep Learning: Promising Applications for Indoor Monitoring," in IEEE Signal Processing Magazine, vol. 36, no. 4, pp. 16-28, July 2019.

What if I can't get MOCAP?

Generative Adversarial Networks



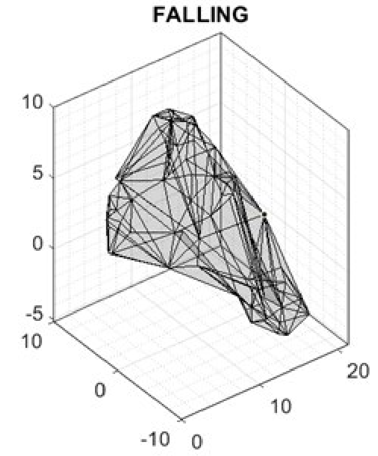


B.Erol, S.Z. Gürbüz, M.G. Amin, "Motion classification using kinematically sifted ACGAN-synthesized radar micro-Doppler signatures ," IEEE Trans. Aerospace and Electronic Systems, Vol. 56, Iss. 4, pp. 3197 - 3213, January 2020.

Just How Inaccurate is the ACGAN?

Let's remove outliers using a convex hull defined using PCA

From 40k samples, 9k removed



	TF-AlexNet	TF-VGG16	CVAE	ACGAN	PCA-ACGAN-TOL-1.0	PCA-ACGAN-TOL-0.5
Accuracy	0.765	0.842	0.732	0.825	0.877	0.932

%	Bending	Falling	Gesture	Kneeling	Reaching	Sitting	Standing	Walking
Bending	100	0	0	0	0	0	0	0
Falling	0	90	3	0	2	0	0	5
Gesture	0	0	96	0	0	0	0	4
Kneeling	20	0	0	80	0	0	0	0
Reaching	0	0	0	0	84	16	0	0
Sitting	0	0	0	2	0	98	0	0
Standing	0	0	0	2	0	0	98	0
Walking	0	0	0	0	0	0	0	100

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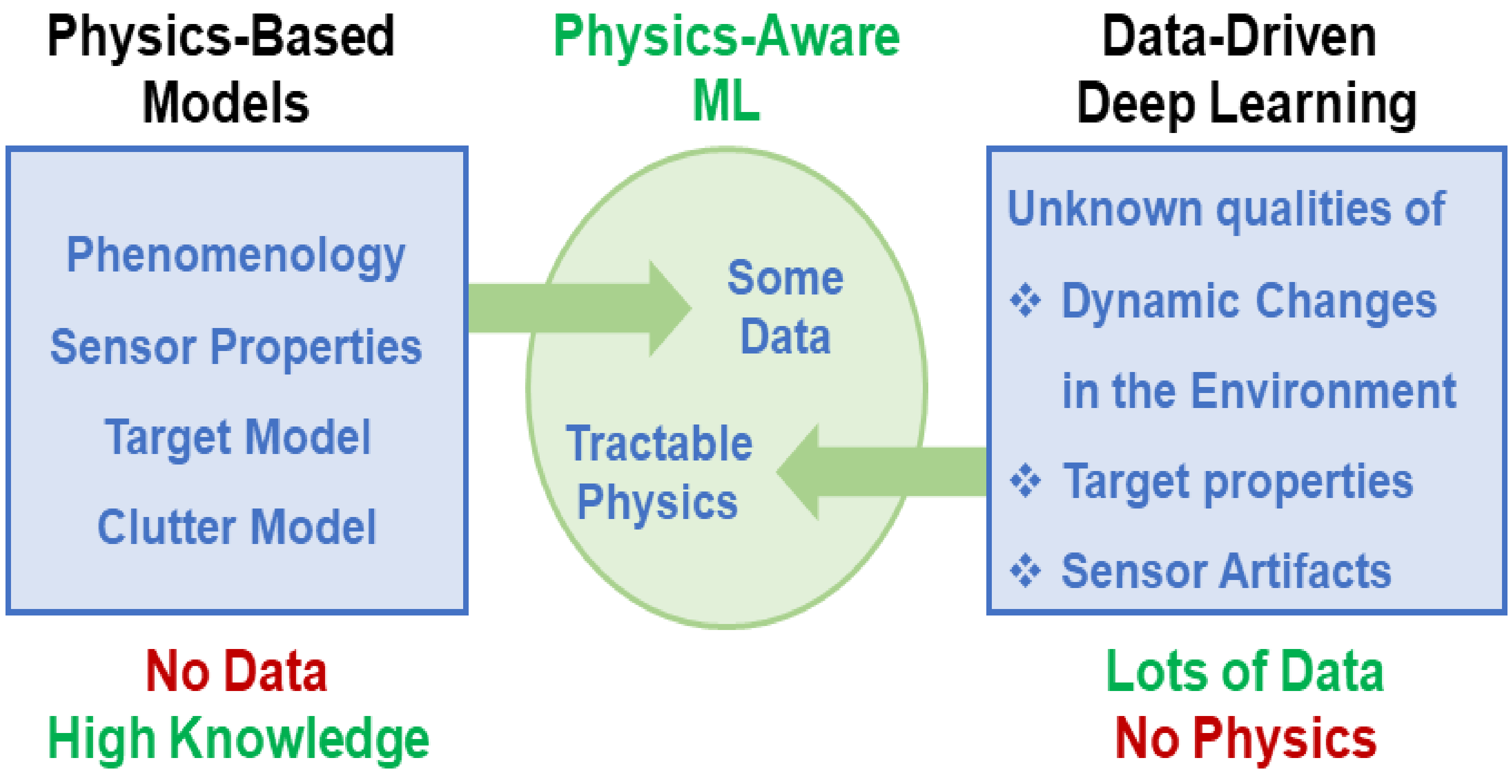
How Can GAN Be Prevented From Making Errors in Target Model?



