The Radio Frequency Fingerprinting: A Deep Learning based Classifier with Self-Learning algorithm

Author : Jusung Kang
Supervisor : Prof. Heung-No Lee

2021.02.17

in

광주과학기술원
Gwangju Institute of Science and Technology

0. Outline

- **1. Introduction - The Radio Frequency Fingerprinting**
  - Authentication in IoT Environment
  - The Radio Frequency Fingerprinting
  - Contributions of this study

- **2. Research Works**
  - Analysis of Radio Frequency Fingerprinting for Frequency Hopping Signals

- **3. Future work**
  - An Unified Framework of Out of Detection and Incremental Learning methods for Frequency Hopping Signals

- **4. Conclusion**

- **Appendix**
  - Publications and Plans
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  - Checklist for graduations
  - Literatures - Radio Frequency Fingerprinting
  - Literatures – Tracking the FH signals
  - Categorizations - Radio Frequency Fingerprinting
  - Self-Studying system for RF Fingerprinting – Mismatch Problem
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Introduction

- The Radio Frequency (RF) fingerprinting -

Jusung Kang

2021.02.17

INFONET² *in* GIST 광주과학기술원 Gwangju Institute of Science and Technology

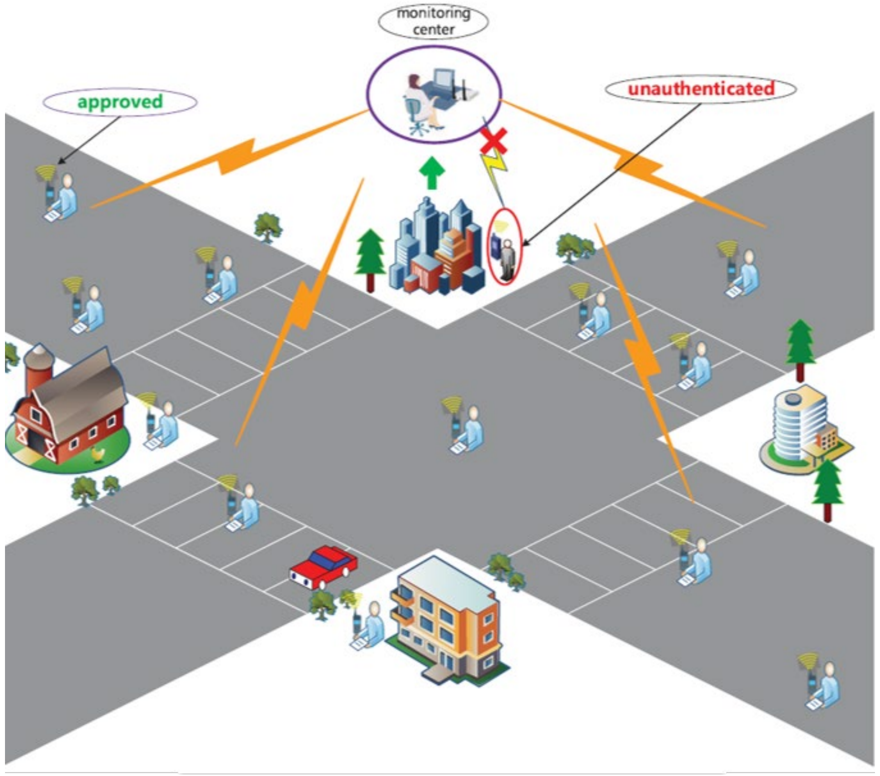
1.1 Authentication in IoT Environment

❖ **In Internet of Things (IoT) environment :**

- The devices needs to be connected to the application server for its intelligence.
- The IoT environment has the following properties :
  - Existing lots (hundred / thousands) of devices
  - Connecting over the air
  - The communication protocol needs to be simples
- The **effective authentication process** is required.

❖ **For authentication process…**

- (For usual) encryption key based approaches on a MAC layer is used.
  - If the key was eavesdropped,
    - ✓ Serious malfunctions can be caused by malicious intent.
  - Even pursuit the perfect authentication process,
    - ✓ The complexity of algorithms are not suitable for an IoT environment.
- The **physical layer authentication can be a great alternative** in IoT environment.
  - It has great attention from researchers **as a pre-authentication process** [A.4].
  - It is **simple** but **effective**.

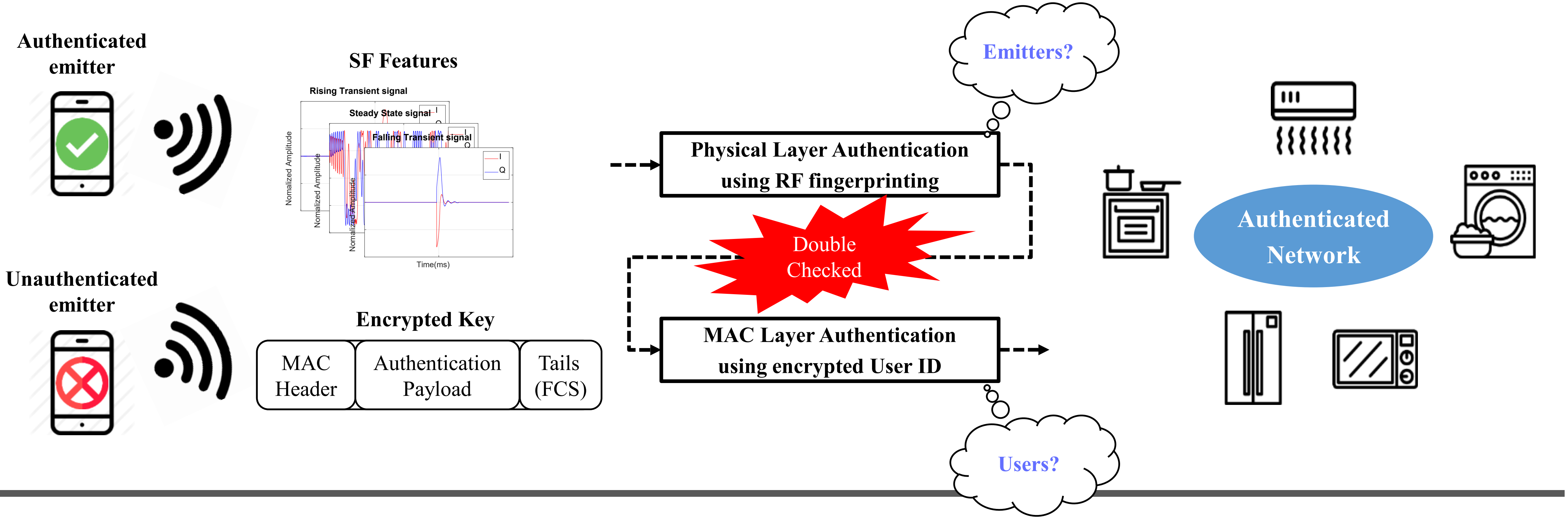


Internet of Things (IoT) environment [36]

1.2 The Radio Frequency Fingerprinting

❖ The Radio Frequency (RF) Fingerprinting

- It is an identification method that **utilizes a signal fingerprint (SF)** in the RF signal **to identify its unique transmission source.**
- As a physical layer authentication, emitter information is identified using the RF fingerprinting method.
  - The RF transmission emitted from an unauthenticated emitter is blocked.

