
서강대학교
SOGANG UNIVERSITY

# 강화학습을 이용한 표적 식별용 인지 레이다

서강대학교 전자공학과

김영욱

2023.8.23

AirLab

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- Implementation of cognitive radar using RL

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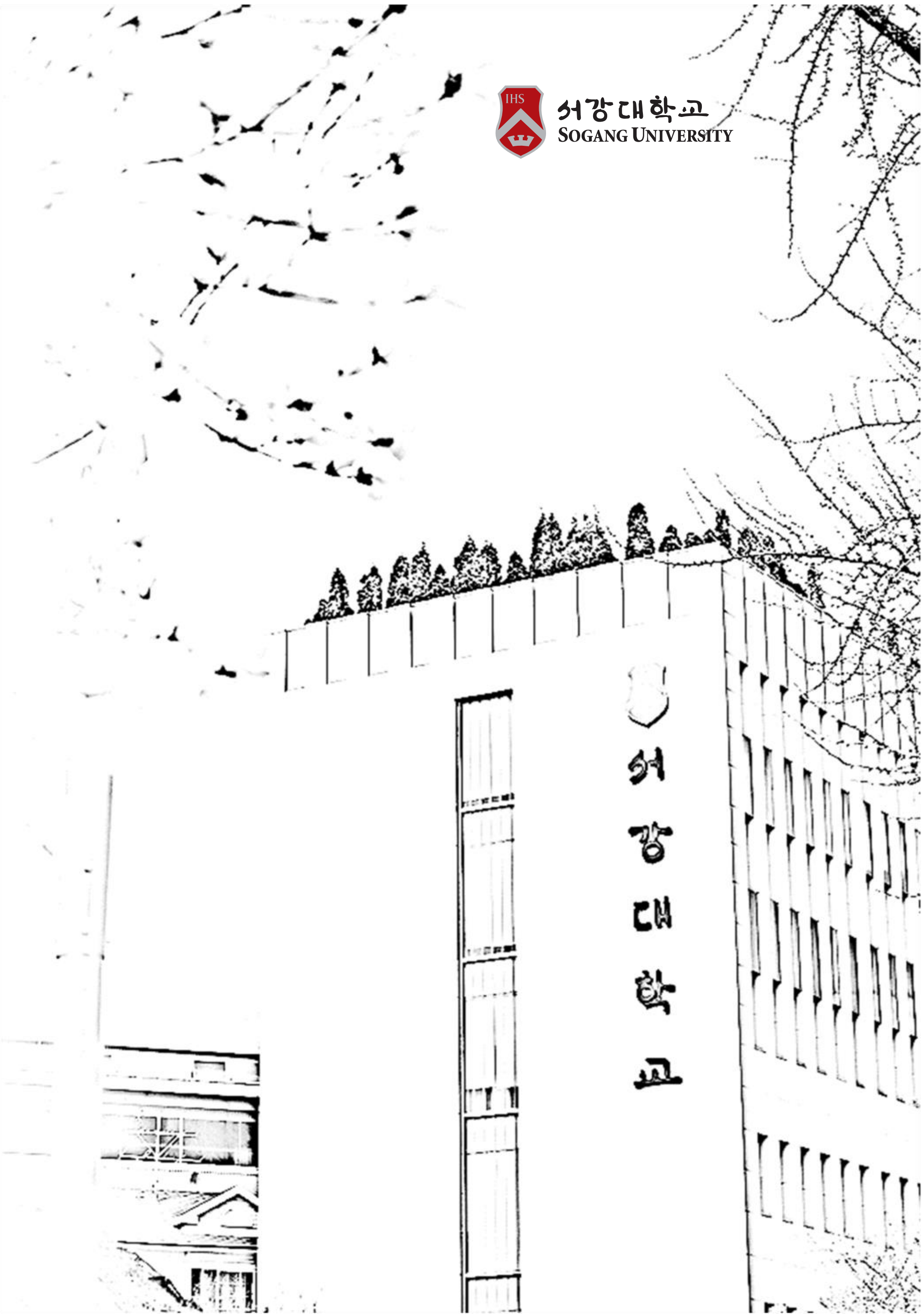
# 1. Micro-Doppler Signatures

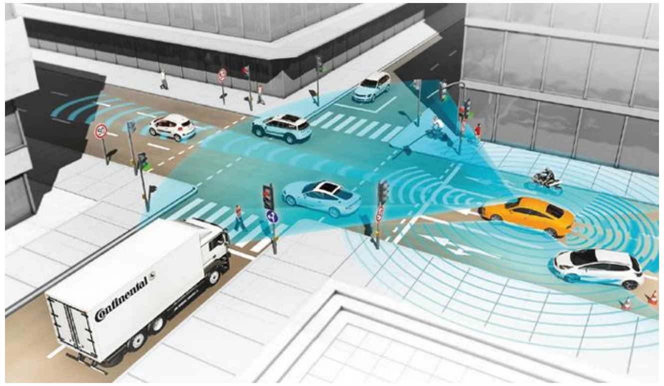


# Application of Human Monitoring Using Electromagnetics

- Human detection and tracking are topics of recent interest because of the increased concerns regarding security and surveillance.


- Can also be applied in disaster search-and-rescue operation, physical security, law enforcement, and border patrol.

- Important topic for the autonomous vehicle development.



# Application of Human Monitoring Using Electromagnetics

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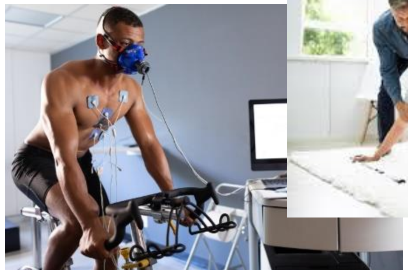
## Application to Civilian

- Human computer interface
- Walking style analysis
- Patient monitoring
- Senior fall detection
- Cardiopulmonary motion analysis
- Life pattern analysis (Long-term correlation)






- However, human detection poses a distinct challenge because humans are generally present in highly cluttered environment with the presence of other moving targets such as animals.

Objective: Continuous monitoring human activities through Electromagnetics

# Micro-Doppler Signatures

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(1) Vibration

$$\phi = \beta \sin(w_v t)$$

$$s(t) = A\exp[j(2\pi f_o t + \phi)] \qquad s(t) = A\exp[j(2\pi f_o t + \beta \sin(w_v t))]$$

FFT Extension with Bessel function:

$$s(t) = A\sum_{n=-\infty}^{\infty} J_n(\beta)\exp[j(2\pi f_o + n \cdot w_v)t]$$

(2) Rotation

$$\phi = \beta \sin(\Omega t + \theta_0) \qquad s(t) = A\exp[j(2\pi f_o t + \beta \sin(\Omega t + \theta_0))]$$

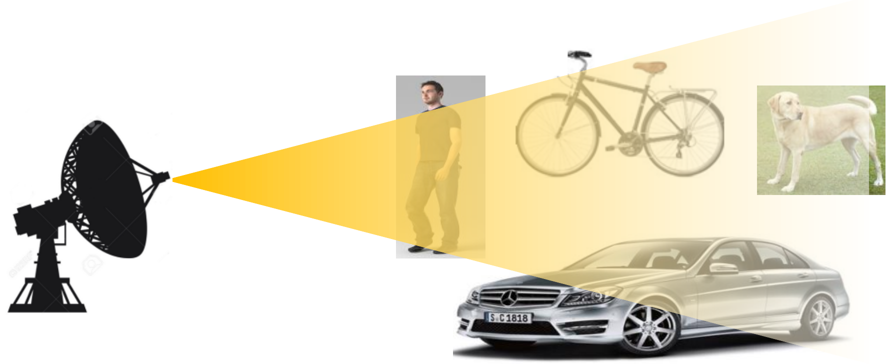
With N rotating points:

$$s(t) = A\sum_{k=0}^{N-1} J_n(\beta)\exp[j(2\pi f_o t + \beta \sin(\Omega t + k2\pi / N))]$$

# Doppler Information from Target

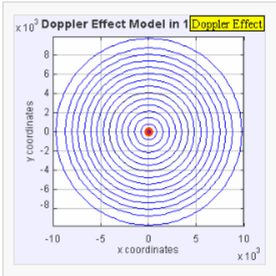
-Detection and analysis of a movin g human with *Doppler information*

-Extracting unique signatures of a h uman subject

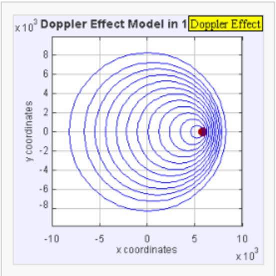


$$S(t) = e^{-jw(t-2(R-vt)/C)}$$

$$f_D = \frac{f_c}{c} \cdot (\vec{T}x - \vec{R}x) \cdot \vec{v}$$




Stationary sound source produces




The same sound source is

Merits of using Doppler information:

(1) Through-wall capability

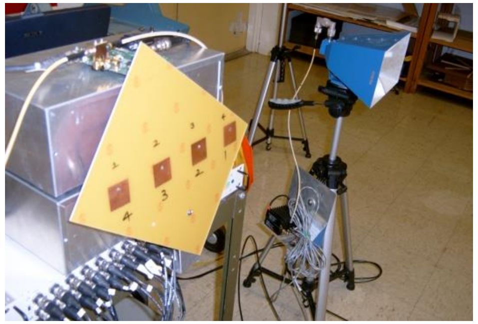
(2) Suppress stationary subjects

(3) Micro-Dopplers

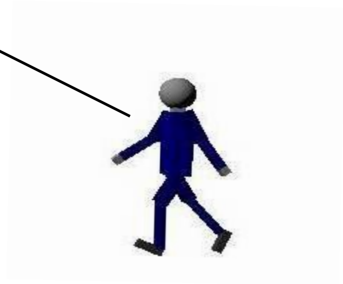
(4) Easy to measure

(5) Low cost

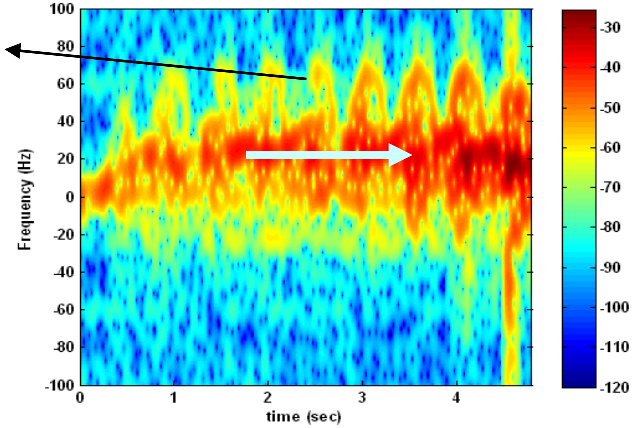
# Measuring Moving Subjects using Doppler Radar



Doppler Sensors



Micro-Dopplers



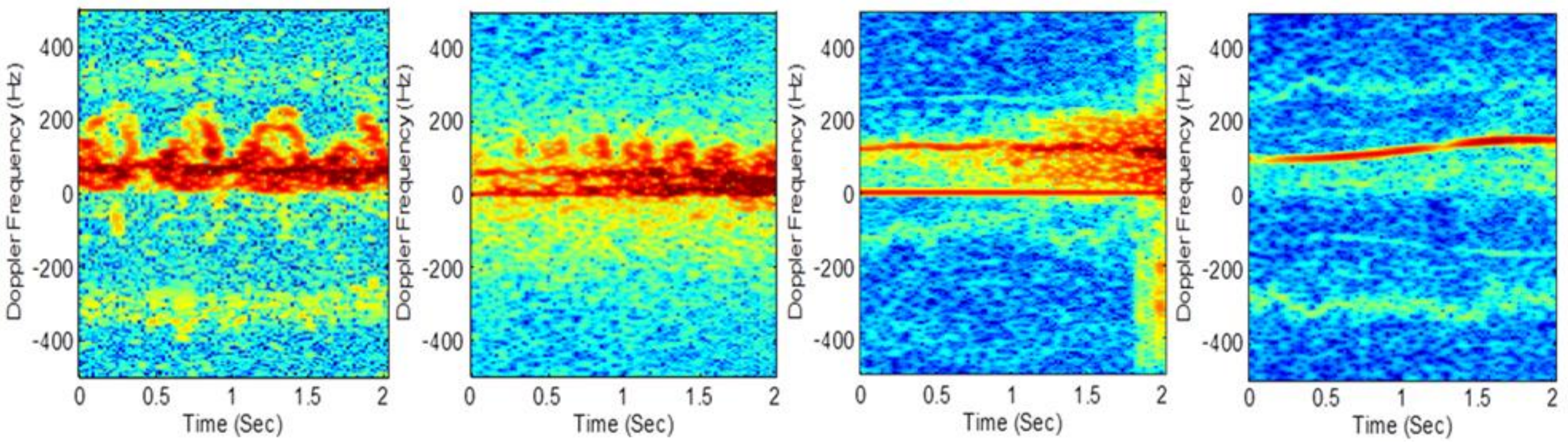

<Spectrogram>

## Problem Setup (Assumption)

1. Human moves toward the radar.
2. Classify only periodic human activities.
3. Single target case.

Micro-Dopplers might give us information about human activity.

# Target Measurement Using Doppler Radar



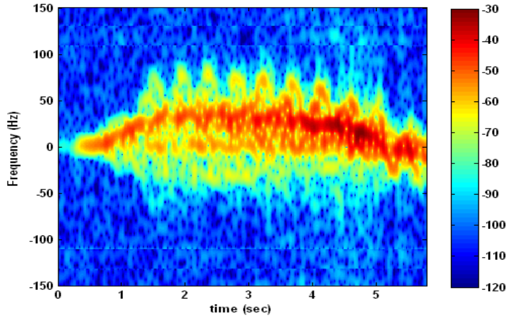

(a) Human (b) Dog (c) Bicycle (d) Car

## Micro-Doppler Signature

- Generated from the non-rigid body motion
- Unique pattern depending on target motion like vibration & rotation
- Modulated components to the torso Doppler
- Overlapped signature in joint time-frequency domain

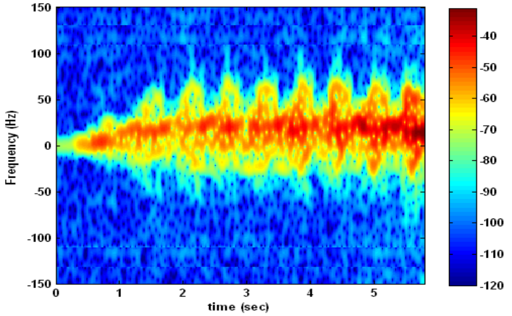
<Y. Kim, S. Ha and J. Kwon, "Human detection using Doppler radar based on physical characteristics of targets," IEEE Geoscience and Remote Sensing Letters, vol.12, pp. 289 – 293, Feb. 2015.>