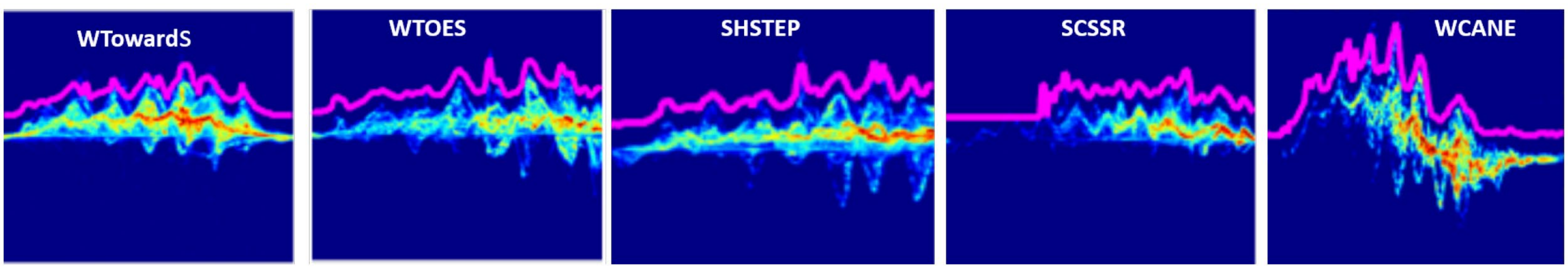
Physics-Aware ML Solution for Human Activity Recognition

We need to integrate our knowledge of human kinematics into the GAN so variants are generated within physical bounds