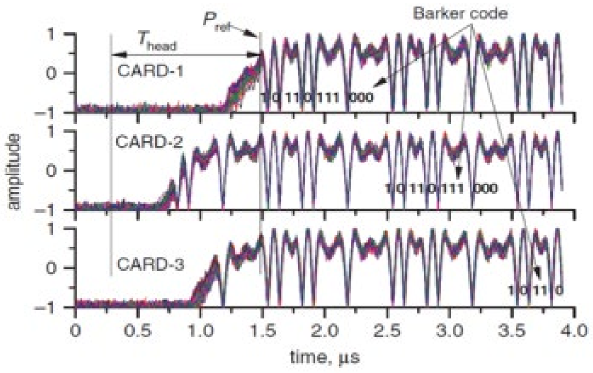


1.2 The Radio Frequency Fingerprinting

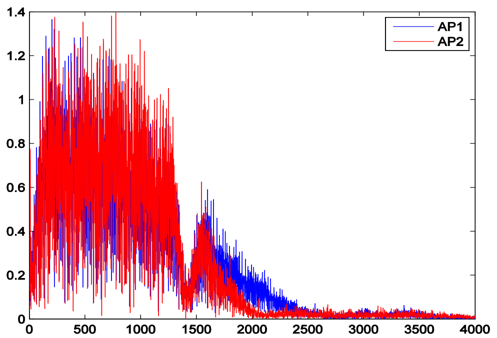
❖ Why simple and effective? - The Signal Fingerprints (SF)

- SF can be defined as **an any numerical value** calculated from the received RF signal **that can distinguish each emitter ID**.
- It caused from **the nature characteristics during manufacturing process**, which means :
  - The characteristics of components on a emitter are slightly different, such as power amplifier or frequency oscillator, etc.
  - **It is not possible to duplicate in H/W manners.**
    - ✓ Recently, GAN based duplication methods in S/W manners are reported [27, 42]
- The differences are coming from…:
  - (On time domain of raw signal) Differences in Rising Transient (RT), Falling Transient (FT), and Steady State (SS) signal
  - (On demodulation domain) I/Q constellation differences
  - (On spatial domain) : Beam pattern differences of beacon signal.

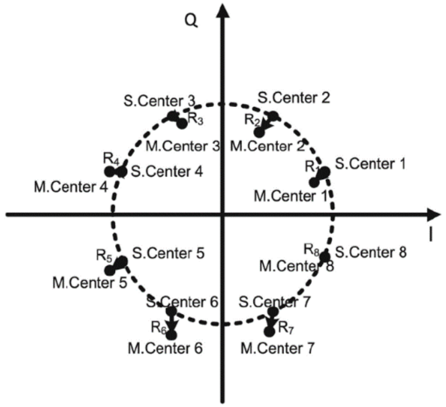
[RT signals]



[SS signals - Preambles]



[I/Q constellation errors]



[Beam pattern]

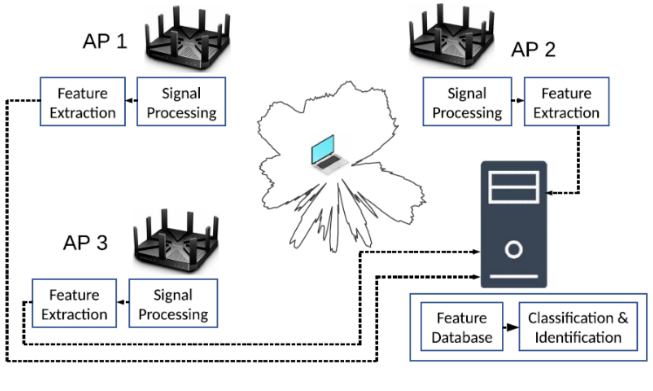
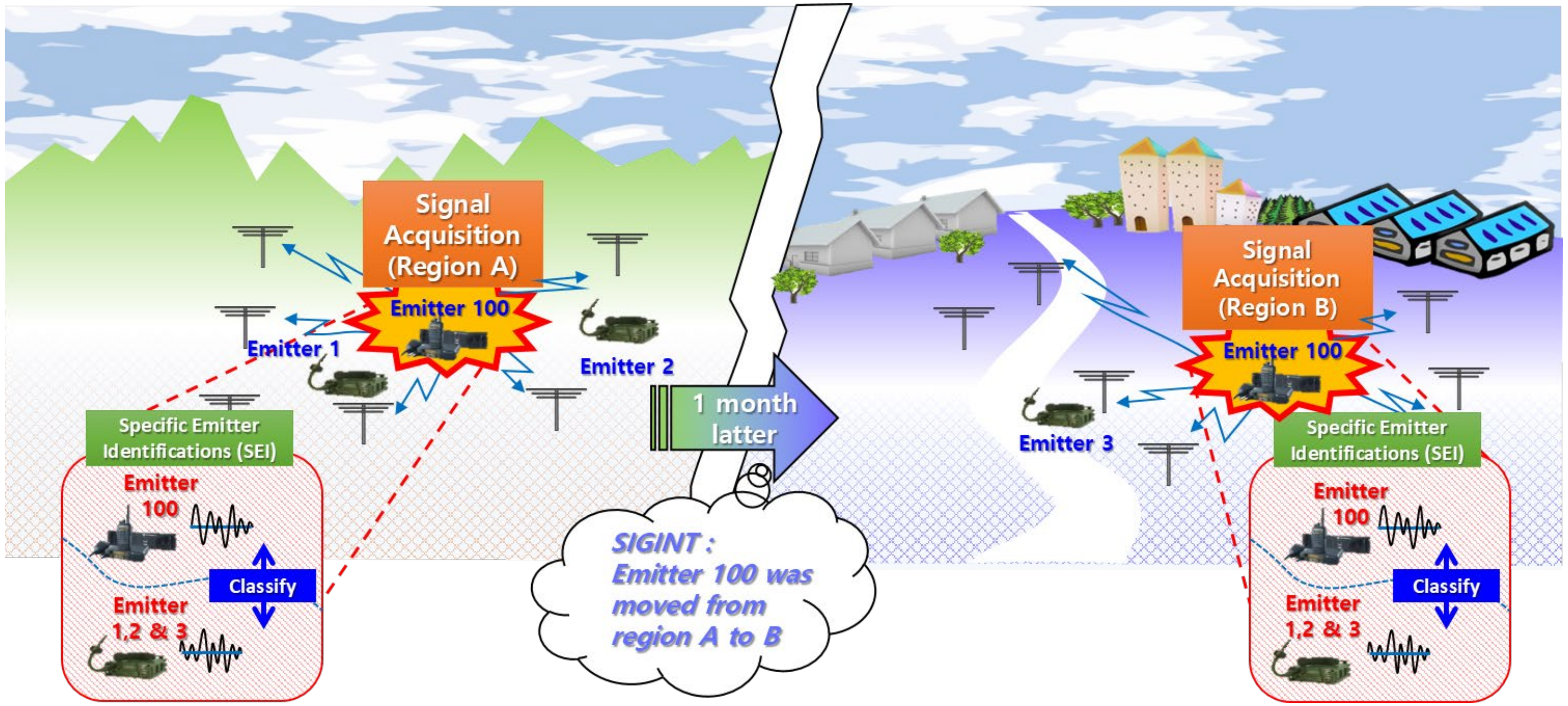


Fig. 1. Conceptual mmWave fingerprinting system architecture.

1.3 Contributions of this study

- **RF fingerprinting in Military usages**
  - **Knowing the unique transmission sources** can greatly benefit **SIGINT purpose**s in electric warfare.
    - (In case of Alliance) Secured communication is possible only with authenticated devices.
    - (In case of Enemy) Tracking the target enemy's emitter is possible.


Signal Acquisition (Region A)
Emitter 100
Emitter 1
Emitter 2
Specific Emitter Identifications (SEI)
Emitter 100
Classify
Emitter 1,2 & 3
1 month latter
SIGINT : Emitter 100 was moved from region A to B
Signal Acquisition (Region B)
Emitter 100
Emitter 3
Specific Emitter Identifications (SEI)
Emitter 100
Classify
Emitter 1,2 & 3

RF fingerprinting usages of SIGINT purpose

1.3 Contributions of this research

❖ Researches and Contributions

- **Thesis goal** :
  - Studying the RF fingerprinting application for military usages.
- **Research objects**:
  - The RF Fingerprinting system targeting for fast frequency hopping (FH) signals.
  - [Self-learning system] Abnormal or Outlier signal detection algorithms with its Incremental learning system targeting for FH signals
- **Contributions**:
  - Studying and Categorizing the RF fingerprinting algorithms from literatures
  - Analyzing the RF Fingerprinting performance even for the highly secured signals, such as FH signals.
  - Considering the system scalability as considering Abnormal or Outlier signal detection with its Incremental learning.