# Spectrograms of Different Activities

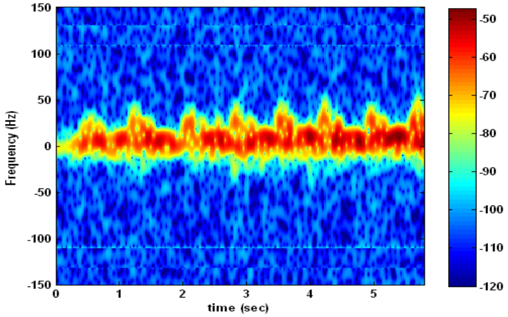


Running

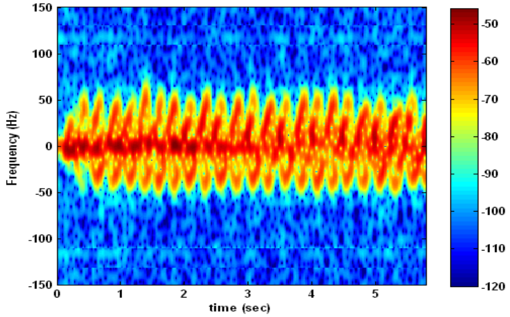




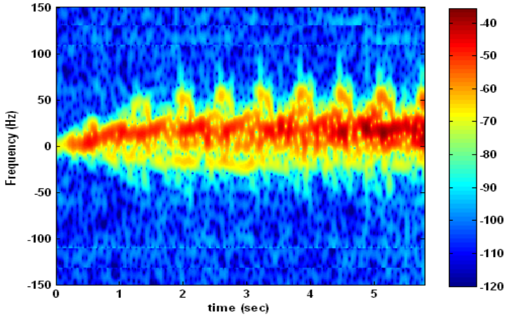
Walking



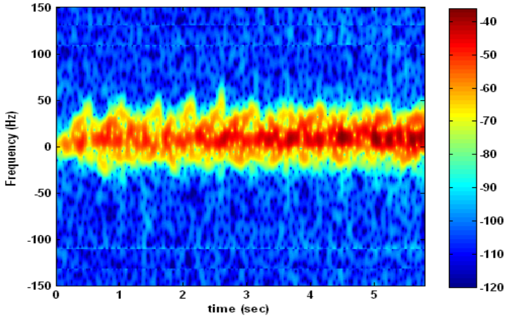
Crawling



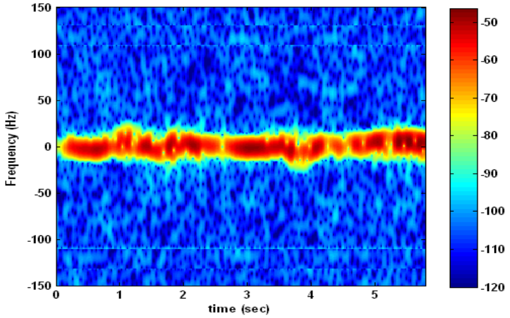
Boxing



Walking w/o moving arms



Boxing with moving forward

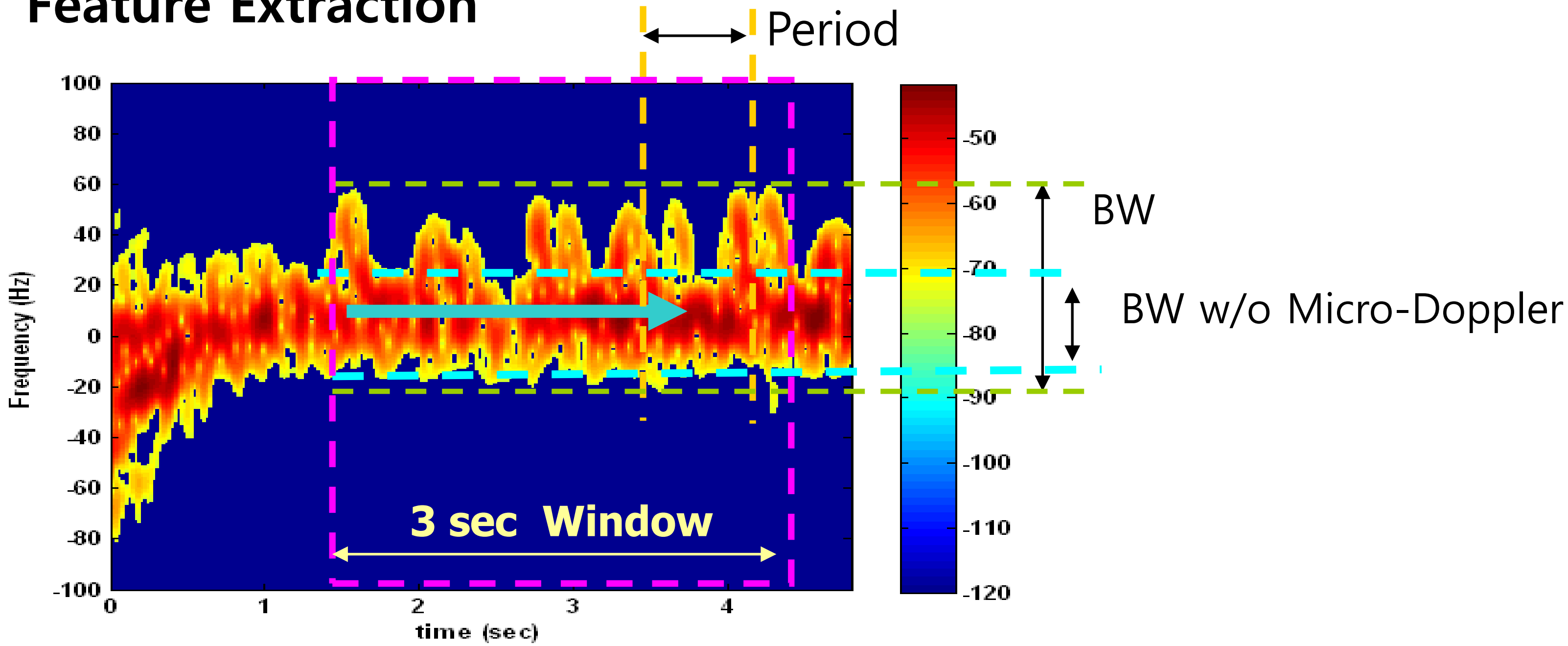


Still

# Feature Extraction from Spectrogram



## Feature Extraction




**Features:**

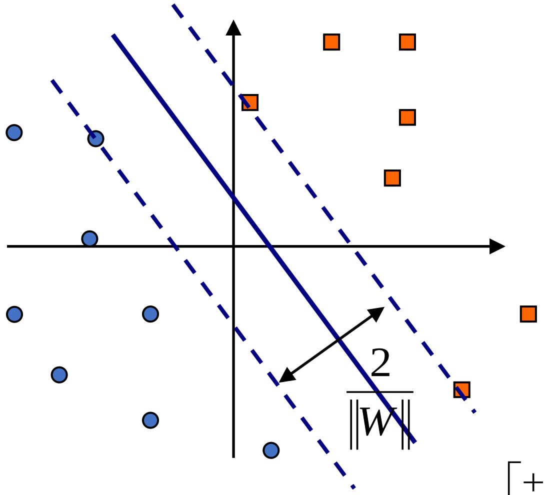
1. Doppler Freq of Torso
2. Bandwidth
3. Offset of Bandwidth
4. Bandwidth without Micro-Doppler
5. Period (Swing Rate)
6. Signal valiance

Subjects: 12
Activity: 7
Realization: 1
2

# Support Vector Machine (SVM)



- Developed by Vapnik
- Binary Classifier
- Based on linear hyper-plane.
- Maximizing margin is a convex optimization with inequality constrained.
- Only support vector will affect the result of optimization.
- Kernel trick is used.




$$W^T \cdot X + b = \begin{bmatrix} +1 \\ 0 \\ -1 \end{bmatrix}$$

Separating hyper-plane is $W^T \cdot X + b = 0$

$$\begin{cases} W^T \cdot X_i + b > 0 & \text{if } y_i = +1 \\ W^T \cdot X_i + b < 0 & \text{if } y_i = -1 \end{cases}$$

Minimizing $\dfrac{W^T W}{2}$ subject to $y_i \cdot (W^T \cdot X_i + b) \geq 1 \quad i = 1 \ldots\ldots N$

=> Quadratic convex optimization with inequality

# Human Activities Classification using SVM

## <Decision Tree>

### <Scheme 1>

| Es \ Ac | Running | Walking | Walking_low | Crawling | Boxing_Forw | Boxing | Still |
|---|---|---|---|---|---|---|---|
| Running | 97% | | | | | | |
| Walking | | 82% | 17% | | 2% | | |
| Walking_Low | 3% | 18% | 81% | | 4% | | |
| Crawling | | | | 95% | 6% | | |
| Boxing Forward | | | 2% | 5% | 78% | 1% | |
| Boxing | | | | | 10% | 99% | |
| Still | | | | | | | 100% |

**Accuracy = 91%**

### <Scheme 2>

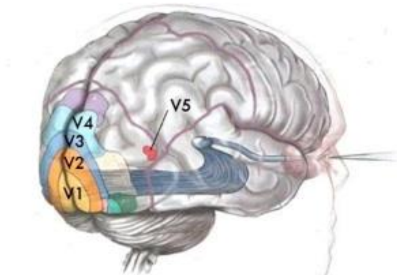
| Es \ Ac | Running | Walking | Walking_low | Crawling | Boxing_Forw | Boxing | Still |
|---|---|---|---|---|---|---|---|
| Running | 95% | | | | | | |
| Walking | 1 | 83% | 15% | | | | |
| Walking_Low | 2 | 17% | 85% | | 3% | | |
| Crawling | 0 | | | 89% | 1% | | |
| Boxing Forward | 0 | | | 11% | 96% | | |
| Boxing | 2 | | | | | 100% | |
| Still | | | | | | | 100% |

**Accuracy = 93%**

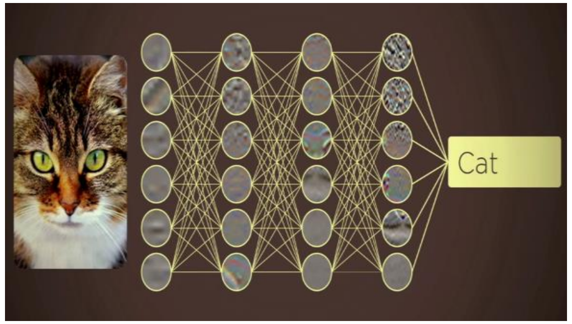
<Y. Kim and H. Ling, "Human activity classification based on micro-Doppler signatures using a support vector machine," *IEEE Transactions on Geoscience and Remote Sensing*, vol. 47, pp. 1328 –1337, May 2009.>

# Deep Learning

- Main idea : **Learn** features ("representations") from data too
  → Then, everything can be learned end-to-end!
- Inspired by human brain, use deep neural networks

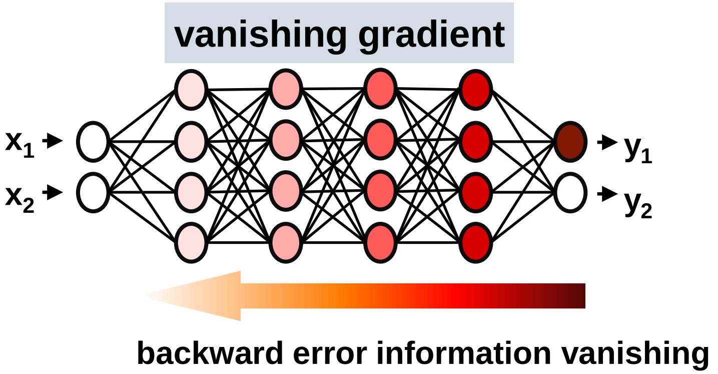



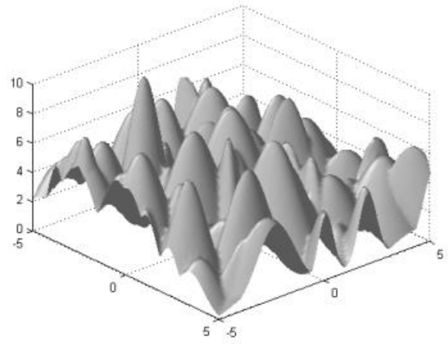

[Human's visual cortex]




[Deep neural network]

**Issues:**
- Gradient
- Local optimal

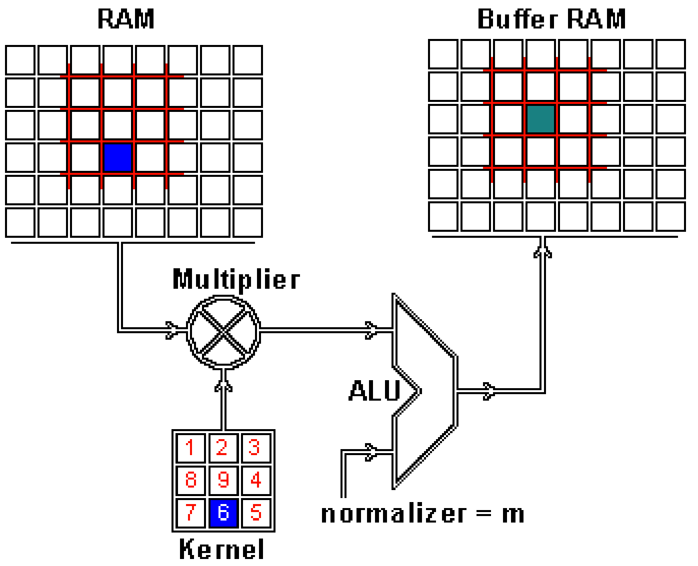


# Convolution filters (kernels)

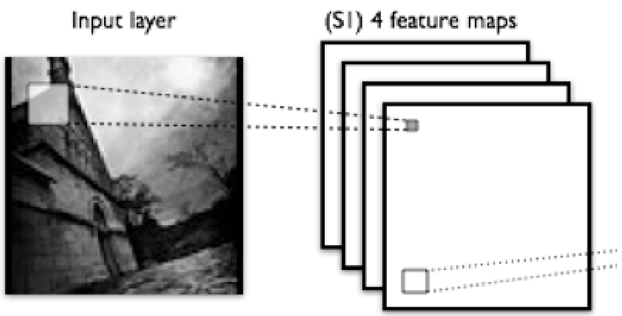
- Sparse, shared weights

**Convolution operator**



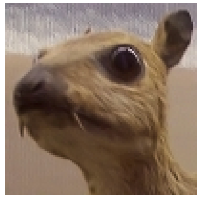

Parameters
: filter weights/size, stride

**Feature maps**




Ex) edge detector

Input image



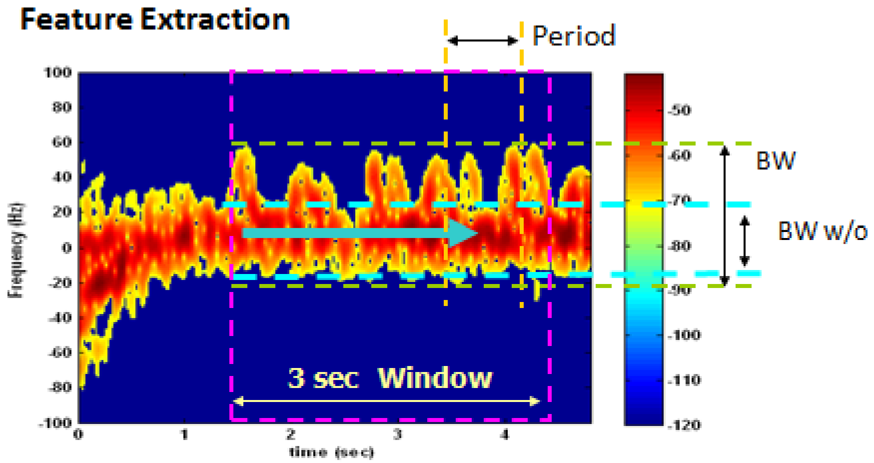
Convolution Kernel

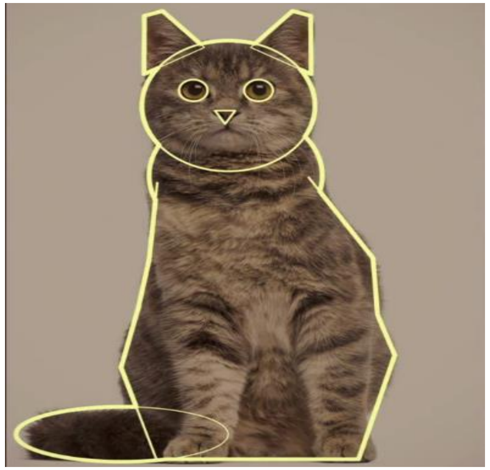
$$\begin{bmatrix} -1 & -1 & -1 \\ -1 & 8 & -1 \\ -1 & -1 & -1 \end{bmatrix}$$

Feature map

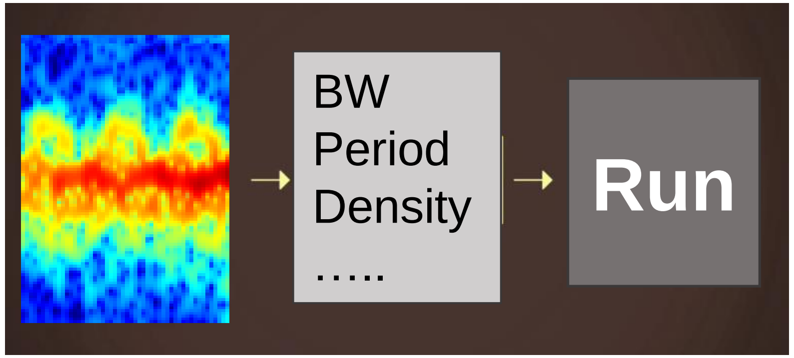
# Micro-Doppler Classification by Supervised Learning

- Devise hand-crafted features
- Requires some domain knowledge

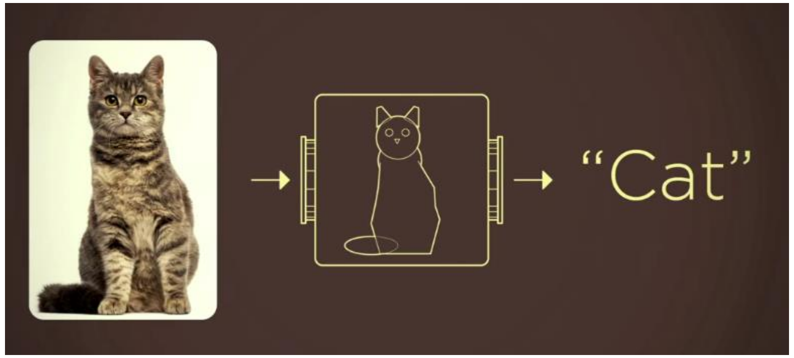


Apply a classifier on extracted features




Apply a classifier on extracted features



# Deep Convolutional Neural Networks (DCNN)

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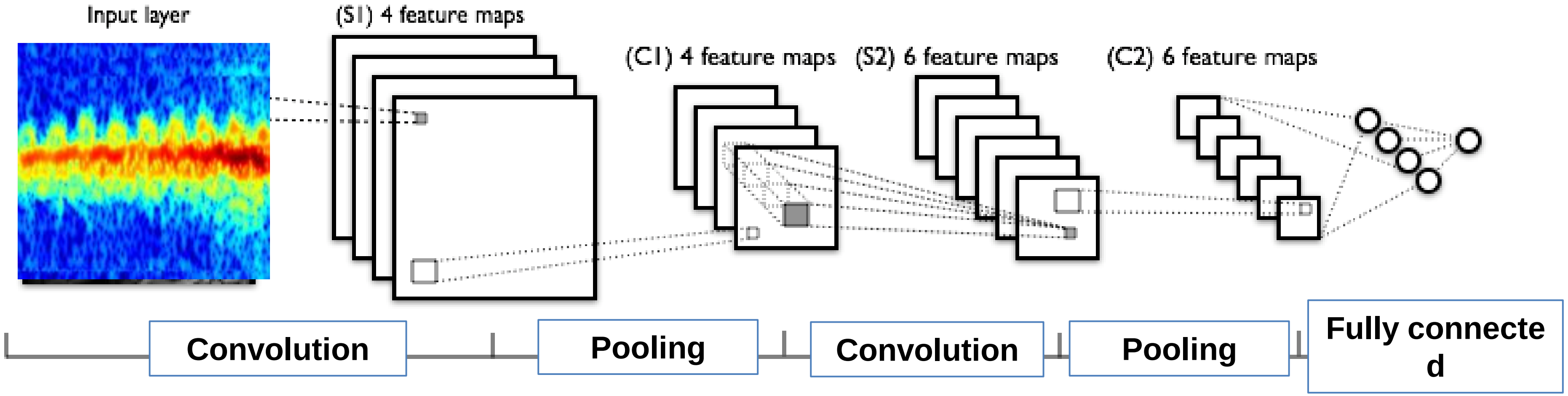
(Convolution + Activation function + Pooling) x k layers
+ Fully connected layer + Classification layer