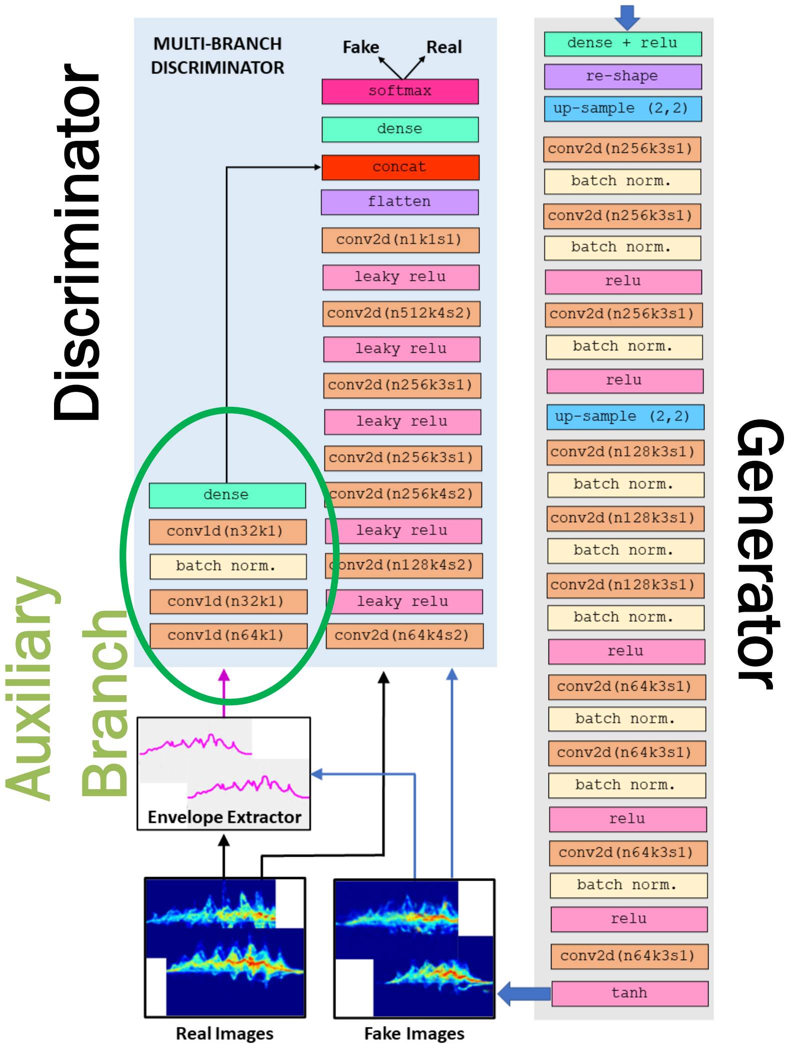
The ENVELOPE of the micro-Doppler signature reflects the

- ❖ *Physical bounds on maximum velocity for a given activity,*
- ❖ *Captures periodicities inherent to the motion*