Research Works

- Analysis of Radio Frequency Fingerprinting for Frequency Hopping Signals -

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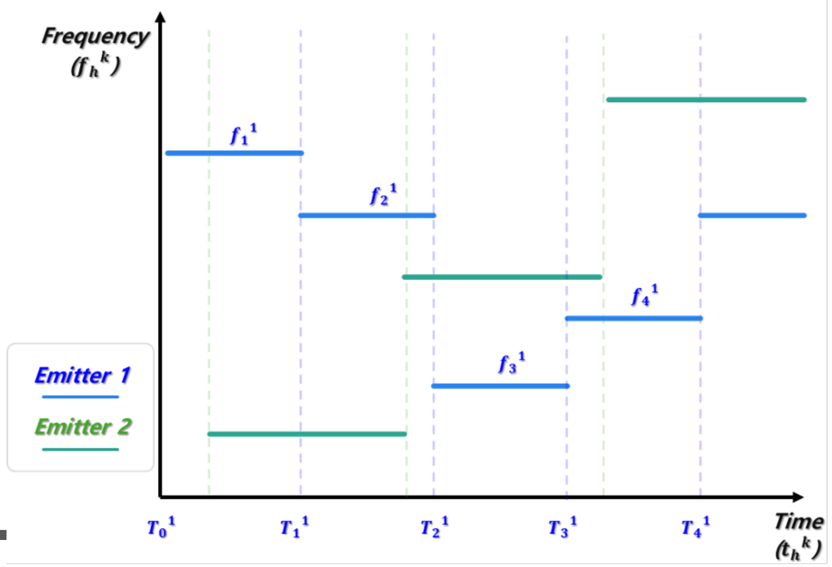
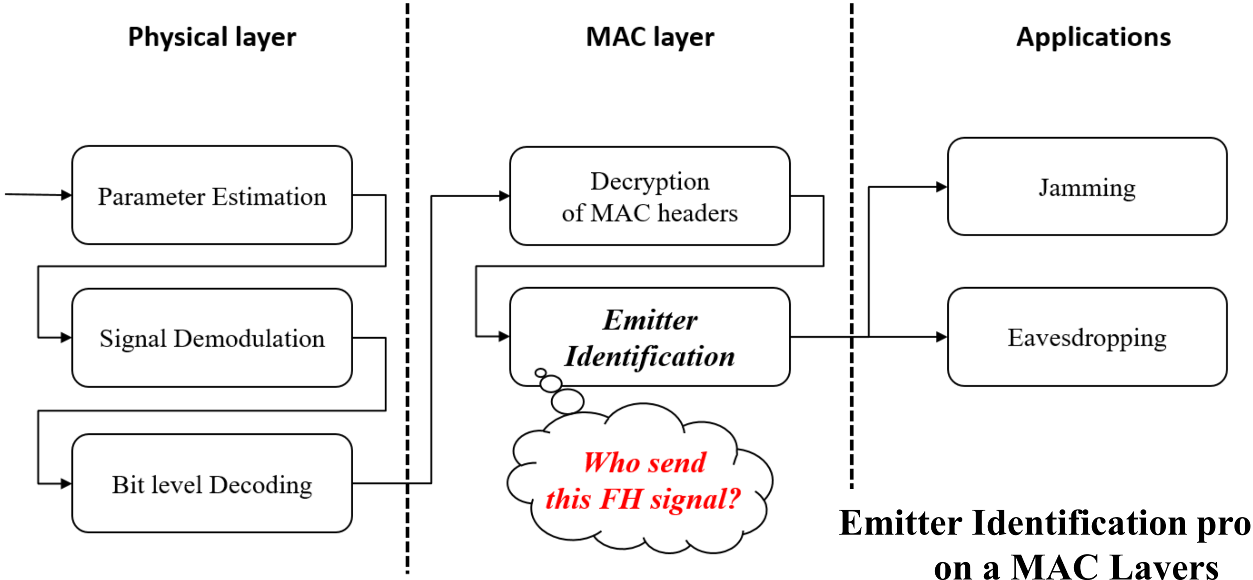
2.1. RF Fingerprinting for FH signals - Introduction

❖ Frequency Hopping Spread Spectrum (FHSS)

- FHSS is one of the highly secured communication protocol frequently used in military system [47].
  - The hopping patterns are known only to transmitter-receiver pairs.
  - For eavesdropping on FH signals, the patterns should be estimated correctly
  - The blind estimation methods in literatures are designed to estimate the hopping frequency or hopping timing [A.5].
- **To estimate the transmission sources in FHSS :**
  - Bit level decoding and decryption of the MAC header are required.
  - On the eavesdropper side, the decoding process is complicated without knowing the protocol details.