**Results:** - After 5 fold validation, the average classification accuracy is 91%.

<Y. Kim and T. Moon, "Human detection and activity classification based on micro-Dopplers using deep convolutional neural networks," *IEEE Geoscience and Remote Sensing Letters*, vol. 13, pp.2-8, Jan. 2016.>

# What affects the classification accuracy?

# Radar Parameters in JTFA

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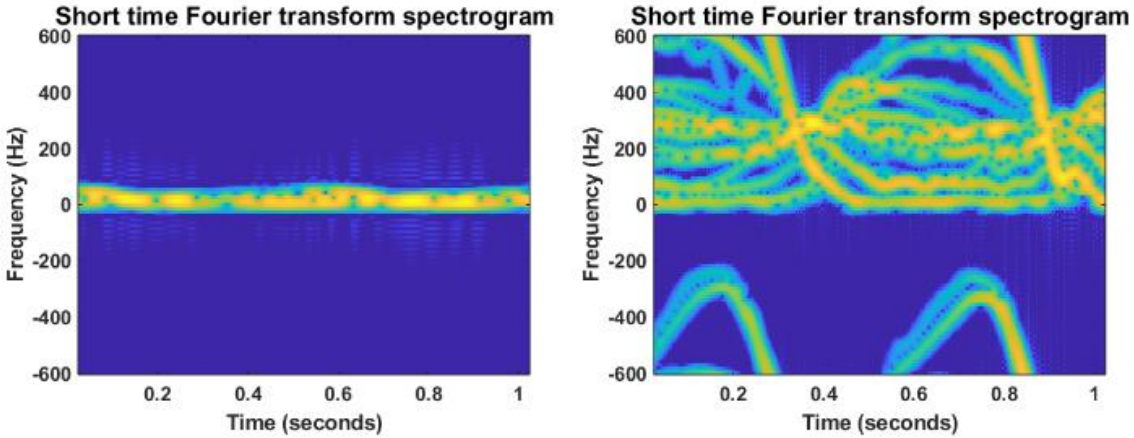
- $f_D = \frac{f_C}{c} \cdot (\overrightarrow{T_x} - \overrightarrow{R_x}) \cdot \vec{v}$ => Carrier frequency determines the max Doppler frequency.

- Nyquist's sampling theorem => Sampling frequency determines the max Doppler frequency that can be sampled without aliasing + time resolution.

**Impact of $f_c$**




(a) (b)

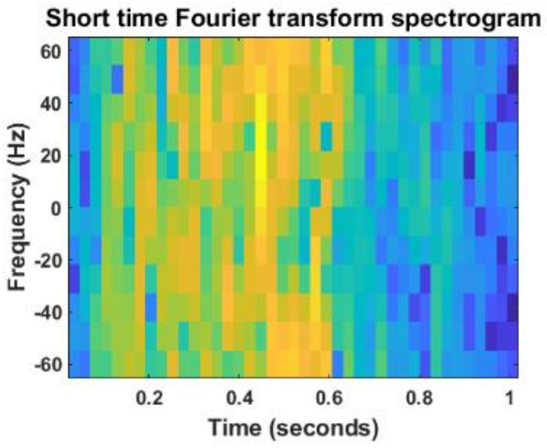
- **(a) Walk motion spectrogram $f_C$ = 1.5GHz and $f_S$ = 1200Hz**
- **(b) Walk motion spectrogram $f_C$ = 30GHz and $f_S$ = 1200Hz**

# Radar Parameters in JTFA

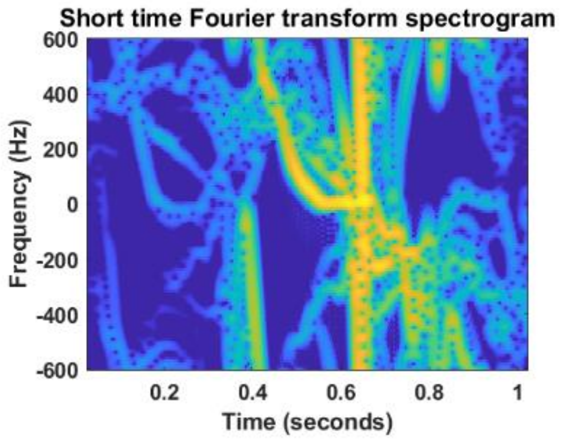
- $f_D = \frac{f_C}{c} \cdot (\overrightarrow{T_x} - \overrightarrow{R_x}) \cdot \vec{v}$ => Carrier frequency determines the max Doppler frequency.

- Nyquist's sampling theorem => Sampling frequency determines the max Doppler frequency that can be sampled without aliasing + time resolution.

**Impact of $f_s$**




**(a)**



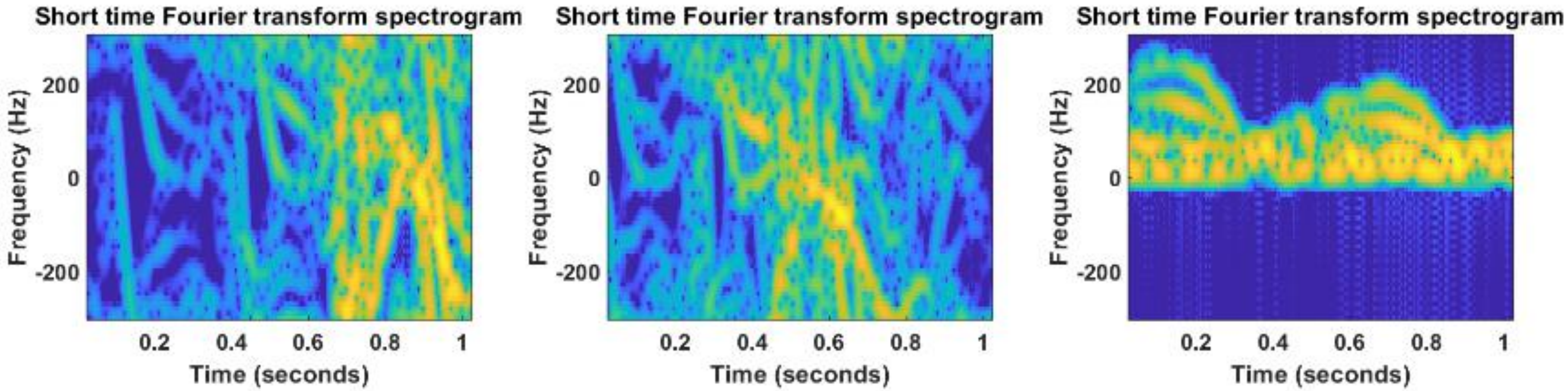

**(b)**

- **(a) Run motion spectrogram $f_C$ = 15GHz and $f_S$ = 200Hz**
- **(b) Run motion spectrogram $f_C$ = 15GHz and $f_S$ = 1200Hz**

# Radar Parameters in JTFA



When we use the fixed radar parameters……………… there are some problems!




(a) (b) (c)

**Three human motions spectrogram when $f_c$ = 10GHz and $f_s$ = 600Hz**
**(a) Run (b) Run with box (c) Walk.**

- High sampling frequency : Requires large memory fast computing hardware
- Low sampling frequency : Cause low time resolution and aliasing
- Necessary to find the optimal radar parameters depending on human motions.

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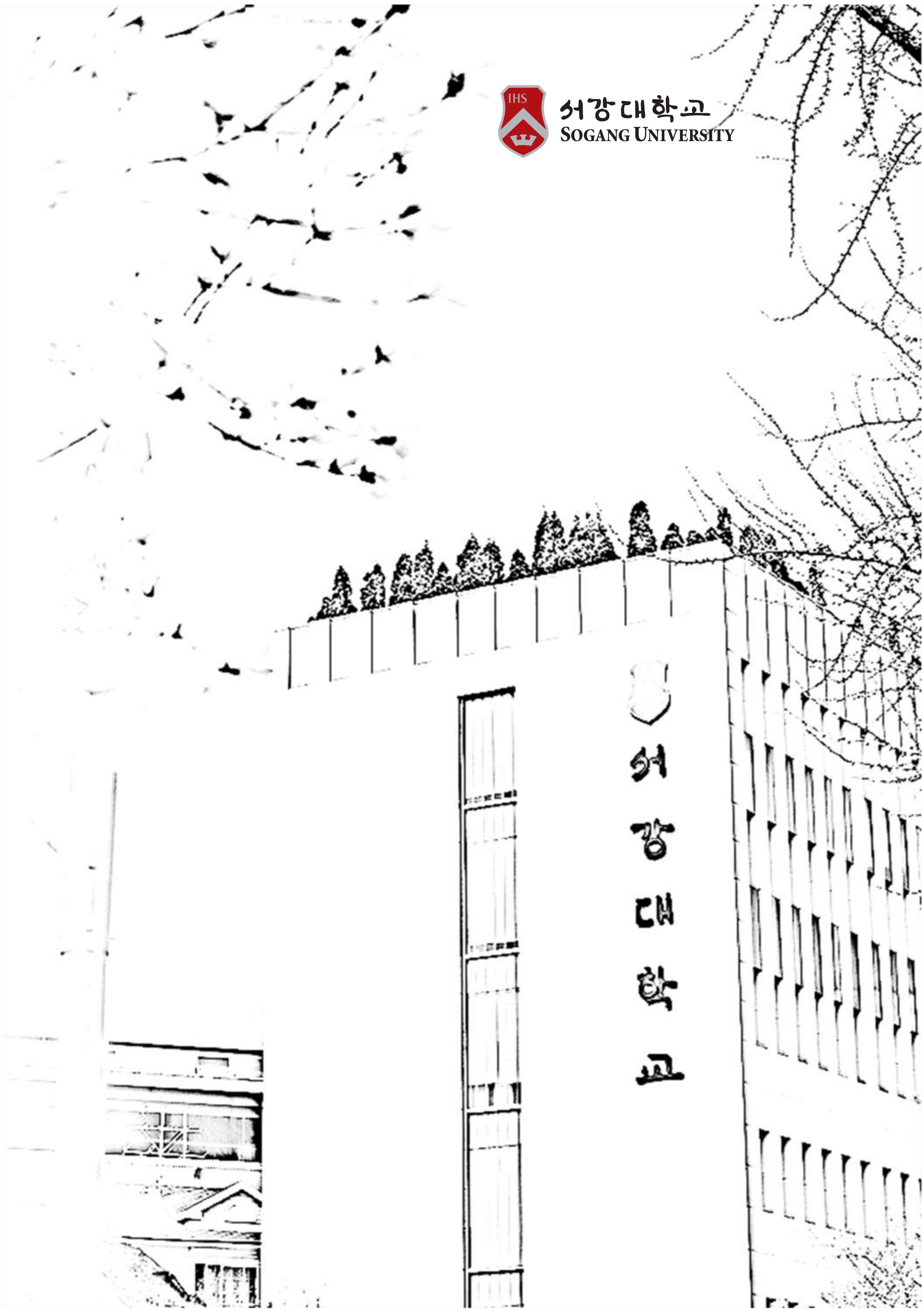
# 2. Cognitive Radar



# Concept and Background of Cognitive Radar

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- Nature has inspired creative endeavors in all facets of human intellect.

- Adaptive radars have the capability of changing the processing of received data as a function of time, while “fully” adaptive radar have the capability to adapt on transmit.

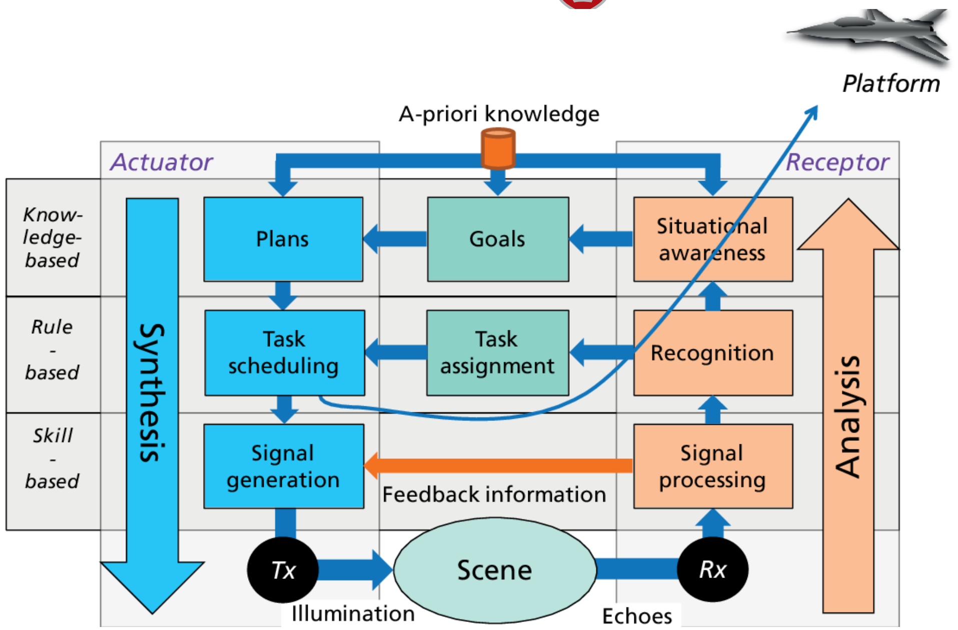
- Cognitive radar (=fully adaptive radar) evokes a vision of biomimetic artificial intelligence fully integrated into the sensing process, emulating human perception.

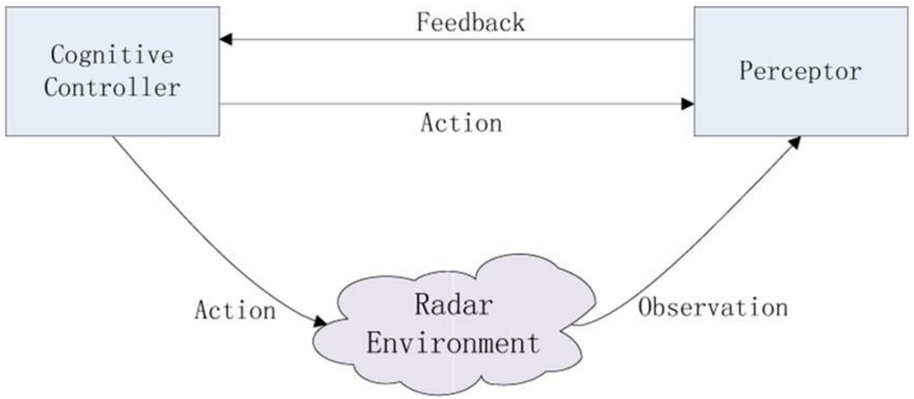
<Gurbuz, Sevgi Zubeyde, et al. "An overview of cognitive radar: Past, present, and future." *IEEE Aerospace and Electronic Systems Magazine* 34.12 (2019): 6-18.>

# Concept and Background of Cognitive Radar

- In traditional radar systems, the information flow is one-way so that the radar interrogates its surroundings by transmitting a fixed, predefined waveform regardless of any changes in the environment.

- Current research on cognitive radar aims at two-way interaction of the radar with its environment by developing not only the adaptive hardware and analytical techniques, but also stochastic control, optimization, ML, and AI.

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# Concept and Background of Cognitive Radar

## Concept of Cognitive Radar

- Cognitive radar refers to a type of radar system that incorporates cognitive capabilities, such as artificial intelligence (AI) and machine learning, to enhance its performance and adaptability. Cognitive radar systems have the ability to learn from their operating environment, make informed decisions, and adjust their settings in real-time based on the changing conditions.

## Advantage of Cognitive

**1.Adaptability :** Dynamically adjust their operating parameters and configurations in response to changing environmental conditions. This adaptability allows them to maintain optimal performance.

**2.Learning and Improvement** : Learn from past experiences and data, allowing them to continuously improve their performance over time. They can identify patterns, anomalies, and new threats that might not be recognized by fixed algorithms.