Normal Walking | Walking on Toes | Short Steps | Scissor Gait | Walking w/Cane



Multi-Branch GAN with Auxilliary Envelope



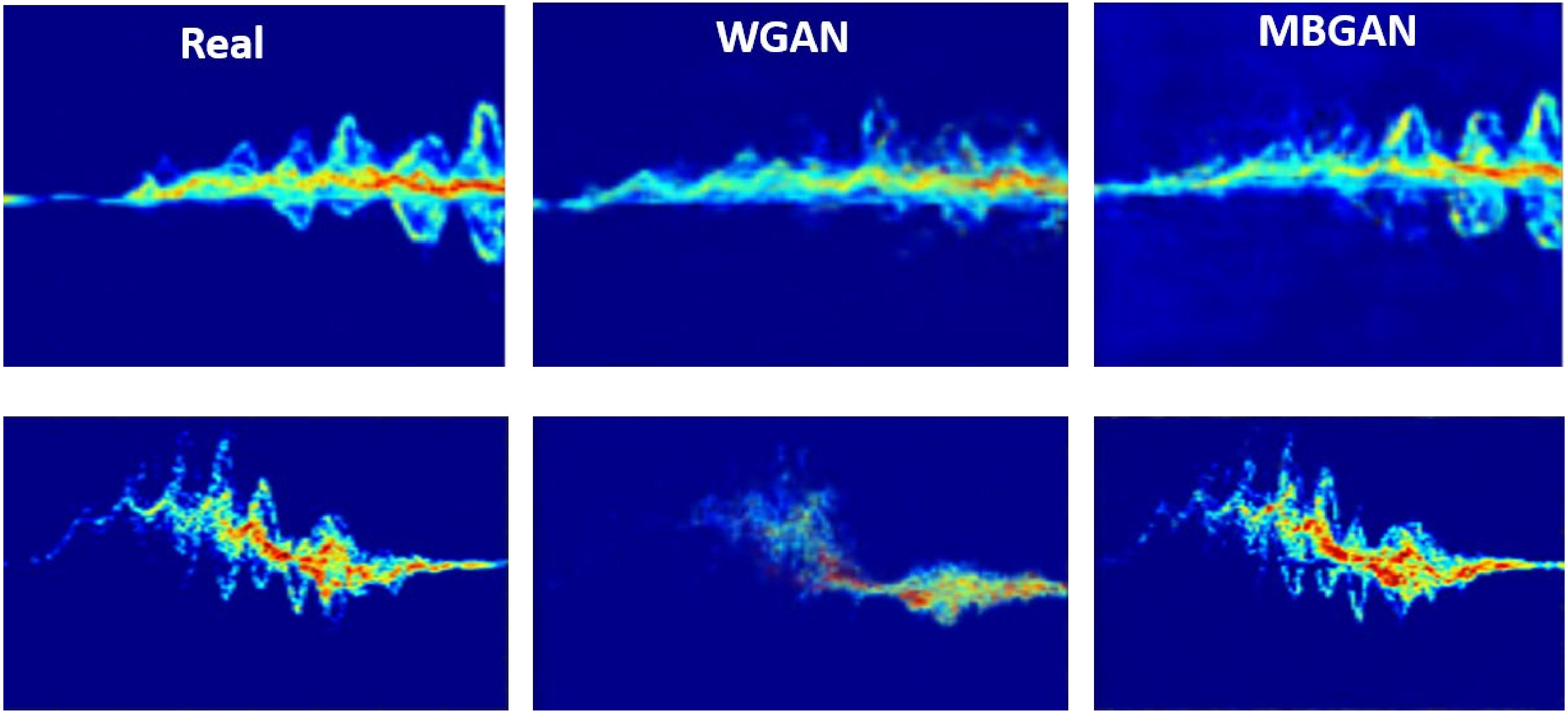
- **Generator:**
  - 10 convolutional layers

- **Discriminator:**
  - *Main Branch*: 8-layer CNN on mD
  - *Auxiliary Branch*: 3 1-D convolutional layers taking mD envelope as input.

- **Conventional Loss Function:**
  - Earth-movers distance of Wasserstein GAN (WGAN)

B. Erol, S. Z. Gurbuz, and M. G. Amin, “Synthesis of micro-doppler signatures for abnormal gait using multi-branch discriminator with embedded kinematics,” in IEEE Int. Radar Conf., 2020, pp. 175–179.

Effect of Adding Auxiliary Branch



How Can We Improve Further?

- Let’s Quantify Kinematic Fidelity…

  - **Curve Matching** as similarity metrics
    - *Dynamic Time Wrapping (DTW)*
    - *Discrete Fréchet Distance (DFD)*

  - ***Pearson Correlation:*** Measure the linear correlation between two random variables by computing the covariance of the two variables divided by the product of their standard deviations.

$$\rho(A, B) = \frac{\operatorname{cov}(A, B)}{\sigma_A \sigma_B}$$

  - It has a value between +1 and -1. A value of +1 is total positive linear correlation, 0 is no linear correlation, and -1 is total negative linear correlation.

Add Kinematic Metric to Loss Function: Loss-Regularized (LR) MBGAN

$$Loss = \underbrace{Loss_{Critic}}_{D(x)-D(G(z))} + \gamma\underbrace{\left(\|\nabla_{\hat{x}} D(\hat{x})\|^2\right)}_{\text{Gradient Penalty}} + \boxed{Loss_{Physics}}$$

New term based on sensor physics, kinematics, etc.