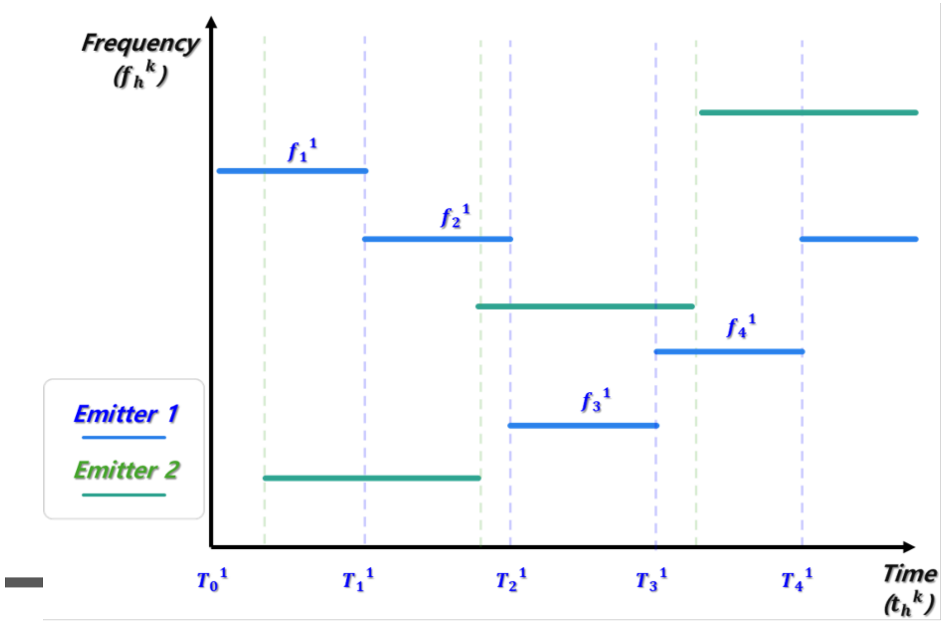


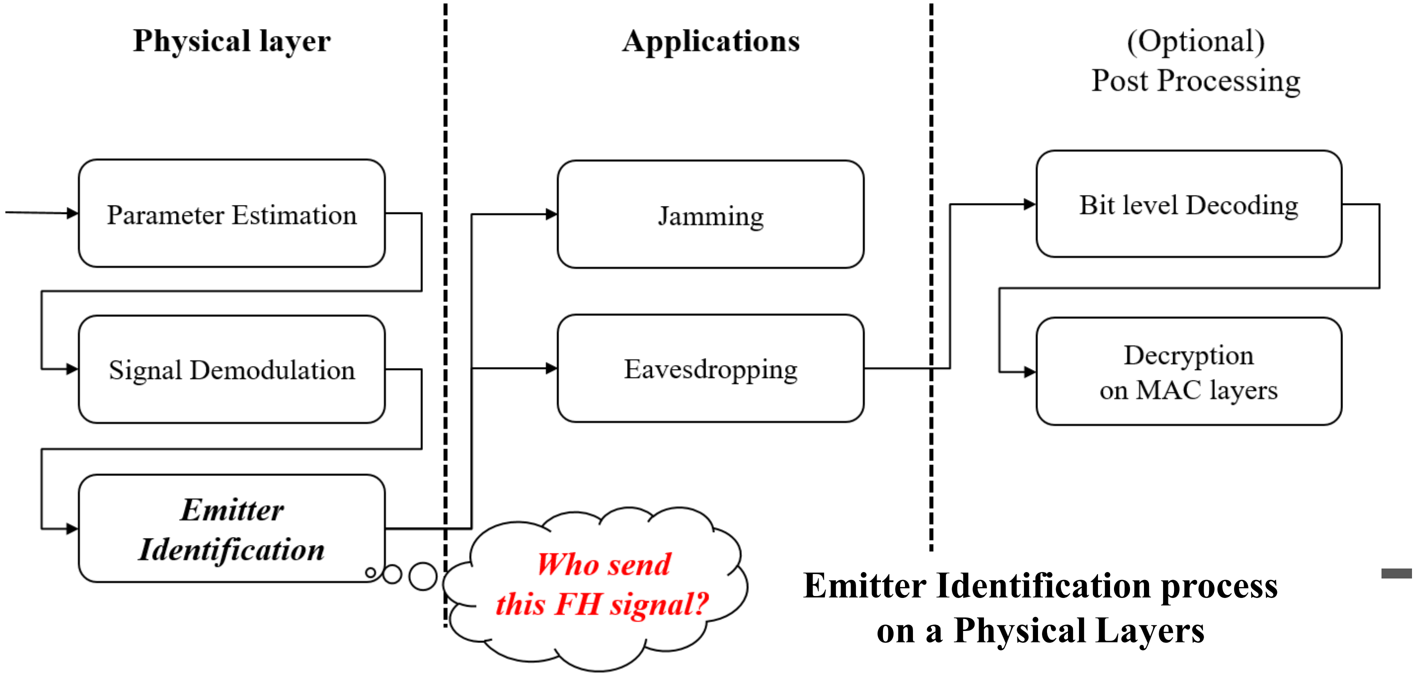
Emitter Identification process on a MAC Layers

2.1. RF Fingerprinting for FH signals - Introduction

❖ Early identification of emitter’s ID on the Physical Layers

- The first priority is to determine if the current FH signal is emitted from the target emitter.
  - If it is the target device :
    - ✓ The attacker can invest more resources in eavesdropping.
  - If it is not the target device :
    - ✓ The attacker can search for other FH signals.
- **[Research Object]**
  - We aim to identify the emitter information of the FH signal without the decoding process.




Physical layer

Applications

(Optional) Post Processing

Parameter Estimation

Signal Demodulation

Emitter Identification

Jamming

Eavesdropping

Bit level Decoding

Decryption on MAC layers

Who send this FH signal?

Emitter Identification process on a Physical Layers

2.2. RF Fingerprinting for FH signals - Contributions

- **Contributions**
  - We apply the RF Fingerprinting algorithms targeting for identification of the FH signals sources before the decoding process.
    - It is first time to apply the RF Fingerprinting for High-speed FHSS emitters.
    - The performance of each Signal Fingerprints were compared on same dataset.
      - ✓ i.e., Rising Transient (RT), Steady State (SS) and Falling Transient (FT)
    - Ensemble approaches which utilize the RT, SS and FT at the same time showed the best results.
  - The algorithm works well without any signal decoding process, such as preamble detection or data demodulation.
    - We analyze the activation maps of deep learning based classifiers.
      - ✓ The algorithm can automatically learn the position of headers and tails of the signal.
      - ✓ Additional decoding steps to extract these information are not required.
      - ✓ Preamble extraction[23] , Calculating the difference between ideally modulated and received signals [11], etc.

2.3. RF Fingerprinting for FH signals – Related works

❖ Related works – Categorization of the literatures [A.6]

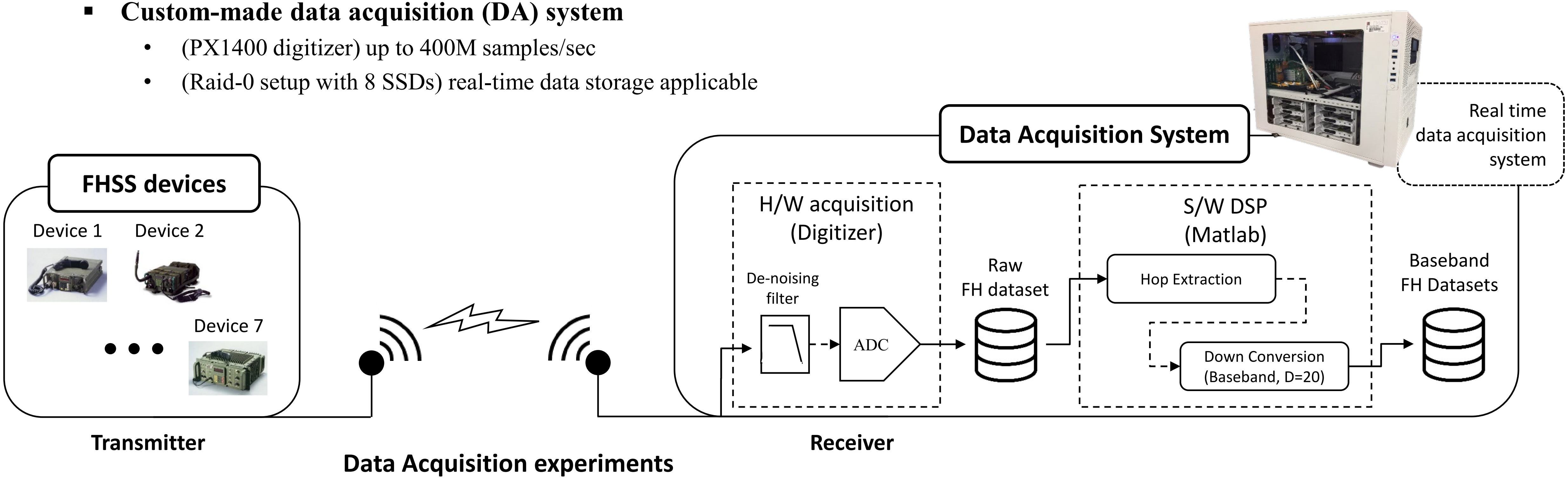
- The possible SFs without decoding steps
  - **Targeting for the RT, SS and FT features**
- Literature is focused on these two ways :
  - Calculating the sophisticated **hand-craft features** from the SFs
  - Training the SF signals on **a deep learning classifiers**

Signal Fingerprints **Feature Extraction**	**RT**	**SS**		**FT**
		Region Of Interest (ROI)		
		Preamble	Data payload	
Hand-craft features	[4][36][44]	[35] [23]	[24][31] [46]	
Time domain (raw) signal	[45]	[40]	[11][14][33]	
Frequency domain signal	[2] [38]	[2]		[2]
Time-Frequency domain signal	[34]		[28][30]	
Other approaches: - I/Q Connotation domain: [20] [41] - GAN approach: [27], [42] - Beam pattern approaches : [43]				

2.4. RF Fingerprinting for FH signals – Dataset generation

❖ Frequency Hopping (FH) Dataset Generations – Signal Acquisitions

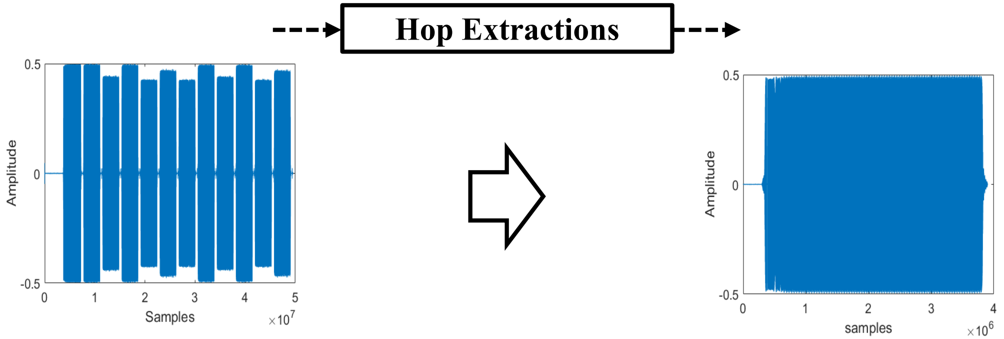
- **Acquisition of FH signals from FHSS devices**
  - # of Target devices : 7 devices
  - Hopping performance : 105 hops / sec
  - Hopping ranges : 30 ~ 88 MHz
  - FM modulated secure voice communications.
- **Custom-made data acquisition (DA) system**
  - (PX1400 digitizer) up to 400M samples/sec
  - (Raid-0 setup with 8 SSDs) real-time data storage applicable