**3.Improved Performance**: Target detection and classification accuracy, even in cluttered or noisy environments using AI.

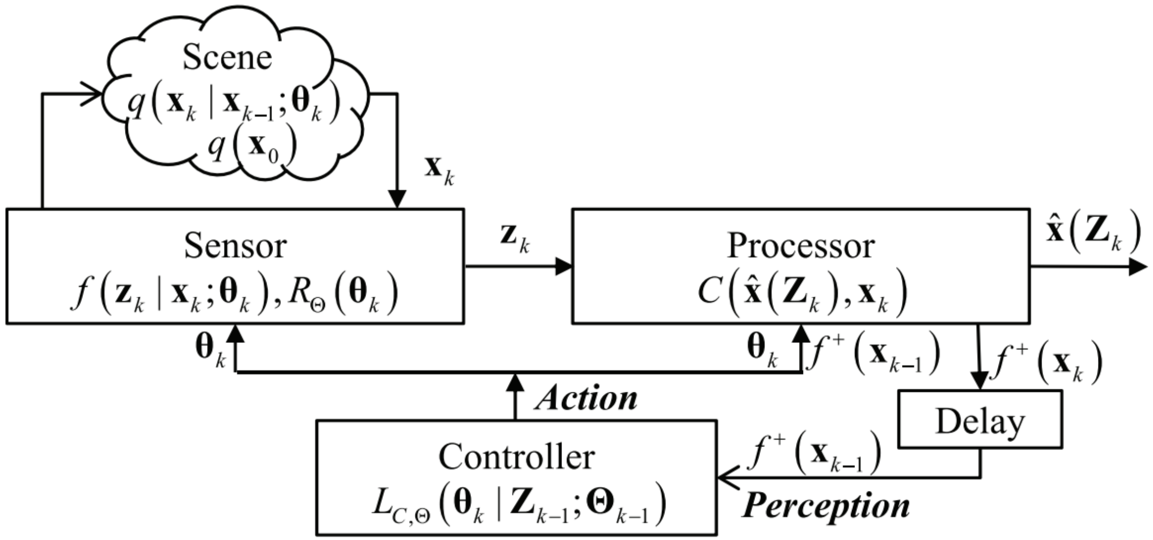
**4. Countermeasures and Anti-jamming**: Adapt its strategies in response to intentional interference or jamming attempts, making it more resilient and effective against electronic warfare tactics.

Radar parameters that can be changed: Frequency, Waveform, Bandwidth, PRF, polarization and so on.

# Example of Cognitive Radar -1

Bell, Kristine L., et al. "Cognitive radar framework for target detection and tracking." *IEEE Journal of Selected Topics in Signal Processing* 9.8 (2015): 1427-1439.

- Develops a general cognitive radar framework for a radar system engaged in target detection and tracking and shows the cognitive radar offers significant performance gains over a standard feed-forward system.




- **The system consists of:**
- The scene; the target and the environment
- The sensor; observes the scene
- The processor; converts the observed data into a perception of the scene
- The controller; the novel component. It decides on the next value for the sensor parameter by minimizing a loss function $L_C$.

# Example of Cognitive Radar - 1

- In a high-resolution case, the static system has similar or a little better performance for the track initiation and termination than the cognitive radar (BLR is higher for the equal sensor parameter when k=5 (the target is present) and k=50 (the target disappears))

- The PC-CRLB is higher for the static system than the cognitive system while the target is under track.

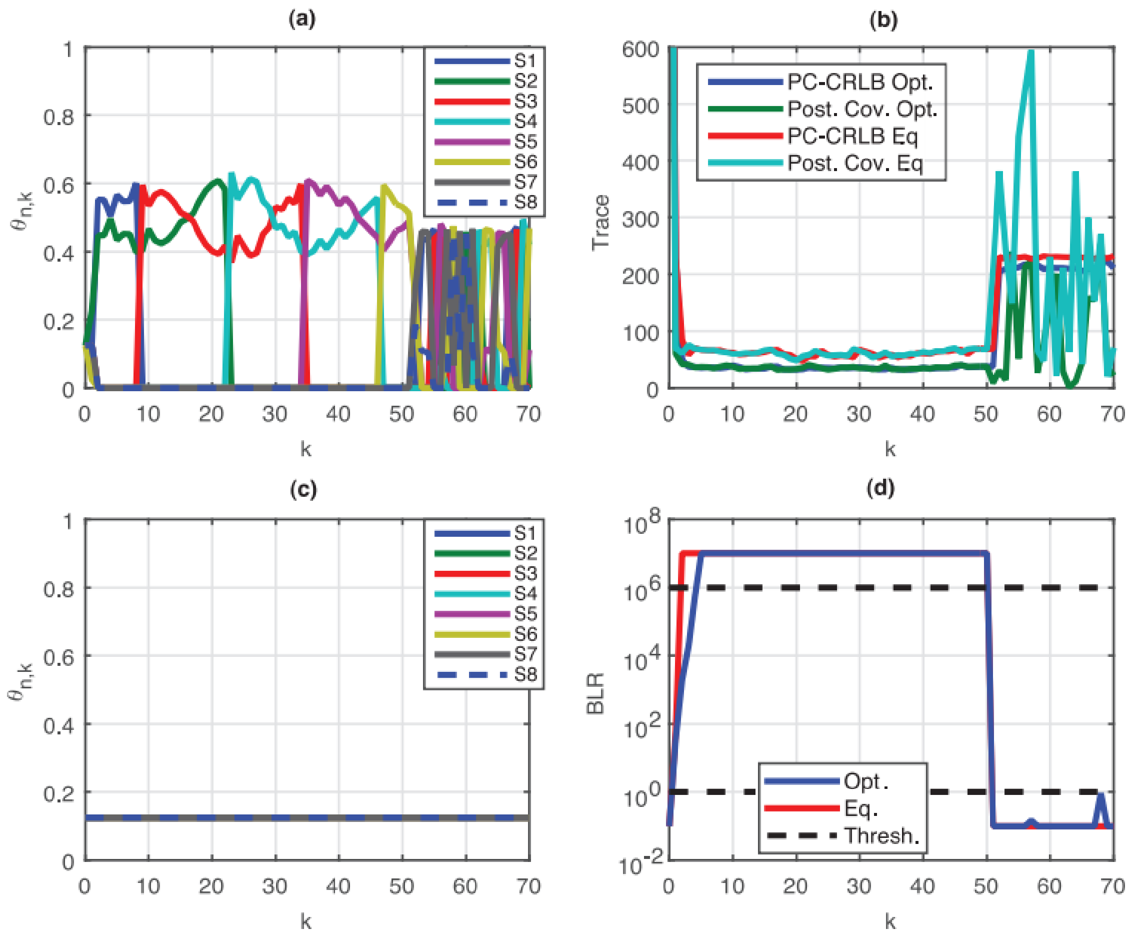



Fig. 3. Sensor parameters, PC-CRLB, and BLR for high resolution case. (a) Optimal Sensor Parameters, (b) Trace of PC-CRLB & Posterior Covariance Matrix, (c) Equal Sensor Parameters, (d) BLR.

# Example of Cognitive Radar - 1



- In a low resolution, the static system shows significantly pooper performance. The PC-CRLB is much higher and the BLR is much lower than for the cognitive system.

- These two examples show that the cognitive system makes better use of the system resources and achieves better tracking performance than the static system.

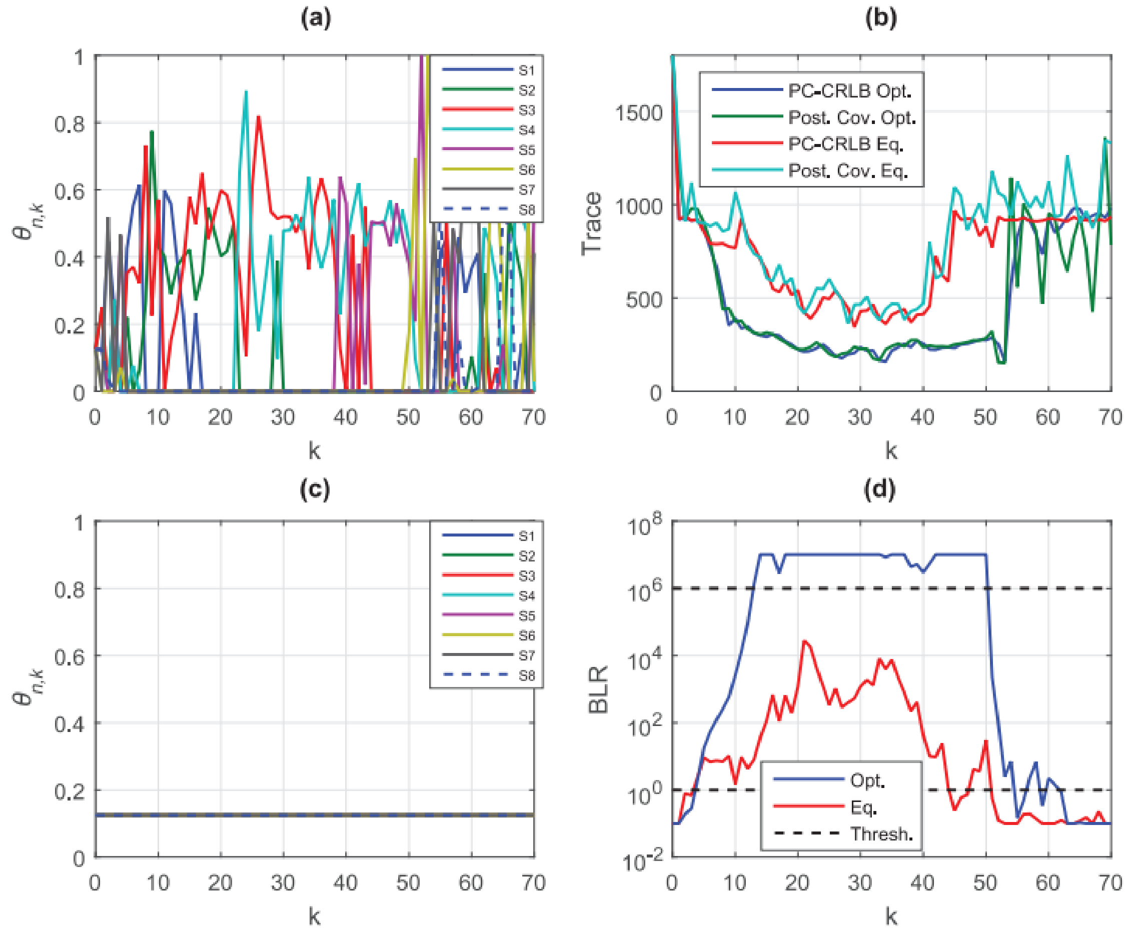


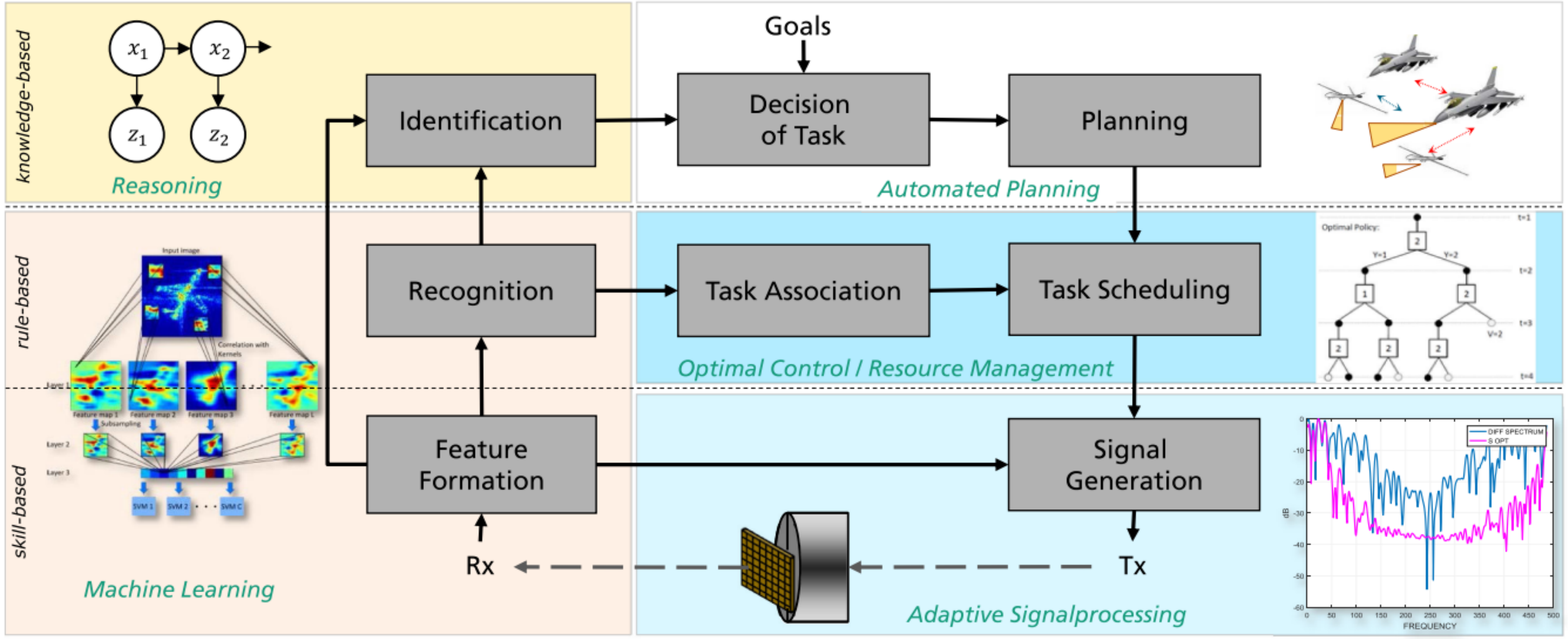

Fig. 5. Sensor parameters, PC-CRLB, and BLR for low resolution case. (a) Optimal Sensor Parameters, (b) Trace of PC-CRLB and Posterior Covariance Matrix, (c) Equal Sensor Parameters, (d) BLR.

# Example of Cognitive Radar - 2



Brüggenwirth, Stefan, et al. "Cognitive radar for classification." IEEE Aerospace and Electronic Systems Magazine 34.12 (2019): 30-38.

- Illustrated cognitive approaches for target classification within a three-layer cognitive radar architecture. The skill-based layer represents subconscious, the rule-based layer represents reactive behavior, and the knowledge- based layer provides goal-oriented computation in unfamiliar situations.



# Example of Cognitive Radar - 2

- DL methods are well suited to bridge the gap between the radar input data and higher level semantic processing.

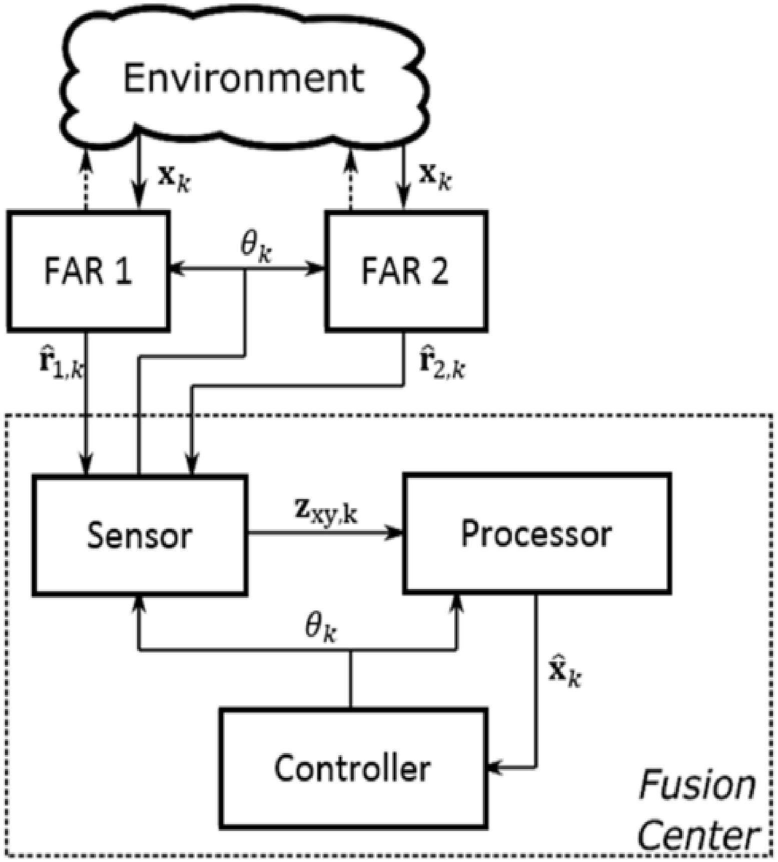
- First results of adaptive waveform design were shown, however, further experimental validation is required

- For an optimal performance, consistent behavior generation on all three abstraction layers is required. This remains a major challenge in the design and implementation of comprehensive cognitive radar architectures

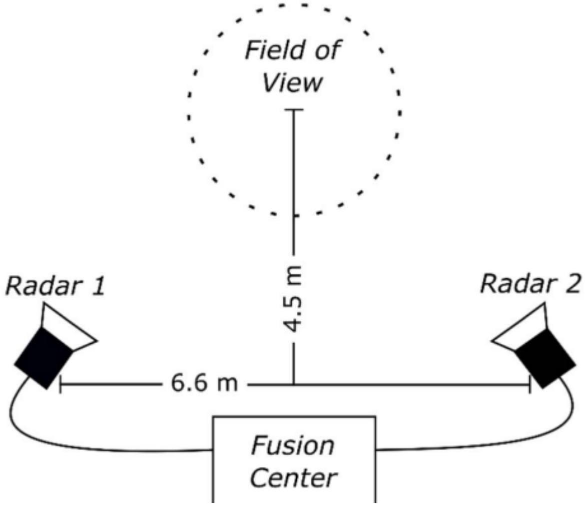
# Example of Cognitive Radar - 3

Mitchell, Adam E., et al. "Single target tracking with distributed cognitive radar." 2017 IEEE Radar Conference (RadarConf). IEEE, 2017.