- *x*: Real data instance
- *z*: Noise
- D(x): Discriminator's estimate of the probability that the real data instance *x* is real
- D(G(z)) : Discriminator's estimate of the probability that a fake instance is real

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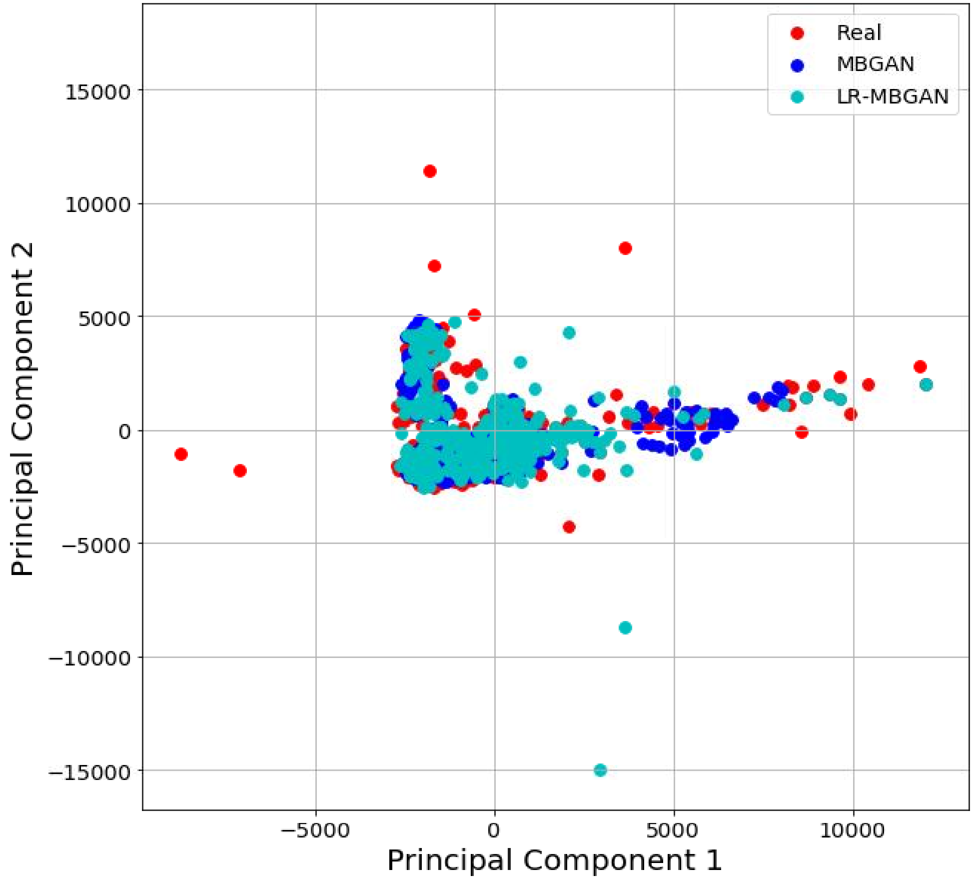
Results of Adding Kinematic Loss



M. Rahman, S. Z. Gurbuz and M. G. Amin, "Physics-aware design of multi-branch GAN for human RF micro-Doppler signature synthesis ," in 2021 IEEE International Radar Conference (RADAR), Atlanta, GA.

Classification Accuracy

- Real samples: 60 samples per class (5 classes)
- Synthetic samples: 500 samples/class for each GAN
- Convolutional Autoencoder (CAE)
  - Three blocks; each block has 2 convolutional layers + concatenation + max pooling

Synthesized Data Sourceer	Classifier	Accuracy
WGAN	CAE	86.64%
MBGAN	CAE	88.13%
LR-MBGAN	CAE	**89.83%**