2.4. RF Fingerprinting for FH signals – Dataset generation

❖ Frequency Hopping (FH) Dataset Generations – Dataset Generation

- **Signal processing in S/W (Matlab)**
  - Hop extraction
    - ✓ Energy detection approach
  - Down conversion to Baseband
    - ✓ Decimation factor D, 20
- **The FH datasets**
  - Baseband hop signals with I/Q values at a 20MHz sampling rate

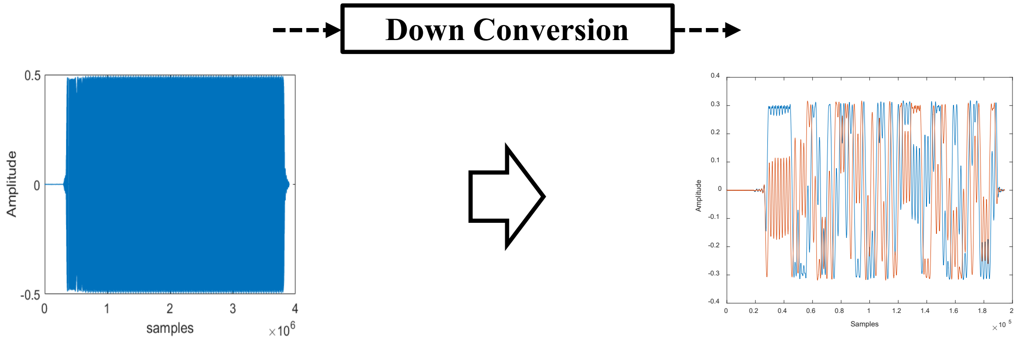


The FH signal

Hop signal

Details of the FH datasets

Class	Model Type	# of Acquisitions	# of samples
Device 1	Model 1	5 times	170
Device 2	Model 1		168
Device 3	Model 1		170
Device 4	Model 1		171
Device 5	Model 2		160
Device 6	Model 2		169
Device 7	Model 2		168
Total classes	7	Total samples	1176



Hop signal

Baseband Hop signal

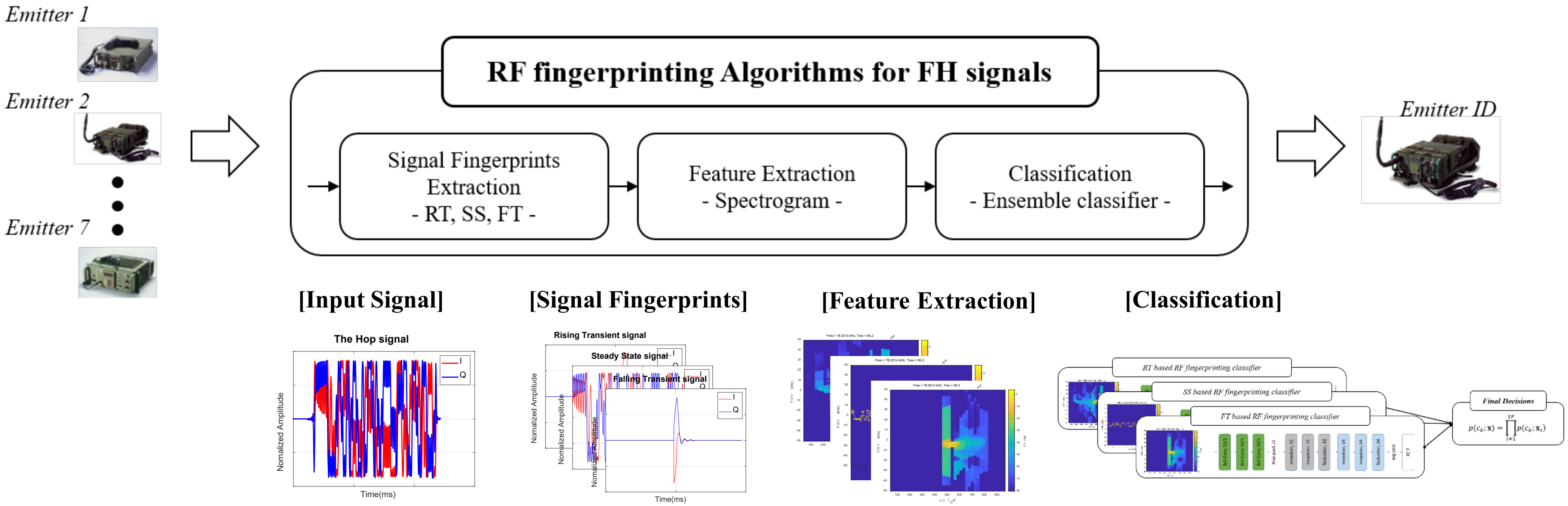
2.5. RF Fingerprinting for FH signals – Methods

❖ Problem Formulation – the RF fingerprinting algorithms

- It is the classification problem by following expressions :

$$y = F_{\mathrm{RFFP}}(\mathbf{x})$$

  - $\mathbf{x} \in \mathbb{C}^{N \times 1}$ is the FH signal
    - ✓ N is the length of complex-valued FH signals
  - $y \in \mathbb{R}^{C \times 1}$ is the output vector of algorithm
    - ✓ C is the number of emitters
  - $F_{\mathrm{RFFP}}(\cdot)$ is a mapping function from the signal space to ID space.
    - ✓ i.e., RF fingerprinting algorithm.



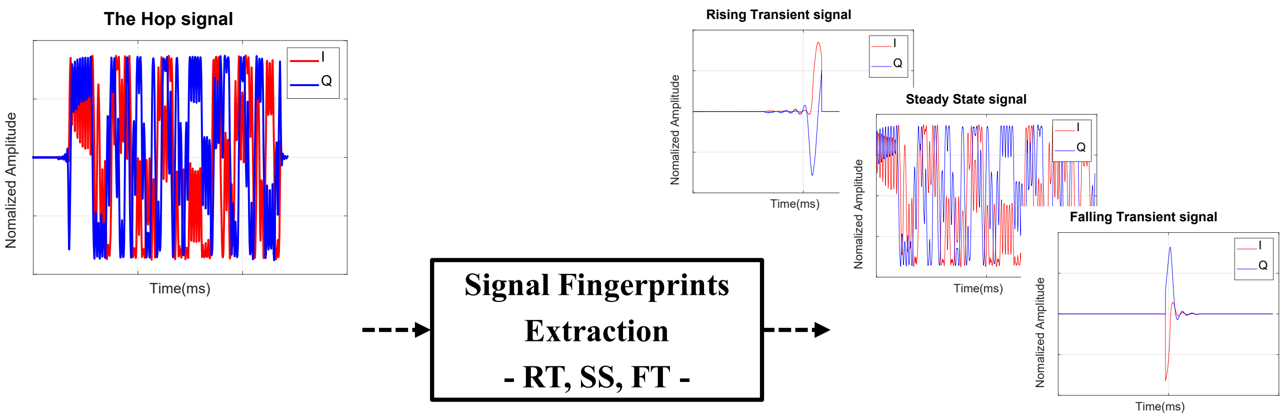
2.5. RF Fingerprinting for FH signals – SF extraction

❖ The signal fingerprints extraction process

- The SF could be represented by :