- Presents the application of the fully adaptive radar (FAR) framework for cognition to a distributed radar network. Multiple instances of the FAR framework were arranged hierarchically.




- Two monostatic radar nodes are connected through a fusion center, and their transmitted waveforms are adapted in real-time.



# Example of Cognitive Radar - 3

- Both approaches successfully tracked the target, but the adaptive system produced a tighter track when the target changed directions at the center point.

- The fixed parameter system yielded average root mean squared errors (RMSE) , of 0.517 m in position and 0.653 m/s in velocity, while the adaptive system resulted in marginally better tracking performance; the average RMSE was 0.498 m in position and 0.630 m/s in velocity.

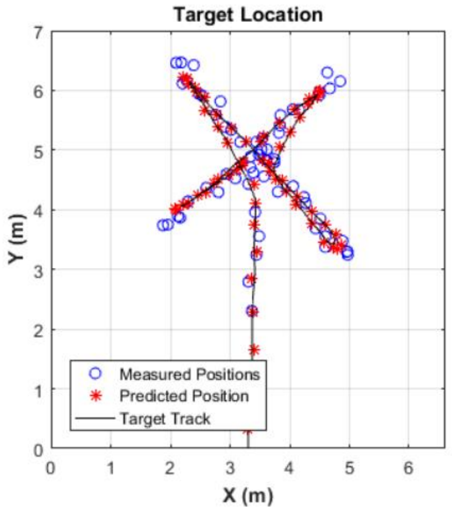



**Fig. 3** The Cartesian target track produced by the radar network's fusion center when the target followed an 'X' pattern and the waveform parameters were fixed.

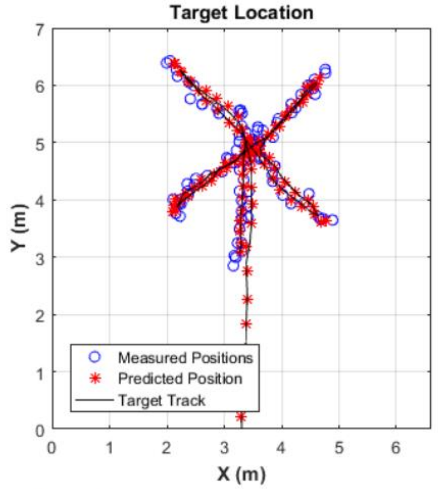



Fig. 4. The Cartesian target track produced when the networked radars operated with adaptive waveform parameters.

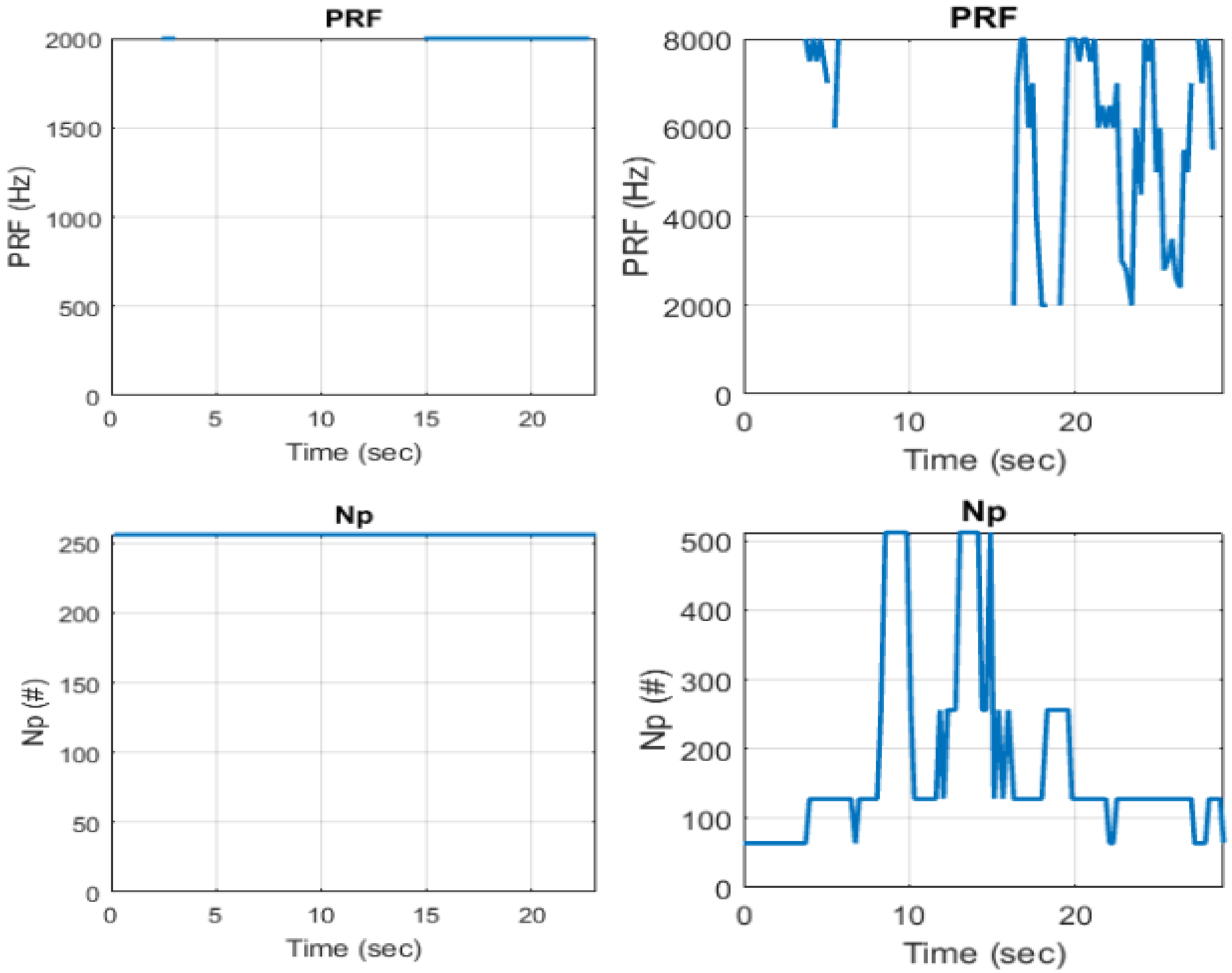
# Example of Cognitive Radar - 3



Mitchell, Adam E., et al. "Single target tracking with distributed cognitive radar." 2017 IEEE Radar Conference (RadarConf). IEEE, 2017.

- With adaptive parameter, PRF and Np were successfully adjusted to keep the velocity and range standard deviations near or below the goal values.

- Experimental results confirmed that hierarchical FAR processing could yield a reasonable RMSE at all levels of the cognitive structure while adapting waveform parameters in real time to track a human target.




waveform parameter fixed | adaptive waveform param.

# Example of Cognitive Radar - 4

Mendis, Gihan J., Jin Wei, and Arjuna Madanayake. "Deep learning cognitive radar for micro UAS detection and classification." 2017 Cognitive Communications for Aerospace Applications Workshop (CCAA). IEEE, 2017.

- Proposes an intelligent cognitive radar system for detecting and classifying the micro unmanned aerial systems (micro UASs). It designed a low-complexity binarized deep belief network (DBN) classifier that recognizes the signature patterns generated by using a Doppler radar based solution.

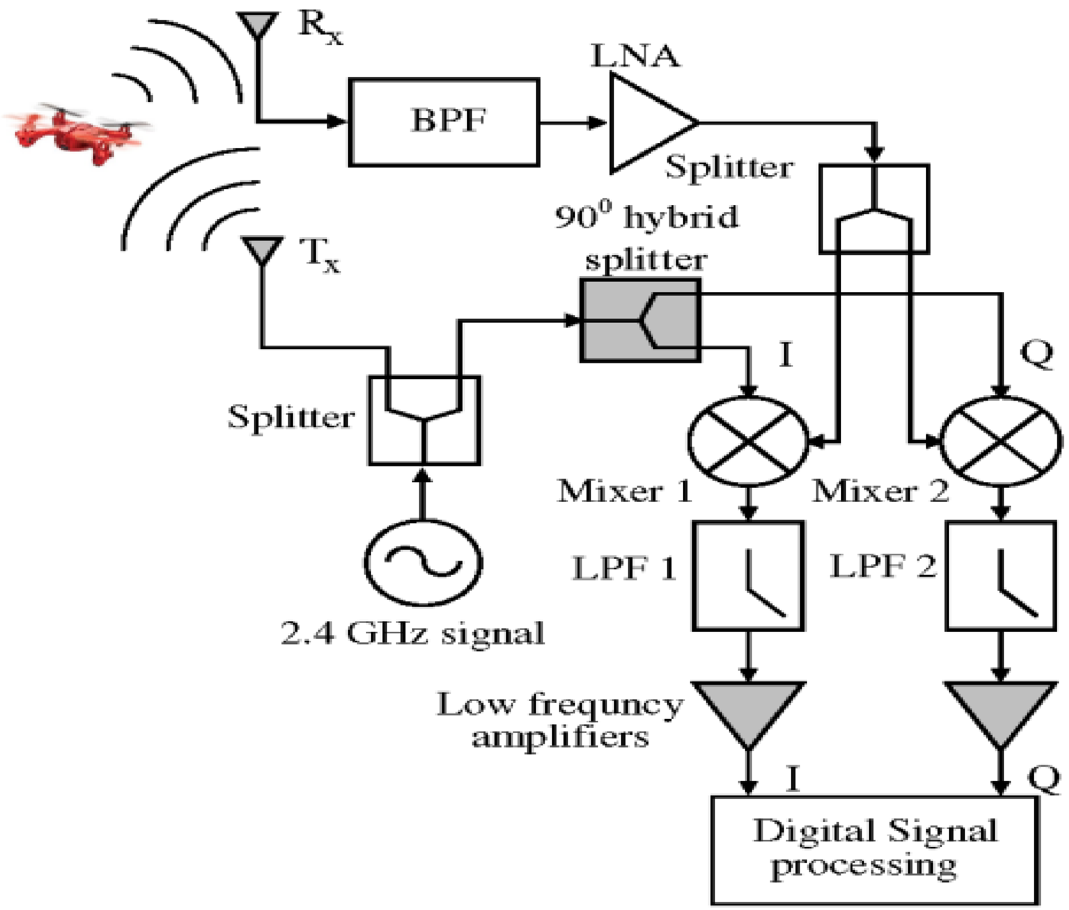



Fig. 1. Radar front-end.

# Example of Cognitive Radar - 4



- Low-complexity DBN shows above 86% accuracy for detecting micro UASs even when the SNR level is as low as -5dB.

- The percentage of false alarm remains less than 10% for SNR > 0dB.

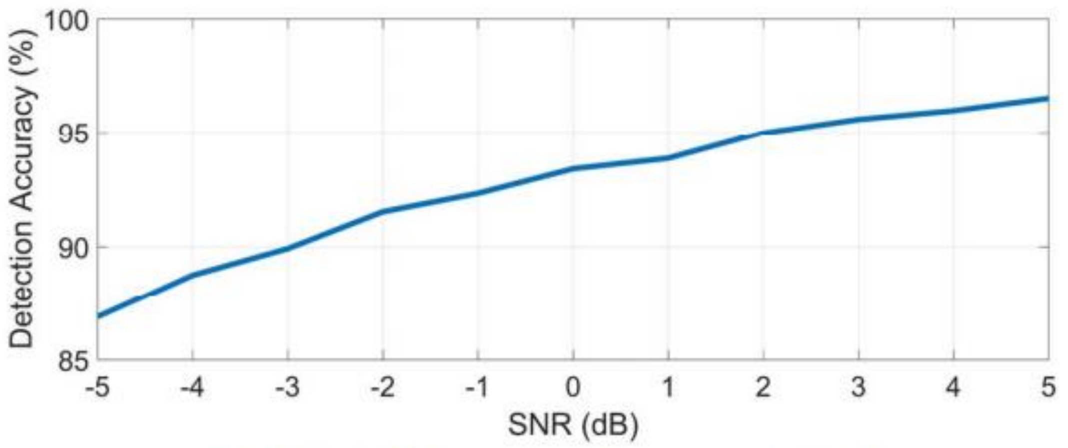



Fig. 5. Micro UAS detection accuracy with SNR.

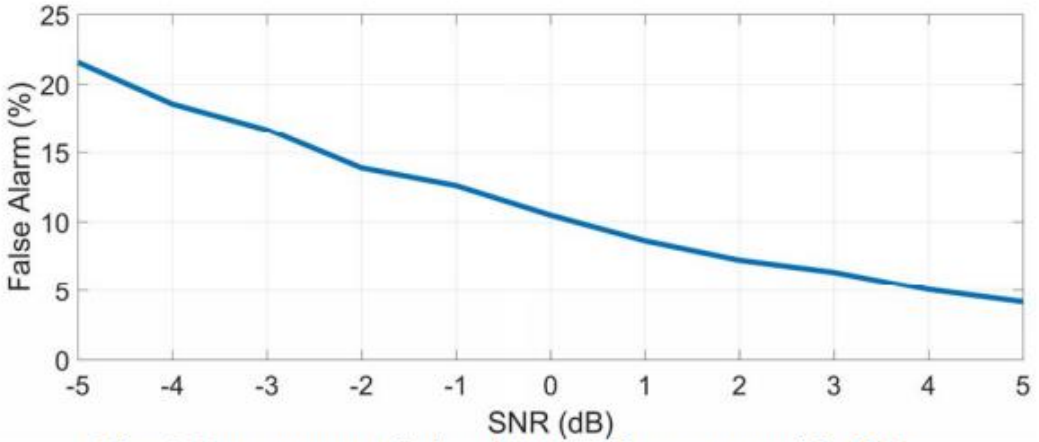



Fig. 6. Percentage of false alarm of the system with SNR.

# Example of Cognitive Radar - 4

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- Both low-complexity DBN and regular DBN outperform the MAXNET ANN based method.
- It can be concluded that that the low-complexity DBN performs comparably to the regular DBN for the classification of micro UAS SCF signature patterns.

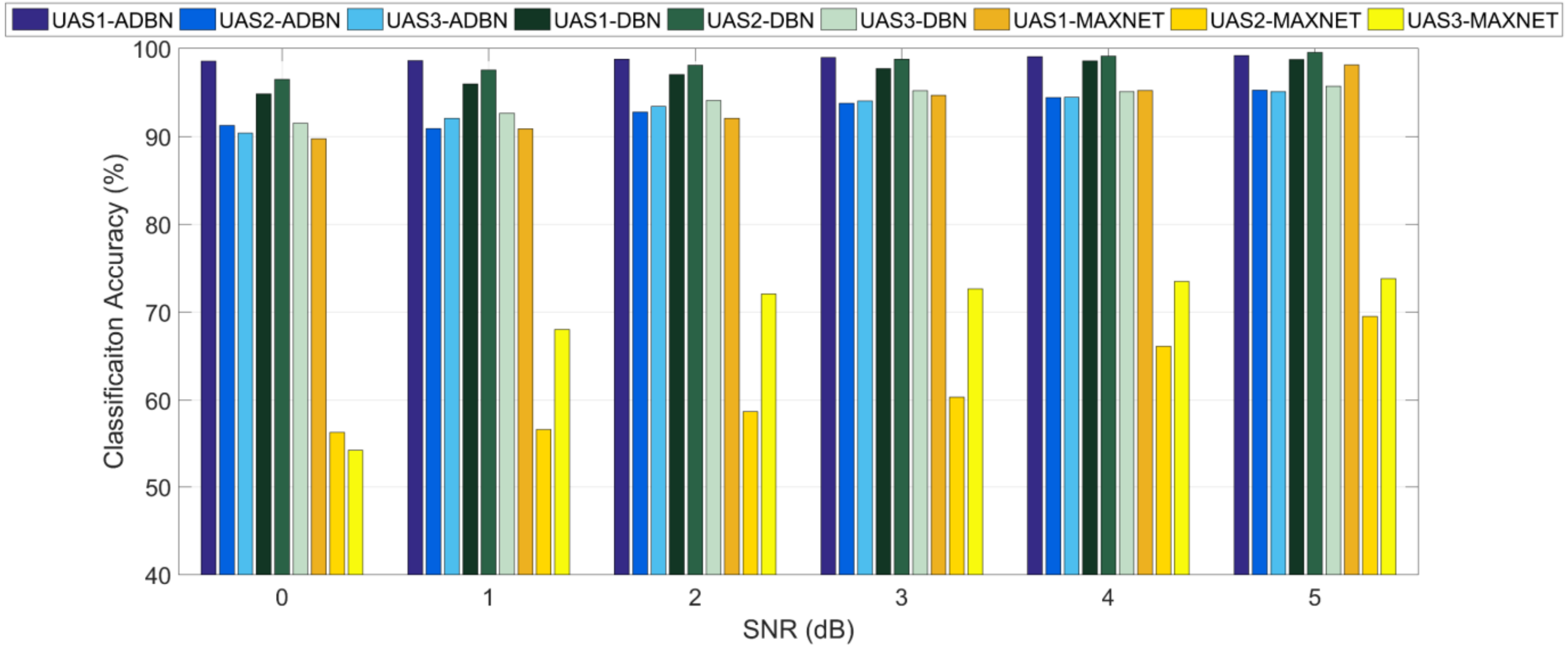


Fig. 7. Classification accuracy of different micro UASs for low-complexity DBN (ADBN), regular DBN, and MAXNET ANN based methods.