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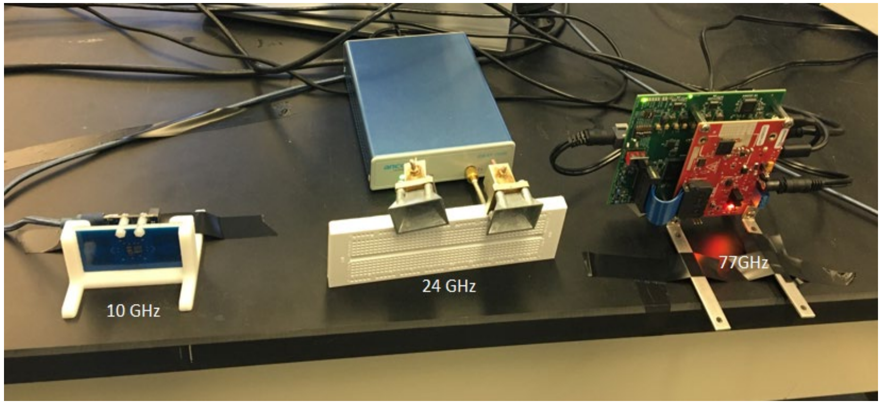
How Can We Exploit "Datasets of Opportunity" ?

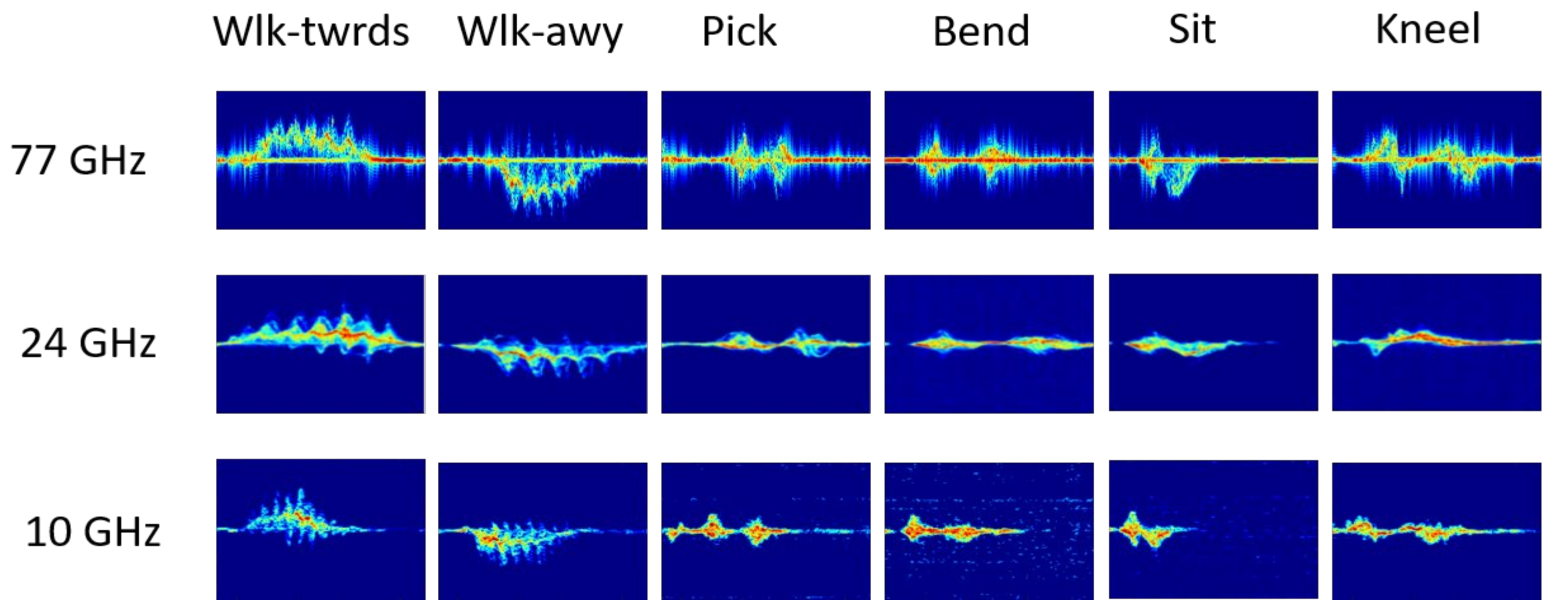
- Different sources of real RF data:
  - In an RF sensor network:
    - Different frequency
    - Different angle
    - But observing the same participant
  - Similar experiments conducted elsewhere
    - Same/different frequency/angle
    - Different participants
  - RF datasets of motion classes, frequency, angle, and participants