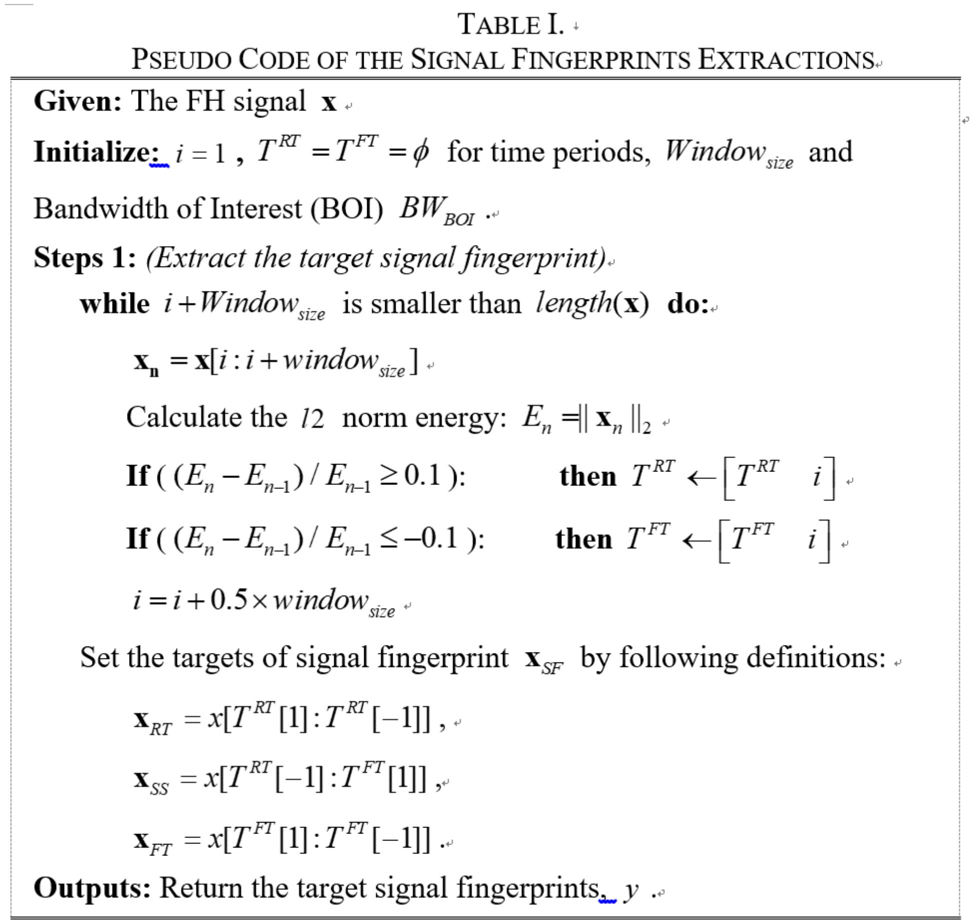
$$\mathbf{x}_{\mathrm{SF}} = \mathrm{g}_{\mathrm{SF}}(\mathbf{x})$$

  - $\mathbf{x}_{\mathrm{SF}} \in \mathbb{C}^{\mathrm{M}_{\mathrm{SF}} \times 1}$ is the SF selected from a possible set
    - ✓ i.e., $\mathrm{SF} \in \{\mathrm{RT}, \mathrm{SS}, \mathrm{FT}\}$
    - ✓ M_{SF} is the length of the SFs
  - $\mathrm{g}_{\mathrm{SF}}(\cdot)$ is the extraction function for the SFs
- **[Extraction rule] l2** norm energy differences within sliding windows
  - [RT / FT signal]: a signal in which the l2-norm energy of the sliding window is **increased / decreased** by 10% or more.
  - [SS signal]: the signal between the RT and FT signals.



Signal Fingerprints Extraction
- RT, SS, FT -

TABLE I.
PSEUDO CODE OF THE SIGNAL FINGERPRINTS EXTRACTIONS



```
Given: The FH signal $\mathbf{x}$
Initialize: $i = 1$ , $T^{RT} = T^{FT} = \phi$ for time periods, $Window_{size}$ and Bandwidth of Interest (BOI) $BW_{BOI}$ .
Steps 1: (Extract the target signal fingerprint)
    while $i + Window_{size}$ is smaller than $length(\mathbf{x})$ do:
        $\mathbf{x_n} = \mathbf{x}[i : i + window_{size}]$
        Calculate the $l2$ norm energy: $E_n =\| \mathbf{x}_n \|_2$
        If ( $(E_n - E_{n-1}) / E_{n-1} \geq 0.1$ ):    then $T^{RT} \leftarrow [T^{RT} \quad i]$
        If ( $(E_n - E_{n-1}) / E_{n-1} \leq -0.1$ ):   then $T^{FT} \leftarrow [T^{FT} \quad i]$
        $i = i + 0.5 \times window_{size}$
    Set the targets of signal fingerprint $\mathbf{x}_{SF}$ by following definitions:
        $\mathbf{x}_{RT} = x[T^{RT}[1] : T^{RT}[-1]]$ ,
        $\mathbf{x}_{SS} = x[T^{RT}[-1] : T^{FT}[1]]$ ,
        $\mathbf{x}_{FT} = x[T^{FT}[1] : T^{FT}[-1]]$ .
Outputs: Return the target signal fingerprints, $y$ .
```

2.5. RF Fingerprinting for FH signals – Feature extraction

❖ The feature extraction process

- The feature extraction process is expressed as follows :

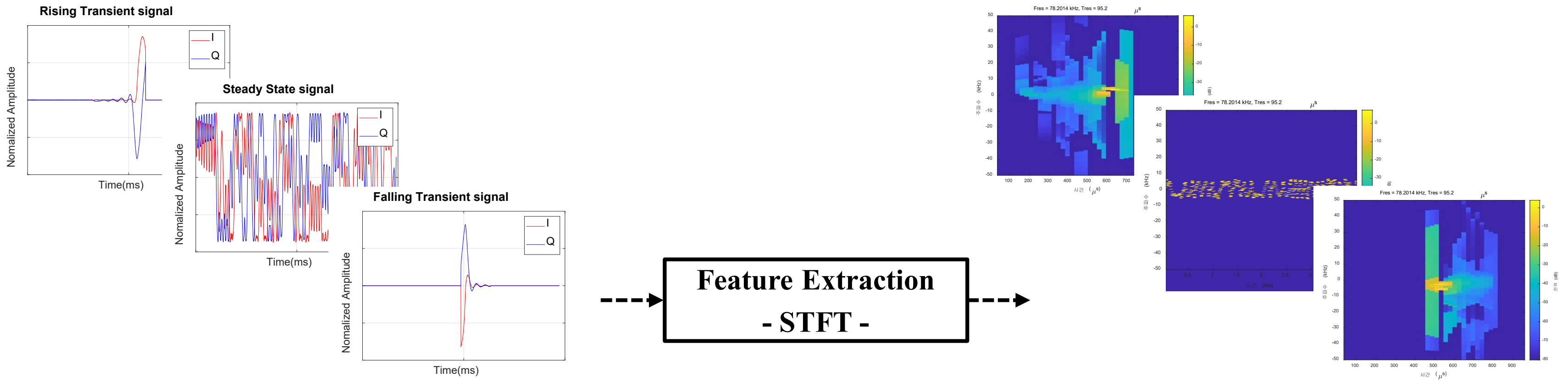
$$\mathbf{X}_{\mathrm{Feature}} = \mathrm{q}_{\mathrm{SF}}(\mathbf{x}_{\mathrm{SF}})$$

  - $\mathrm{q}_{\mathrm{SF}}(\cdot)$ is the extraction algorithm for designed feature, $\mathbf{X}_{\mathrm{Feature}} \in \mathbb{R}^{\mathrm{K}_{\mathrm{SF}}^{\mathrm{f}} \times \mathrm{K}_{\mathrm{SF}}^{\mathrm{t}}}$
    - ✓ $\mathrm{K}_{\mathrm{SF}}^{\mathrm{f}}$ and $\mathrm{K}_{\mathrm{SF}}^{\mathrm{t}}$ are the size of the designed feature in frequency and time indices.