# Example of Cognitive Radar - 5



Reich, Galen M., Michael Antoniou, and Christopher J. Baker. "Memory-enhanced cognitive radar for autonomous navigation." IET Radar, Sonar & Navigation 14.9 (2020): 1287-1296.

- Introduces a cognitive radar system for autonomous robotic navigation. A major element in this work is how forms of artificial memory can be manifested, and how implementing them with a radar system can enhance collision-free navigation.

- Memory in the cognitive functioning of the robot is essential for the robot to maintain a perception of obstacles outside of its field-of-view so that it can take appropriate obstacle avoidance action

| Memory length | Simulation | | Experiment | |
|---|---|---|---|---|
| | Successes | Failures | Successes | Failures |
| 1 (no memory) | 4 | 6 | 4 | 6 |
| 15 (short memory) | 10 | 0 | 9 | 1 |
| 25 (long memory) | 10 | 0 | 7 | 3 |

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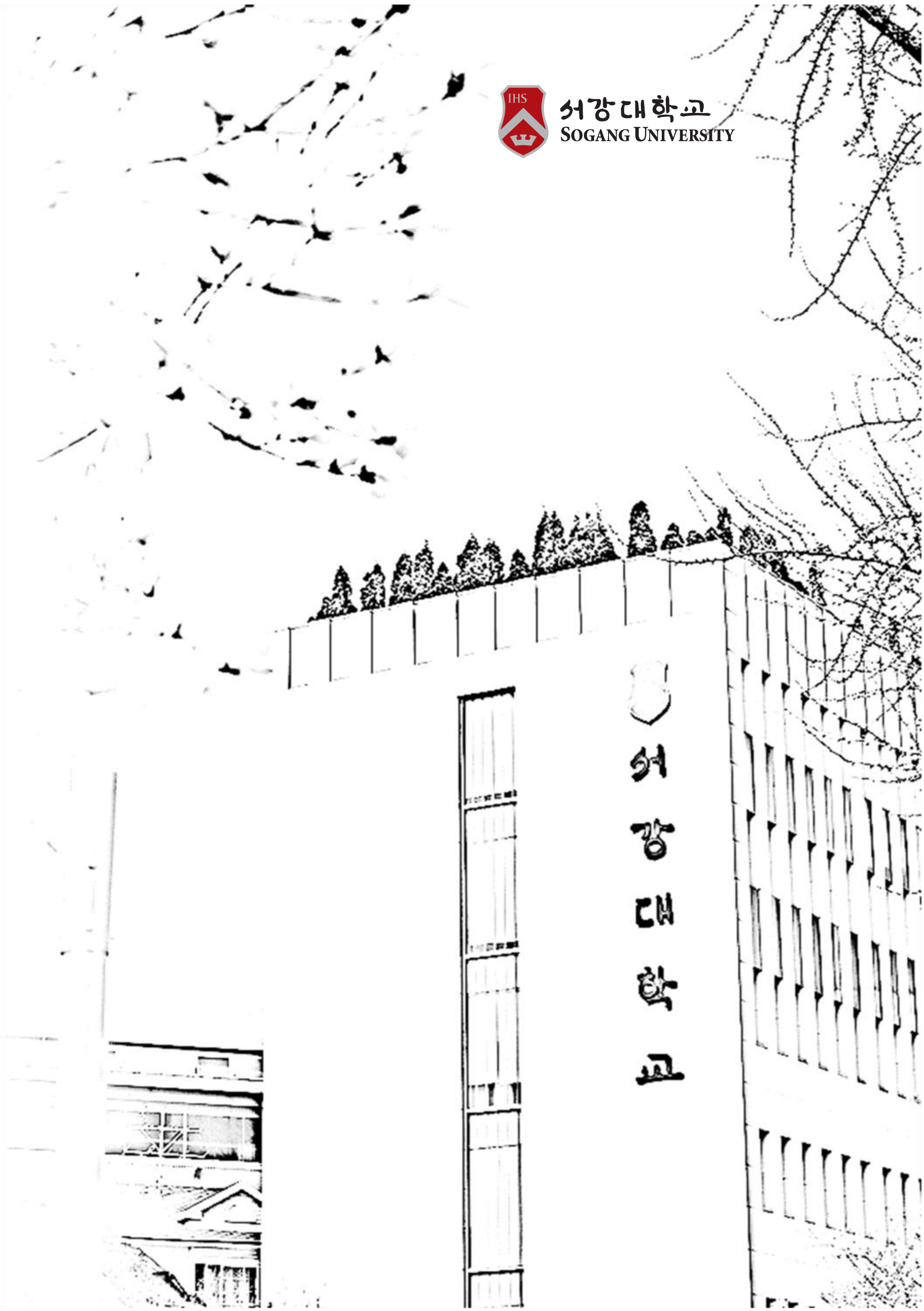
# 3. Reinforcement Learning

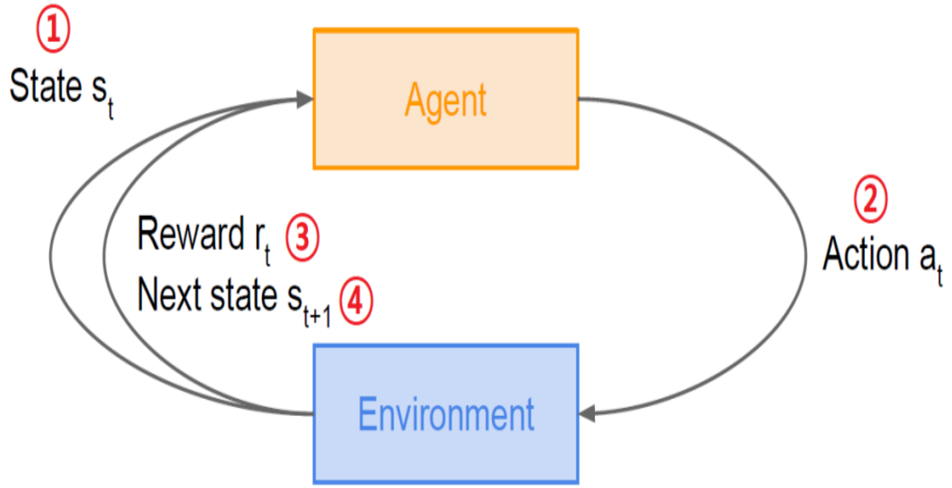


# Reinforcement Learning

## What is RL ?

Training agents to make sequences of decisions in an environment in order to maximize a cumulative reward. It is inspired by behavioral psychology and is often used to model how humans and animals learn to perform tasks through trial and error.

**Learn how to take actions in order to maximize reward?**




RL learns a policy that can maximize the future rewards.

$$\pi^* = \arg\max_{\pi} \mathbb{E}\left[\sum_{t\geq 0} \gamma^t r_t | \pi\right]$$

Example of RL:

Range Doppler Image + Preferable radar parameters → RL → Radar Parameters → Higher tracking maintenance rate/ better classification accuracy

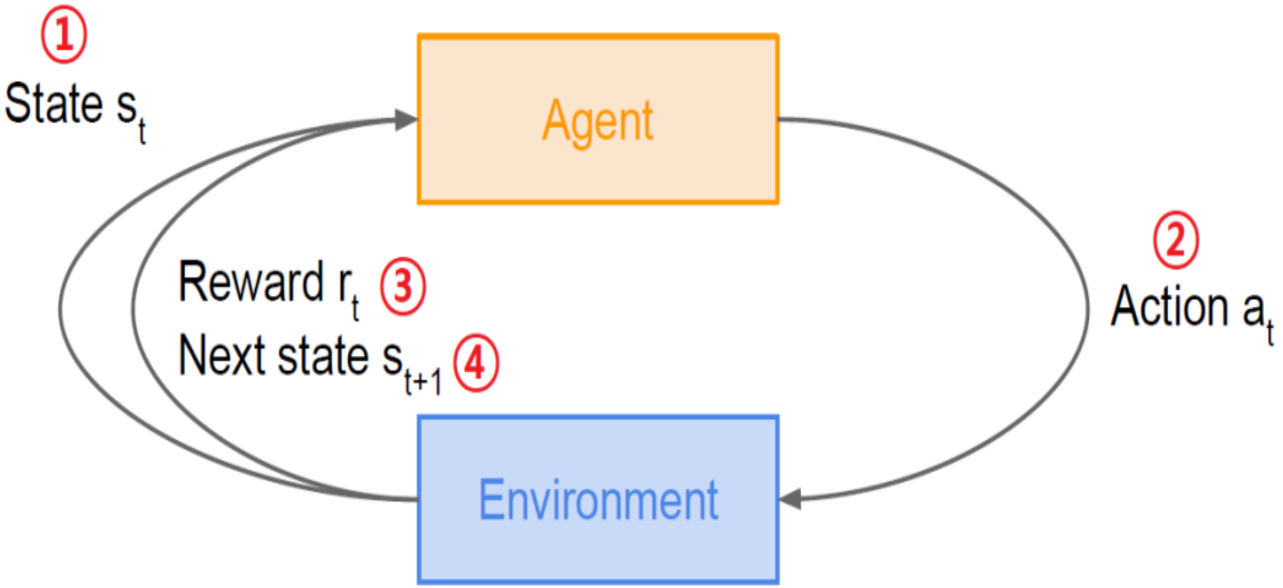
## What is difference between optimization and RL?

- Optimization finds suboptimal or global optimal solution when the cost surface is fixed.
- RL a way to find suboptimal or global optimal solution in a complex cost surface.

- In RL problem, the cost surface changes with action/environment/time.
- At every time, the agent should determine the best sequential action to maximize pote ntial return.
- RL learns how to find the suboptimal solution.

# Reinforcement Learning






**Policy:** Finding an action that maximizing a return given a state

$a = \pi\ (s)$

RL is the process to find the policy

**Model:** State Transition Probability

$P(s' \mid s_1, a_t) = 0.8$

**Return:** Sum of potential rewards

$G_t = \sum_{k=0}^{\infty} r^k \ R(S_{t+k})$

**Value:** Expectation of sum of potential re wards

State value function:
$V(s) = E(G_t \mid =s)$

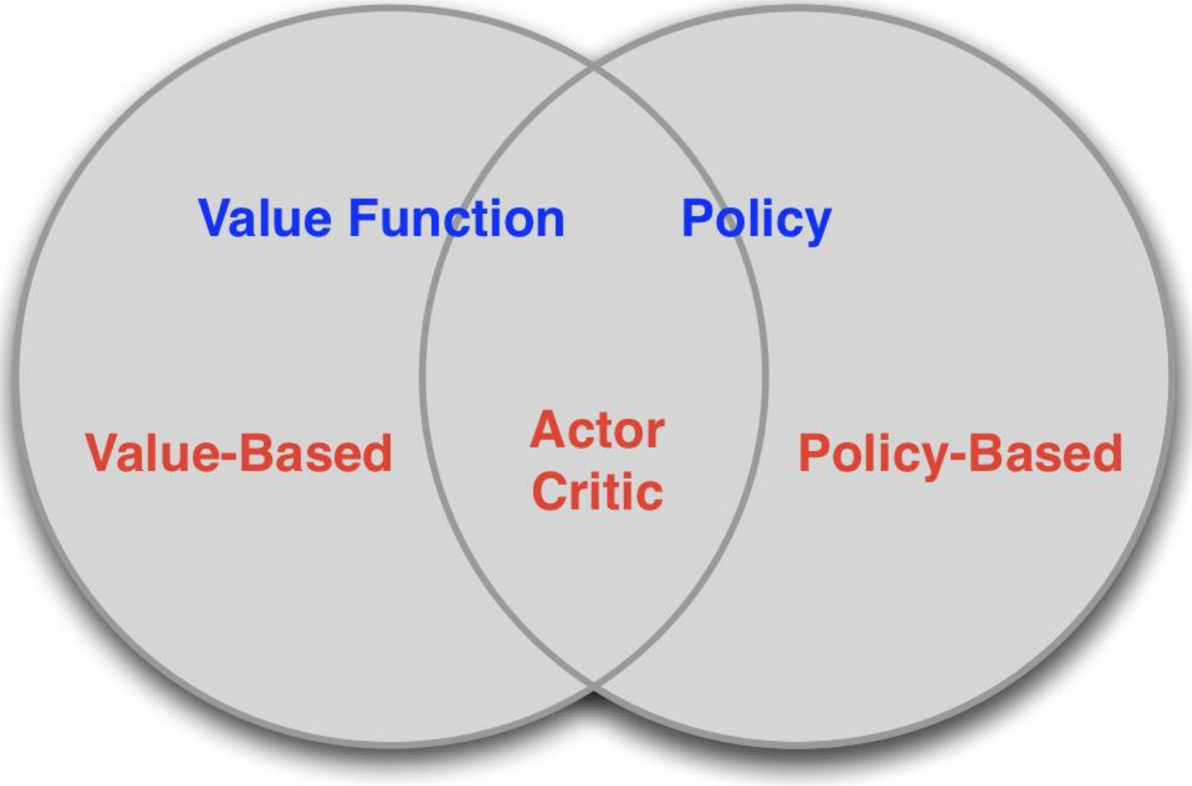
Action value function:
$Q(s,a)$

# Reinforcement Learning

Model-Based: Because the state transition probability is given, we can calculate the value function.

Model – Free: - Monte Carlo

- Time Difference



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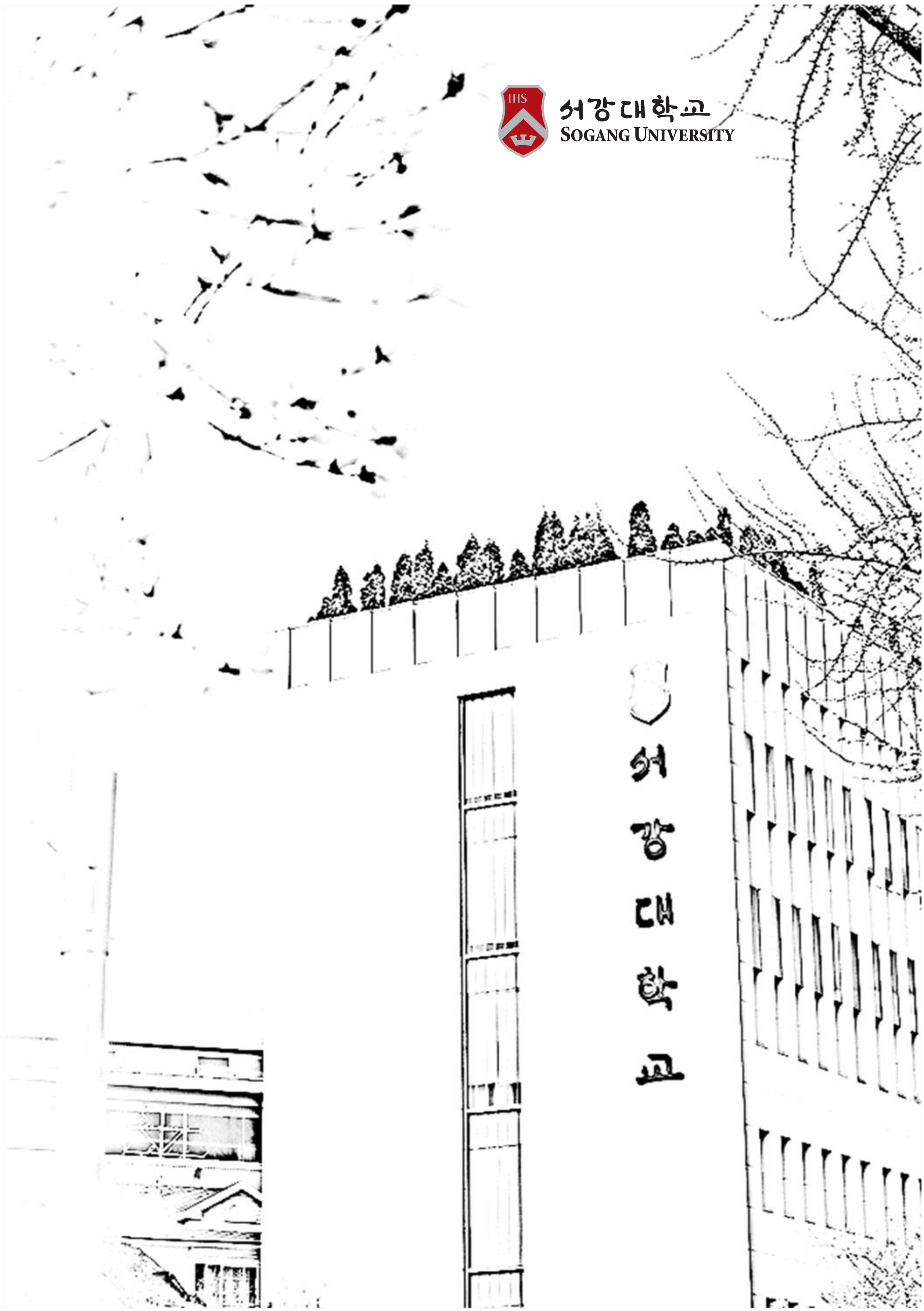
# 4. Radar Parameter Optimization using RL for Human Activity Classification