Cross-Frequency Training of RF Data

Three RF Sensors:

- **77 GHz** TI IWR 1443
- **24 GHz** Ancortek SDR-KIT
- **<10 GHz** XeThru X4M03





Cross-Frequency Classificiation with Transfer Learning from VGGnet

❑ VGG16 net with top layer modification

- Global average pooling followed by 2 fully connected layers
- Drop out: 0.5
- 77 GHz: batch size 8,Learning rate 2e-4, two Dense layers of size 256, Decay 1e-6, Adam Optimizer
- 24 GHz: batch size 32,Learning rate 1e-4, two Dense layers of size 256, Decay 1e-6, Adam Optimizer
- 10 GHz: batch size 8,Learning rate 2e-4, two Dense layers of size 128, Decay 1e-6, Adam Optimizer

Training	Testing	Accuracy (%)
77 GHz	10 GHz	14.28
	24 GHz	16.66
	77 GHz	89.23
24 GHz	24 GHz	85.57
	10 GHz	15.55
	77 GHz	11.13
Xethru	10 GHz	83.00
	24 GHz	14.21
	77 GHz	9.00

Performance degrades while training and testing with different frequency data

Cross-Frequency Classification with Convolutional Auto-Encoder (CAE)

❑ **11 different classes:**

- 60 samples per class for 77 & 10 GHz

- 150 samples per class for 24 GHz

❑ **CAE:** Total of 5 layers

- **When decoder removed, 2 dense layers followed by a soft-max layer added**
- **Number of filters in each layer: 64**
- **Filter Size: 3x3 & 9x9 filters are concatenated**

Pre-train	Fine Tune	Test	Testing Accuracy
77 GHz	77 GHz	77 GHz	91.5%
		24 GHz	22.5%
		10 GHz	18.9%
	24 GHz	24 GHz	74.4%
	10 GHz	10 GHz	75.5%
24 GHz	24 GHz	24 GHz	91.2%
		77 GHz	28.5%
		10 GHz	40.5%

Pre-train	Fine Tune	Test	Testing Accuracy
24 GHz	77 GHz	77 GHz	83.8%
	10 GHz	10 GHz	81.6%
10 GHz	10 GHz	10 GHz	91.8%
		77 GHz	24.1%
		24 GHz	18.8%
	77 GHz	77 GHz	80.0%
	24 GHz	24 GHz	79.1%

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Cross-Frequency Pre-Training on GAN-Synthesized Signatures

- ❑ CAE trained on synthetic data, and fine tuned on real data
  - 100 vs 20 epochs
  - Trained on 77 GHz synthetic data and fine tuned on each sensor individually
  - Testing done on data from all 3 frequencies

Pre-Training	Fine Tune	Test	Testing Accuracy
Synthetic 77 GHz	77 GHz	77 GHz	$\boxed{85.40\%}$
		24 GHz	8.85%
		10 GHz	7.20%
	24 GHz	24 GHz	$\boxed{77.15\%}$
	10 GHz	10 GHz	$\boxed{80.80\%}$

- ❑ GANs-based model performs slightly worse
  - ❑ Presence of kinematically inaccurate data
  - ❑ PCA sifting algorithm not selective enough (remove outliers)
  - ❑ Similarity among classes like picking up an object, bending causes GAN to learn biased distribution

AI/ML Challenge Dataset Resources

- Publications and Multi-Media videos of conference presentations related to this dataset accessible via

Computational Intelligence for Radar Lab

http://ci4r.ua.edu

Thank You!

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32