- **[Spectrogram]** The power-density behavior of the SF in the time-frequency domain.

$$\begin{aligned}\mathbf{X}_{\mathrm{Feature}} &= \mathrm{spectrogram}\{\mathbf{x}_{\mathrm{SF}}\} \\ &= |\mathrm{STFT}\{\mathbf{x}_{\mathrm{SF}}\}|^2\end{aligned}$$

  - Time-frequency analysis method to visualize the change of frequency components as time has gone.
    - ✓ 4096 point FFT with the window size of 1024 is preformed
    - ✓ The frequency range are limited up to 4 times of signal bandwidth (i.e., $|f| < 100\mathrm{kHz}$)



2.5. RF Fingerprinting for FH signals – Classification

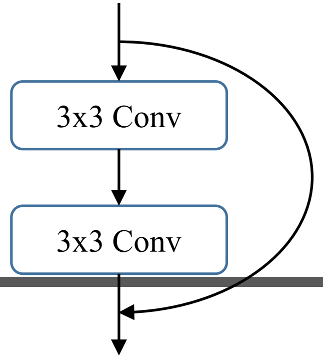
❖ The classification process

- The emitter ID can be obtained by :

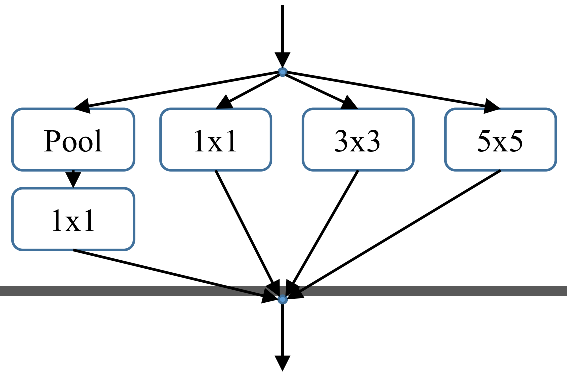
$$y = f_{\text{Classifier}}(\mathbf{X}_{\text{Feature}})$$

  - $f_{\text{Classifier}}(\cdot)$ is the classification algorithm with the output vector y
- **[Basic classifier]** Inception block based deep learning classifier
  - There are two main sub-structures for constructing a deep learning classifier.
    - ✓ The Residual block [52]
      - It allows the features to operate flexibly at depths through the network.
      - It was designed to handle the degradation problem as the network goes deeper.
    - ✓ The Inception block [53]
      - It allows extracting the features separately for different filter sizes.
      - It was designed to operate in parallel for different receptive field sizes.

Residual block [52]



Inception block [53]



2.5. RF Fingerprinting for FH signals – Classification

❖ The classification process – Basic classifiers

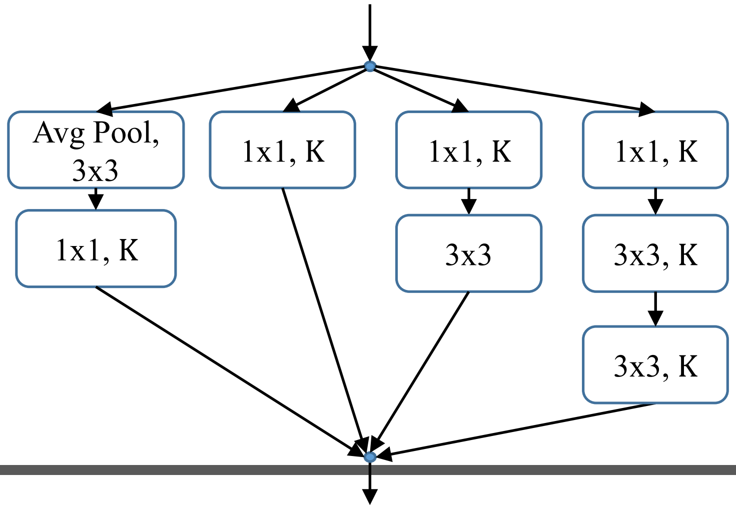
- The emitter ID can be obtained by :

$$y = f_{\text{Classifier}}(\mathbf{X}_{\text{Feature}})$$

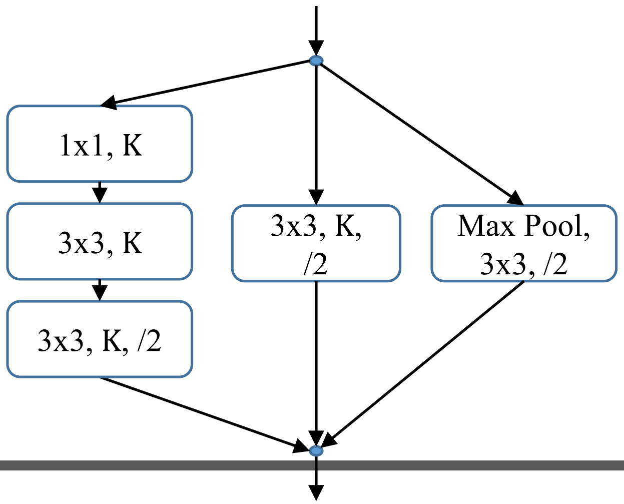
  - $f_{\text{Classifier}}(\cdot)$ is the classification algorithm with the output vector y

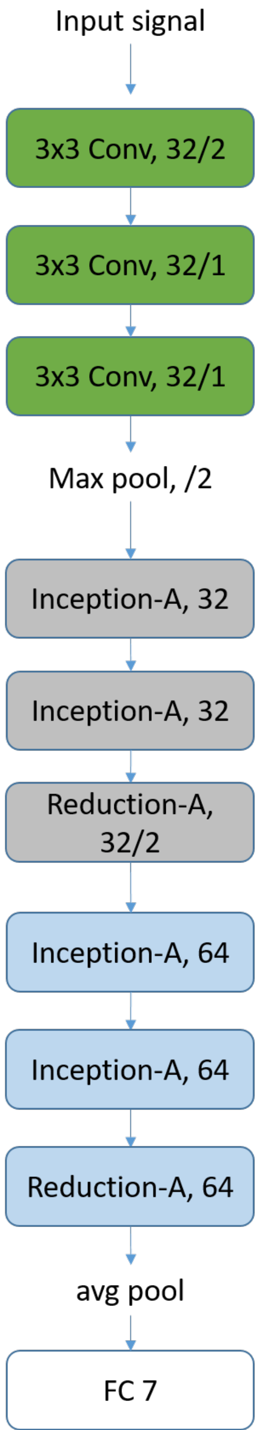
- **[Basic classifier]** Inception block based deep learning classifier
  - We construct the deep inception networks as a basic classifier
    - ✓ To measure the features in spectrogram with multiple filter scales
    - ✓ Inception-A, Reduction-A blocks of Inception_v4 classifier [53] are applied

Inception-A block



Reduction-A





Architectures of used Deep Inception Network

2.5. RF Fingerprinting for FH signals – Classification

❖ The classification process – Ensemble approaches

- The emitter ID can be obtained by :

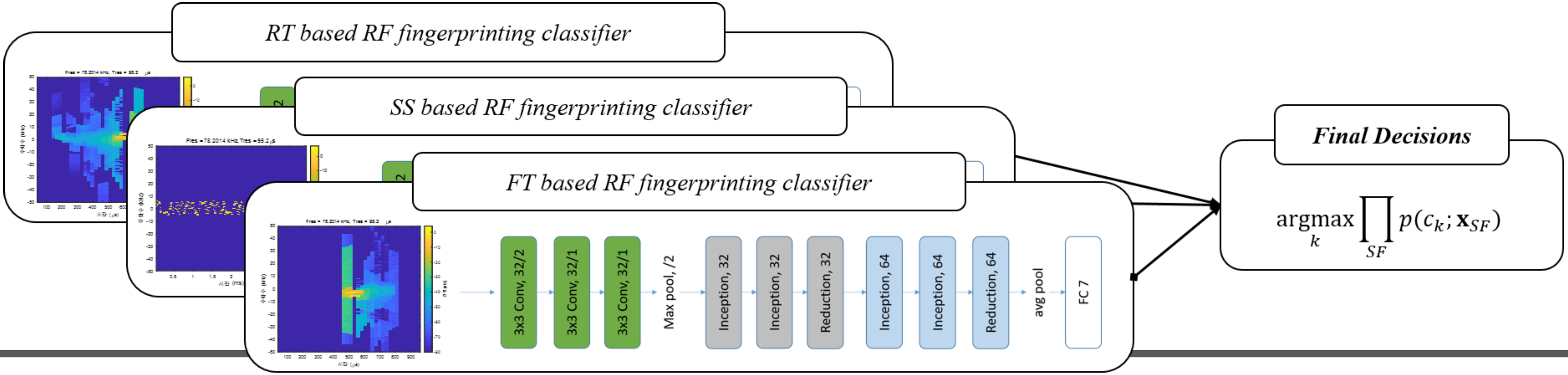
$$y = f_{\mathrm{Classifier}}(\mathbf{X}_{\mathrm{Feature}})$$