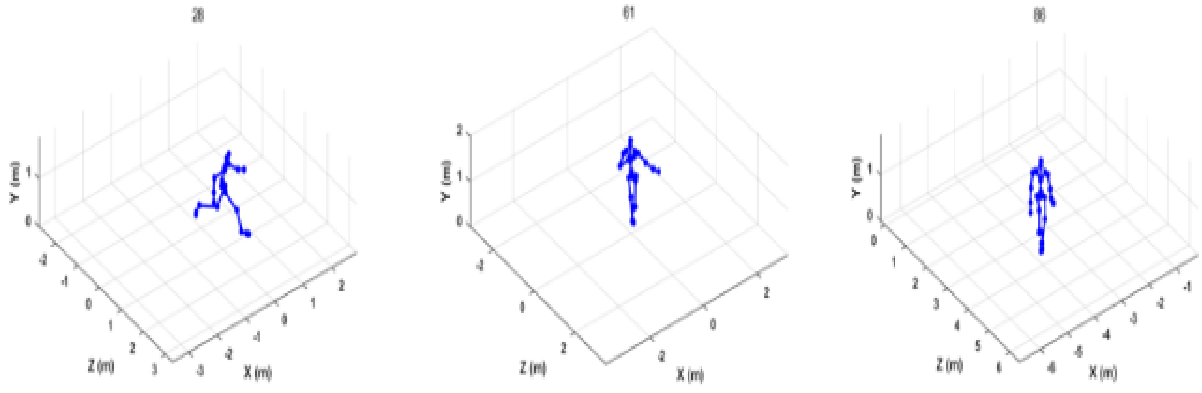
# Goal of Research

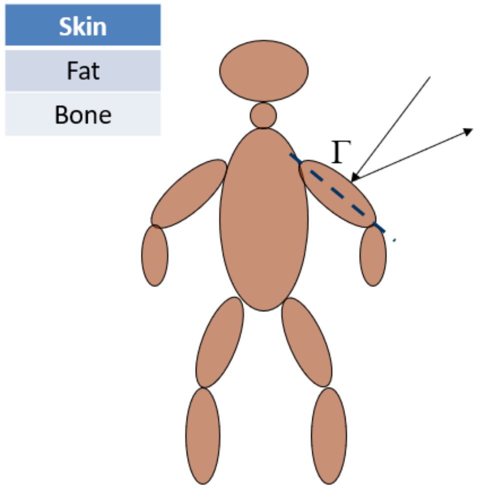


## Classification Techniques for Human Micro-Doppler Signals

Utilization of Specific Vectors Extracted through EMD for Data Classification

Deep Learning(DCNN, RNN, GAN) Approaches for Human Micro-Doppler Signal Analysis



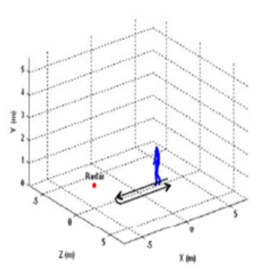

<Human modeling using ellipsoid>

RCS of Ellipsoid:

$$\sqrt{\sigma} = \left[ \Gamma \cdot \frac{\frac{1}{4}\pi \mathrm{Re}^4\, He^2}{\mathrm{Re}^2 \sin(\theta) + \frac{1}{4} He^2 \cos(\theta)} \right] \cdot e^{-j\frac{2\pi}{\lambda}2r}$$

Given RCS and velocity of the ellipsoid, the Doppler signal can be calculated.

Left Parametric (SEP) Right Fixed (FEM)

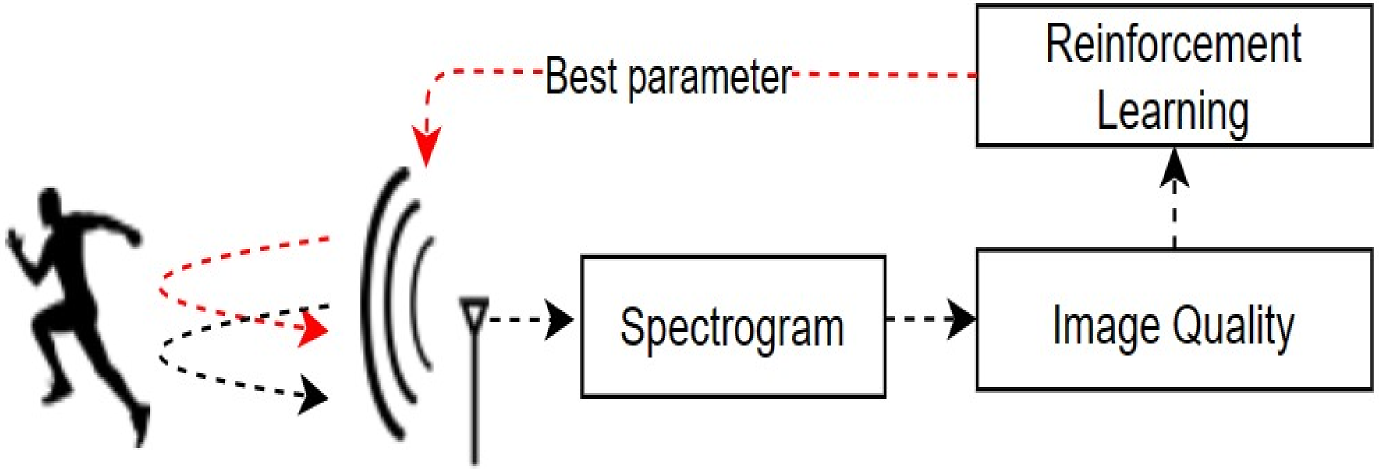


# Goal of Research

The Quality of Spectrogram Images Affects the Performance of DCNN
Spectrogram Influences on Human Movement Characteristics and Radar Parameters (Carrier Frequency, Sampling rate)
Integrating Cognitive radar Concepts to Maximize DCNN Performance

## Cognitive radar

Intelligent System for Adaptive Radar Parameter Adjustment Based on Prior Knowledge from Previous Observations and Databases



# Classification Accuracy with Radar Parameters

**Alexnet properties**

Human motion type : running, run with box, run to crouch, crouch to run, skipping, walk, walk to hop to walk

# for each motion : 50

inputSize = [227 227 3]

Train data : Validation data = 0.76 : 0.24

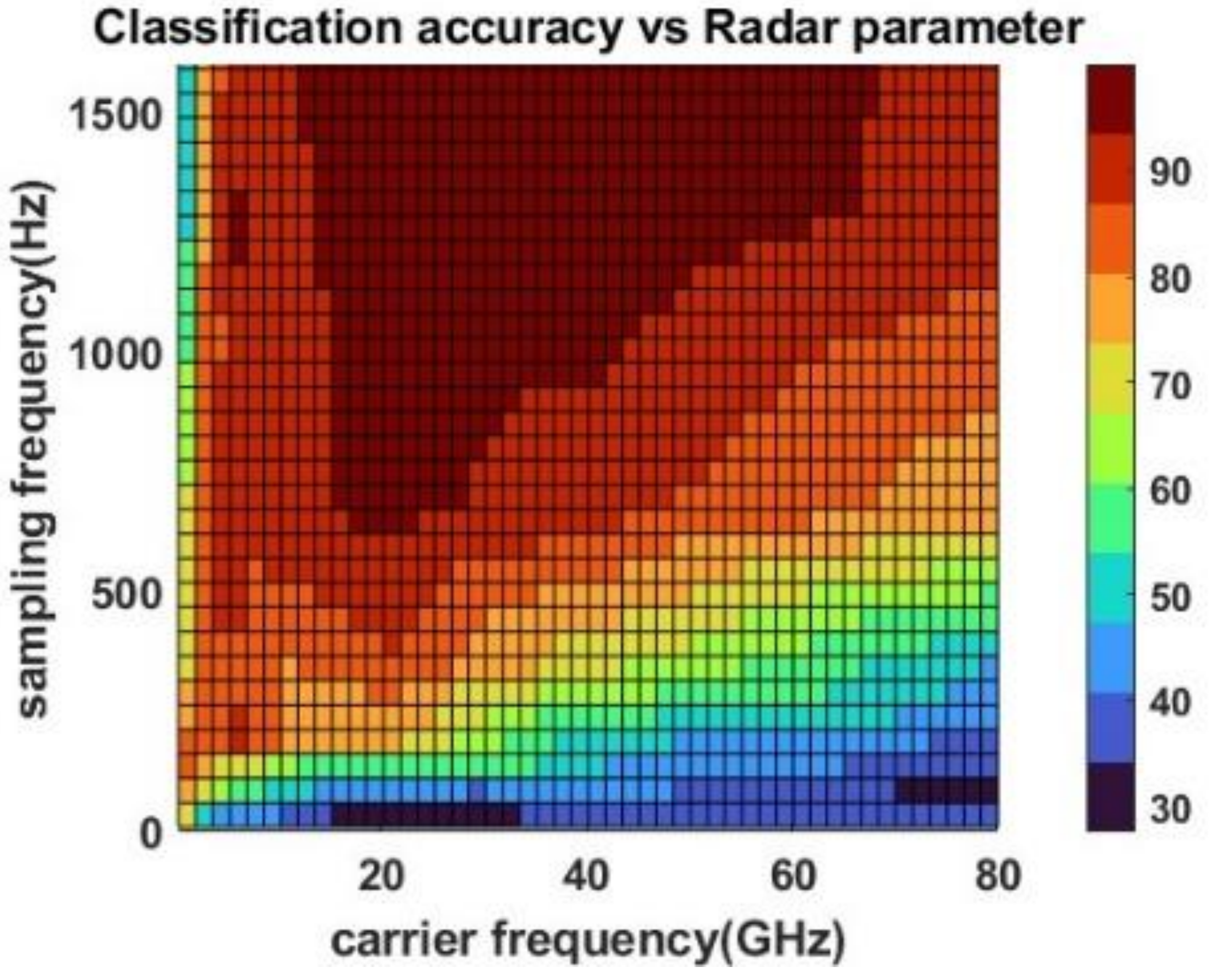
**Parameter Conditions**

Carrier frequency : logscale 0.3125GHz ~ 80GHz

Sampling frequency : logscale 10Hz ~ 2560Hz

Radar is placed collinearly with the motion movement

Motion time duration : 1sec

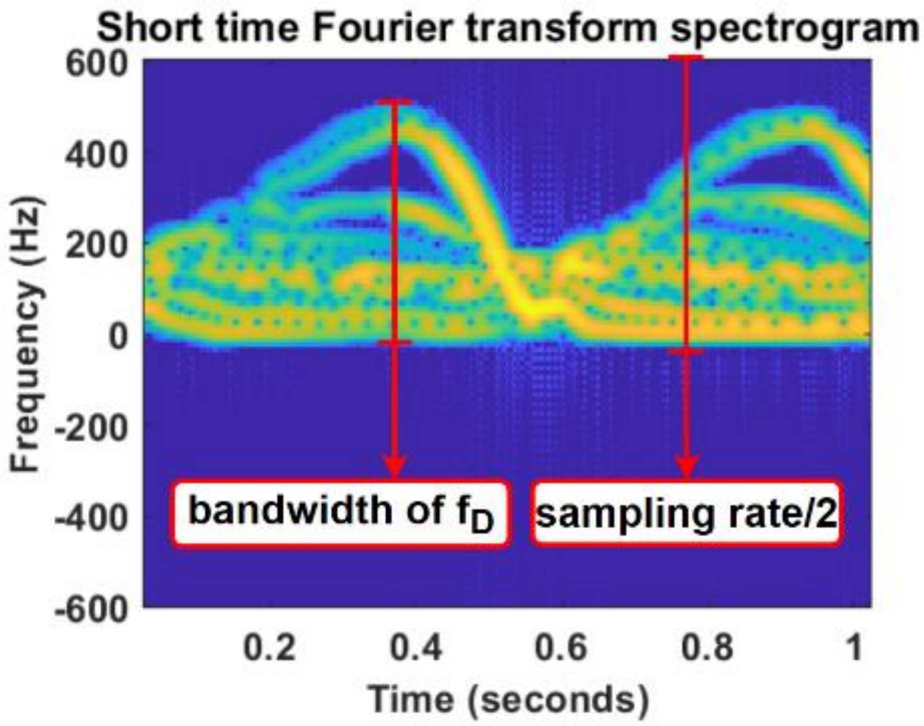


# Radar Parameters and Spectrogram Quality



- **Definition of Folding rate**

$$\text{Folding rate} = \frac{2fD}{Sampling\ rate} \times 100$$



# Radar Parameters and Spectrogram Quality

**Definition rate = Sampling rate**

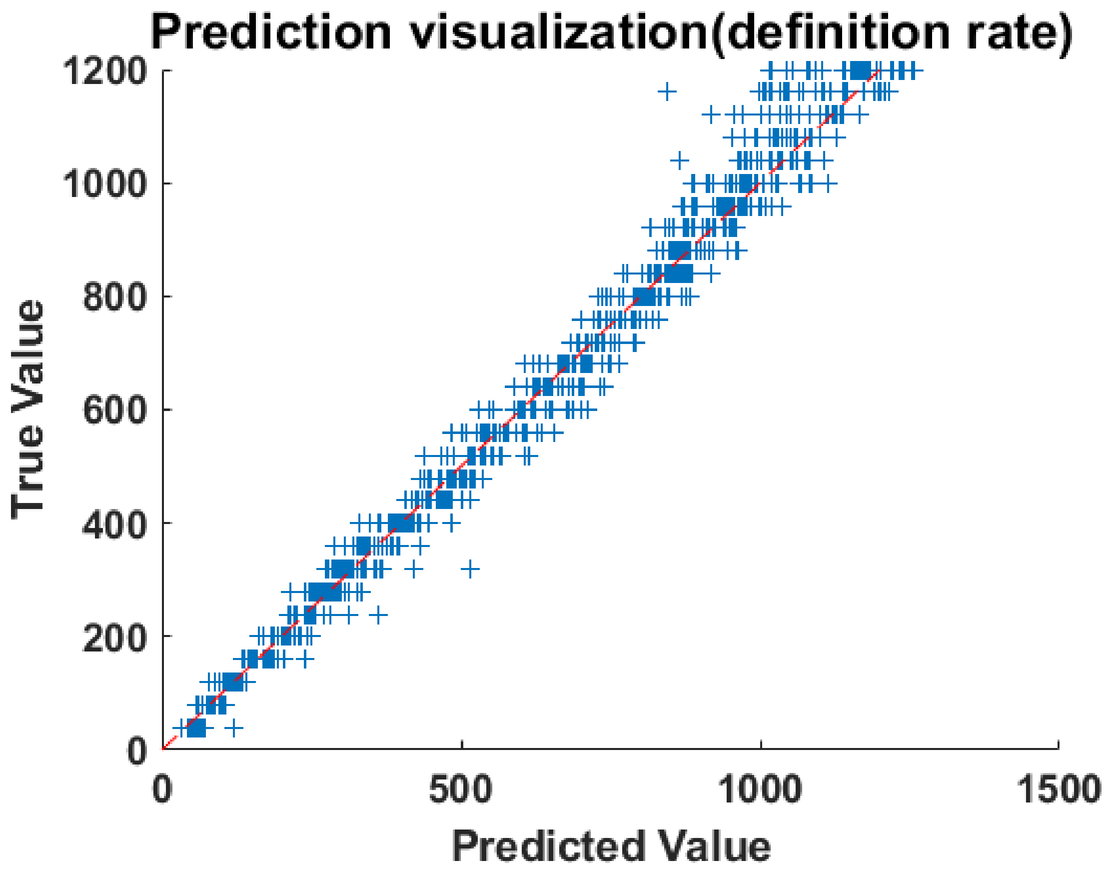
**DCNN regression model properties**

# for each motion : 500
inputSize = [656 875 3]
Train data : Validation data = 0.75 : 0.25
Minibatchsize = 32
maxEpoch = 50

**Parameter Conditions**

Carrier frequency : 20GHz
Sampling frequency : linscale 120Hz ~ 1200Hz

**RMSE = 57.191**



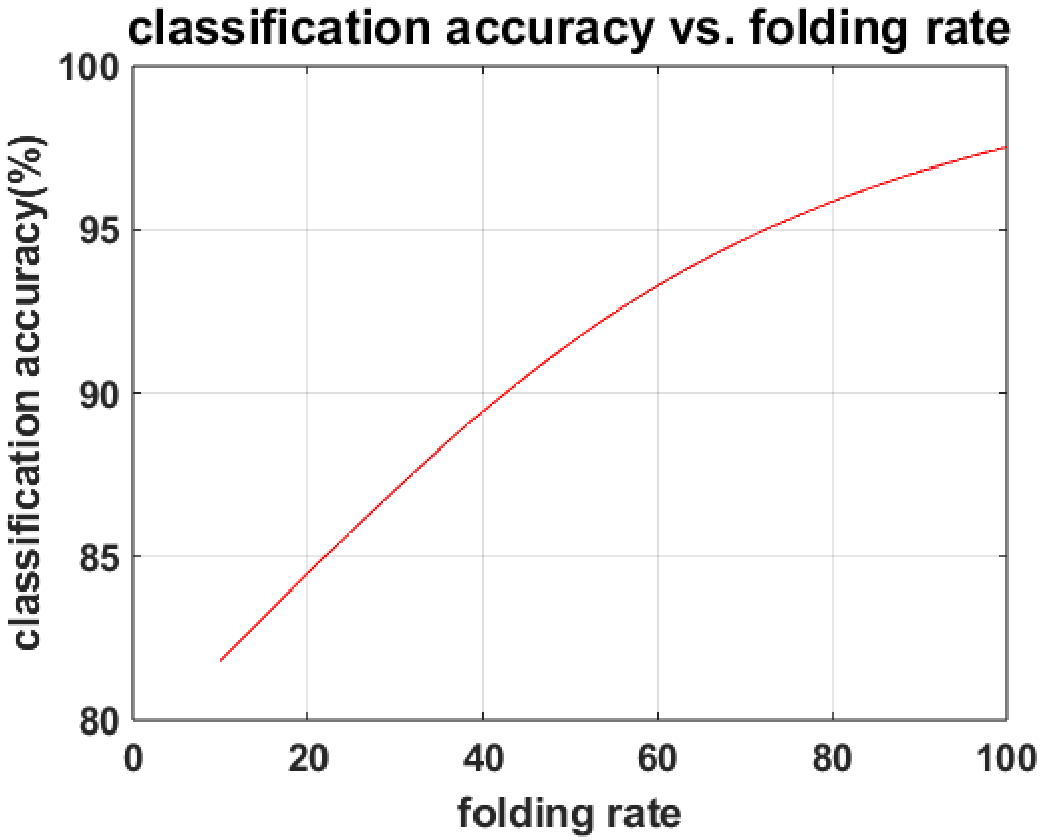
# Image Quality and DCNN Performance



## Alexnet properties

# for each motion : 50
inputSize = [227 227 3]
Train data : Validation data = 0.76 : 0.24

## Near 100 Folding Rate Correlate with Improved DCNN Performance

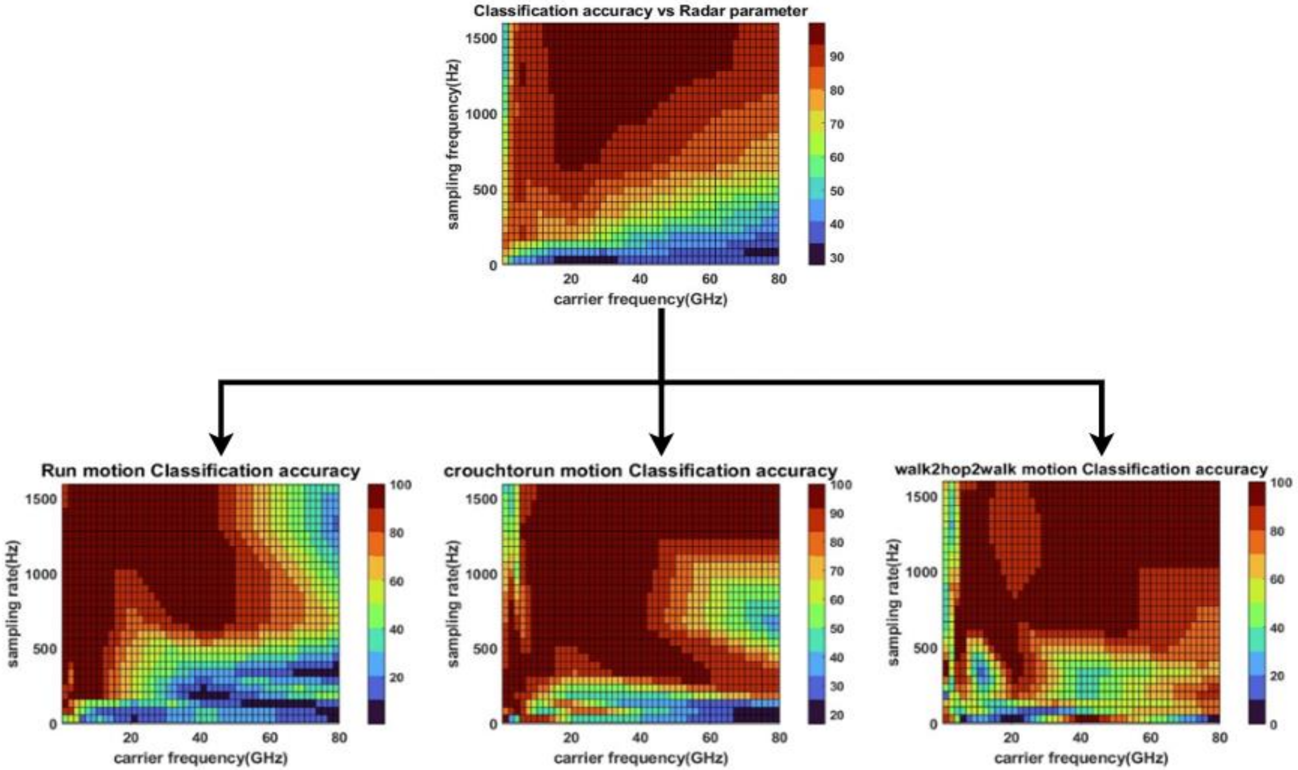


# Image Quality and DCNN Performance



- Analysis of Individual Motion Detection Accuracy

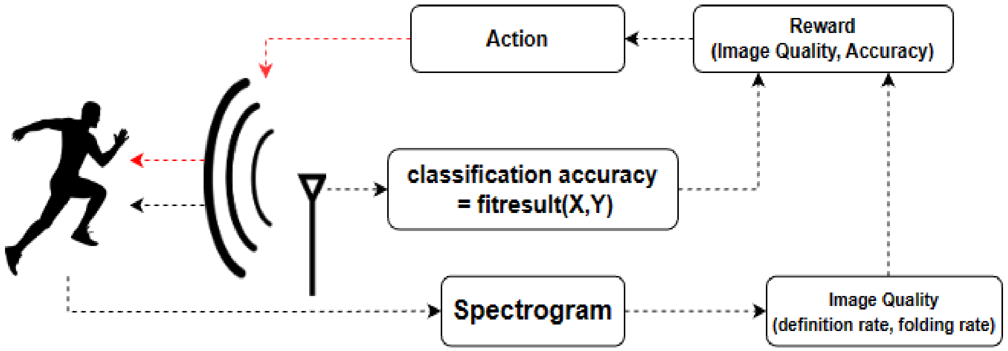
- In activities involving rapid human movements, high carrier frequencies are required to compared to slower motions.




| Human motion | Carrier frequency(GHz) |
|---|---|
| Run | 4.2 |
| Runwithbox | 3.6 |
| Runtocrouch | 6 |
| Crouchtorun | 4.8 |
| Skipping | 11 |
| Walk | 13.5 |
| Walk2hop2walk | 6 |

Radar parameter($f_C$) when human motion spectrogram folding rate is 90

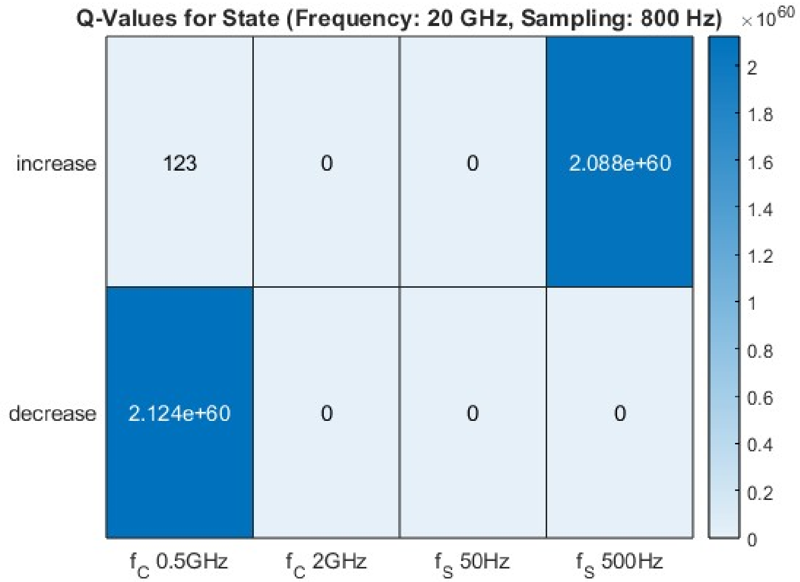
# Reinforcement Learning for Cognitive Radar




## RL algorithm : Q-learning

Learning rate ($\alpha$) : 0.5
Discount factor ($\gamma$) : 0.95
Exploration rate ($\varepsilon$) : 0.1

- $Q_{freqsamp}(S_t, A_t) \leftarrow (1-\alpha)\cdot Q_{freqsamp}(S_t, A_t) + \alpha\left[R_t + \gamma \cdot Q_{freqsamp}(S_{t+1}, A_t)\right]$
- $Q_{foldblur}(S_t, A_t) \leftarrow (1-\alpha)\cdot Q_{foldblur}(S_t, A_t) + \alpha[R_t + \gamma \cdot Q_{foldblur}(S_{t+1}, A_t)]$
- $A \leftarrow \begin{cases} argmax_a \left\{Q_{freq_{samp}}(S, A) + Q_{blur_{fold}}(S, A)\right\} & \epsilon \geq \varepsilon \\ random\ action & \epsilon < \varepsilon \end{cases}$



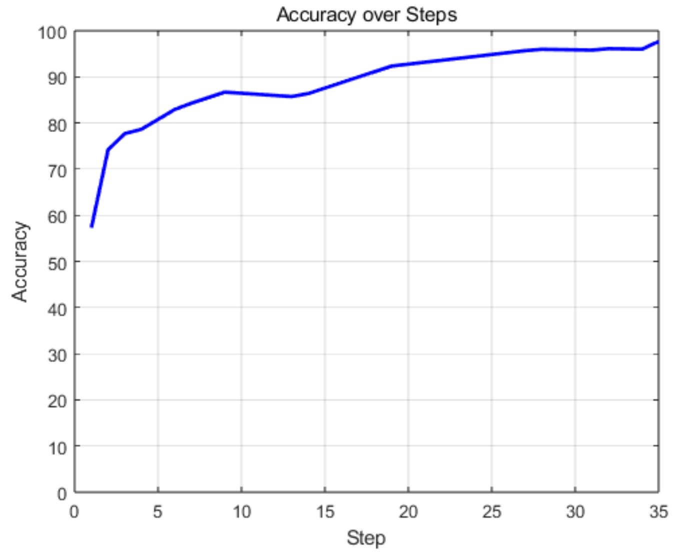
# Reinforcement Learning for Cognitive Radar



**Classification accuracy : 57.29% -> 98.3%**

Environment when $f_C$ = 1Ghz, $f_S$ = 2000Hz, folding rate = 2, definition rate = 2000

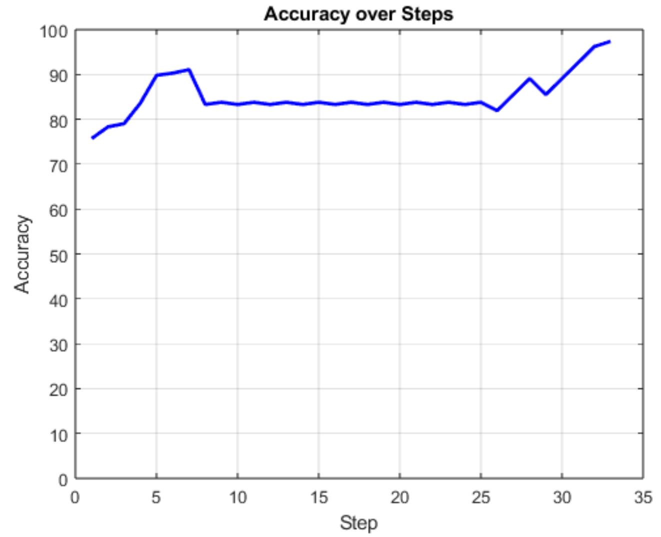
Final agent : $f_C$ = 17Ghz, $f_S$ = 1450Hz, folding rate = 92, definition rate =1450




**Classification accuracy : 75.71% -> 97.38%**

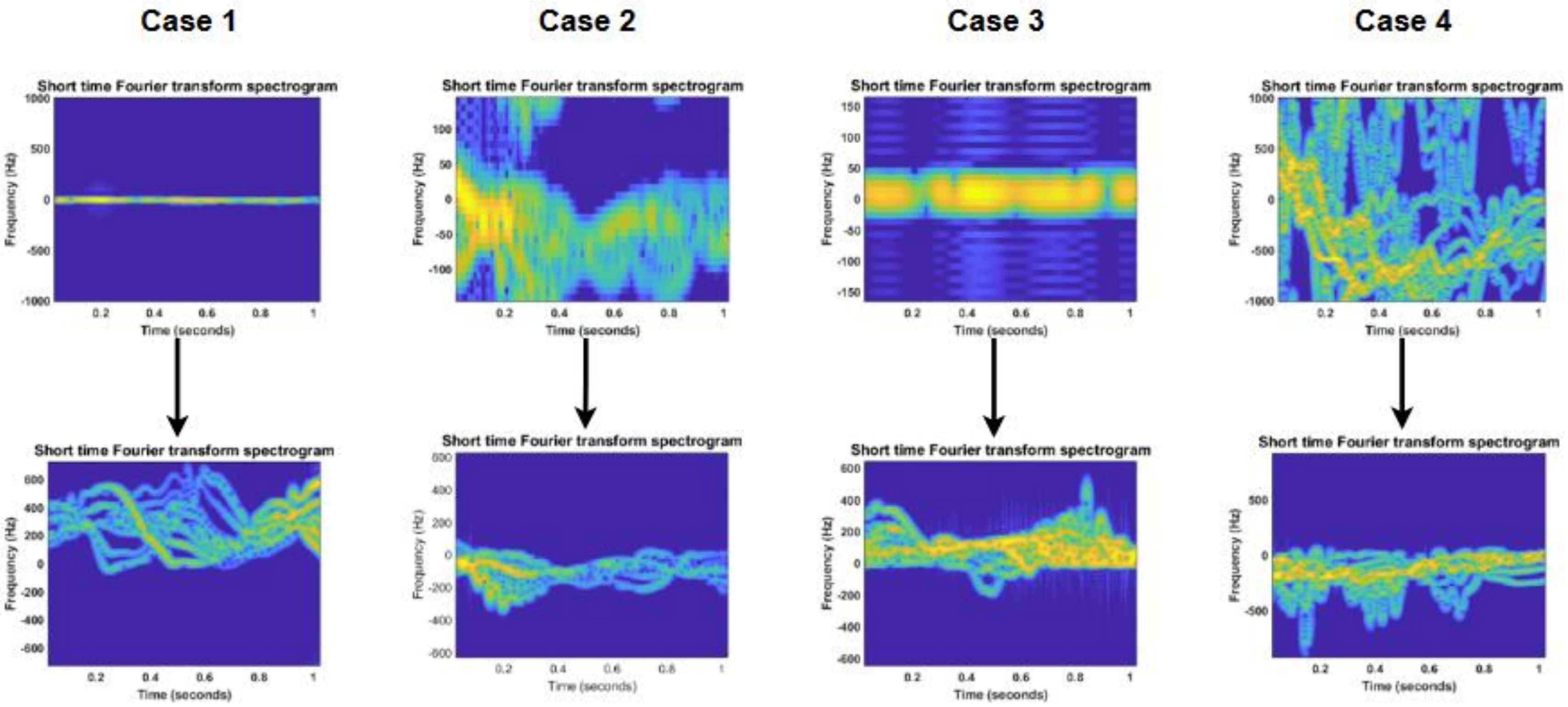
Environment when $f_C$ = 0.5Ghz, $f_S$ = 320Hz, folding rate = 20, definition rate = 320

Final agent : $f_C$ = 7Ghz, $f_S$ = 1270Hz, folding rate = 61, definition rate =1270



# Reinforcement Learning for Cognitive Radar

Case 1 : Low Folding Rate -> Increasing the Folding rate
Case 2 : High Folding Rate -> Decreasing the Folding rate
Case 3 : Low Sampling Rate -> Increasing the Folding rate
Case 4 : High Sampling Rate -> Decreasing the Sampling rate



# Conclusion

## Result

The application of reinforcement learning to cognitive radar systems effectively learns and optimizes radar parameters, leading to improved accuracy in classifying micro-Doppler signals

The adjustment of radar parameters to optimize spectrogram quality contributes to enhancing classification performance

## Future Tasks

Enhancing Radar Performance through Application to Complex Motion Patterns

Radar Performance Enhancement Across Diverse Domains Using Complex Motion Patterns.

# Thank you!

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