  - $f_{\mathrm{Classifier}}(\cdot)$ is the classification algorithm with the output vector y

- **[Ensemble approaches]** Ensemble approaches utilizing the RT, SS, and FT based basic classifiers
  - Final decision rules :

$$\underset{k}{\operatorname{argmax}}\, p(c_k; \mathbf{x}) = \underset{k}{\operatorname{argmax}} \prod_{SF} p(c_k; \mathbf{x}_{SF})$$

    - ✓ $p(c_k; x)$ is the probability of target emitter ID, c_k.



RT based RF fingerprinting classifier
SS based RF fingerprinting classifier
FT based RF fingerprinting classifier
Fres = 78.2014 kHz, Tres = 95.2 μs
3x3 Conv, 32/2
3x3 Conv, 32/1
3x3 Conv, 32/1
Max pool, /2
Inception, 32
Inception, 32
Reduction, 32
Inception, 64
Inception, 64
Reduction, 64
avg pool
FC 7
Final Decisions
$\underset{k}{\operatorname{argmax}} \prod_{SF} p(c_k; \mathbf{x}_{SF})$

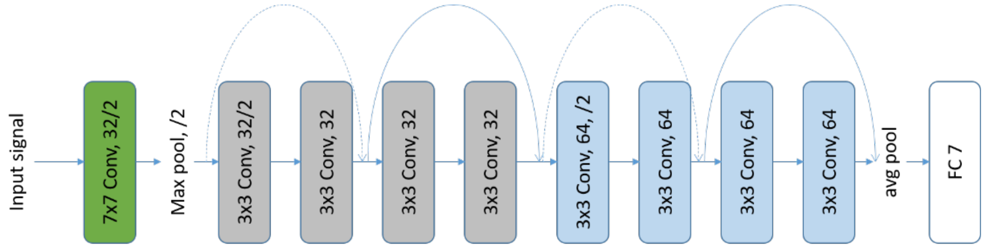
2.6. RF Fingerprinting for FH signals – Baselines

❖ The Baseline algorithms

- **Baseline 1** : Statistical moments approach of [23]
  - [Signal fingerprints]: Targeting for SS signals segmented by 10.
  - **[Feature extractions]**
    - ✓ (Sub-features) the instantaneous amplitude, phase, and frequency [23], the time, frequency, and time–frequency axes of the spectrogram [4]
    - ✓ (Hand-craft features) the statistical moments (i.e., mean, variance, skewness, and kurtosis) and its entropies were extracted from each sub-feature.
  - [Classification] the linear SVM [4] is applied.

- **Baseline 2 :** Raw signal approach of [11]
  - [Signal fingerprints] : Targeting for SS signals segmented by 10.
  - [Feature extractions] : Two-channel I/Q vector signal and segmented by 10.
  - **[Classification]**
    - ✓ 1D-CNN classifier described as an identification network for outdoor data is trained for each segments.
    - ✓ (Ensemble approaches) Final decision was performed using an ensemble approach, as in [11].

- **Baseline 3** : Spectrogram approach of [28]
  - [Signal fingerprints] : Targeting for SS signals.
  - [Feature extractions] : Spectrograms are calculated.
  - **[Classification]** : The Residual block based deep learning classifier



2.7. RF Fingerprinting for FH signals - Results

❖ Results : Accuracy Results

- On the signal fingerprints side :
  - The SS signals shows the better performances than others
- On the feature extraction side :
  - The spectrogram approach shows its effectiveness than raw signal or hand-craft feature extractions.
- The ensemble approaches shows its effectiveness by outperforming the accuracy of other baselines.

Table II. Classification Accuracy of Algorithms

	Rising Transient	Steady State	Falling Transient
	Mean Accuracy (%) Standard Deviation		
Statistical moments – SVM *	61.8 ± 0.0	92.6 ± 0.0	66.4 ± 0.0
Raw signal – 1DCNN**	17.7 ± 1.3	89.5 ± 0.7	20.4 ± 2.1
Spectrogram - ResNet***	83.7 ± 2.0	93.7 ± 1.2	93.9 ± 1.2
Spectrogram - Inception [Ours]	84.6 ± 1.5	95.3 ± 1.2	92.8 ± 1.1
Ensembles [Ours]	***97.0*** ± ***0.6***		

*: [Baseline 1] Statistical moments approach of [23]

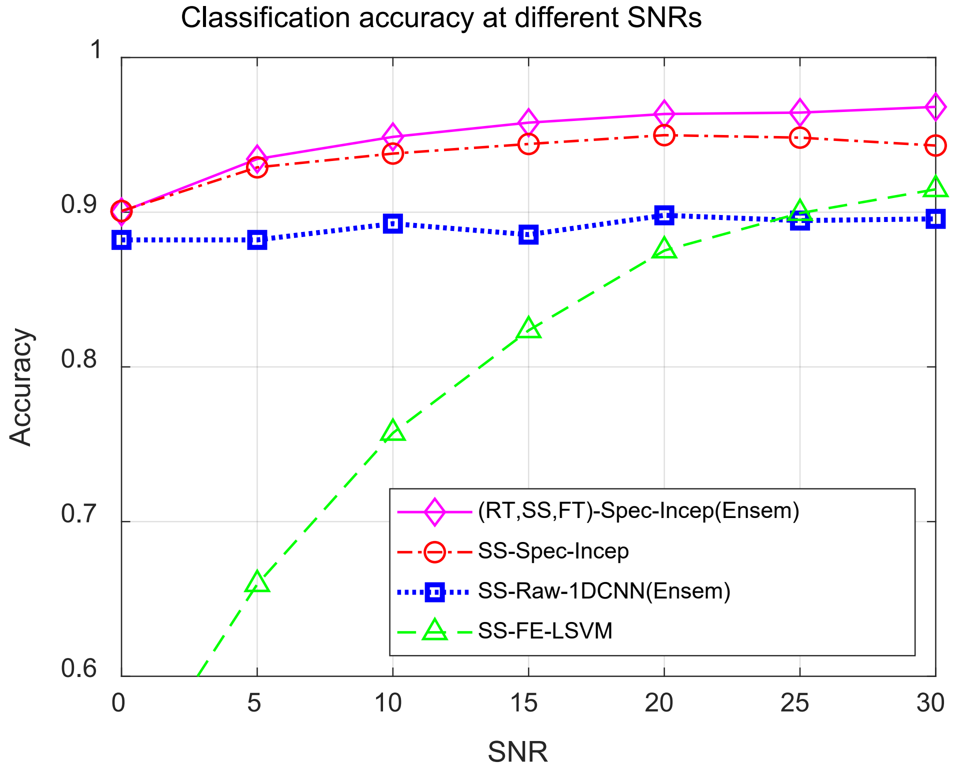
**: [Baseline 2] Raw signal approach of [11]

***: [Baseline 3] Spectrogram approach of [28]

2.7. RF Fingerprinting for FH signals - Results

❖ Results : Accuracy Results over the SNR ranges

- On the accuracy results for different SNRs :
  - The spectrogram approach shows its effectiveness than raw signal or hand-craft feature extractions.
  - Ensemble method outperform the baselines with toe overall SNR ranges
- The RF fingerprinting for FH signals could operate above 10dB SNR, with an accuracy of 94.9%.
  - The operating SNR of the FHSS emitter : 10 ~ 20 dB



2.7. RF Fingerprinting for FH signals - Results

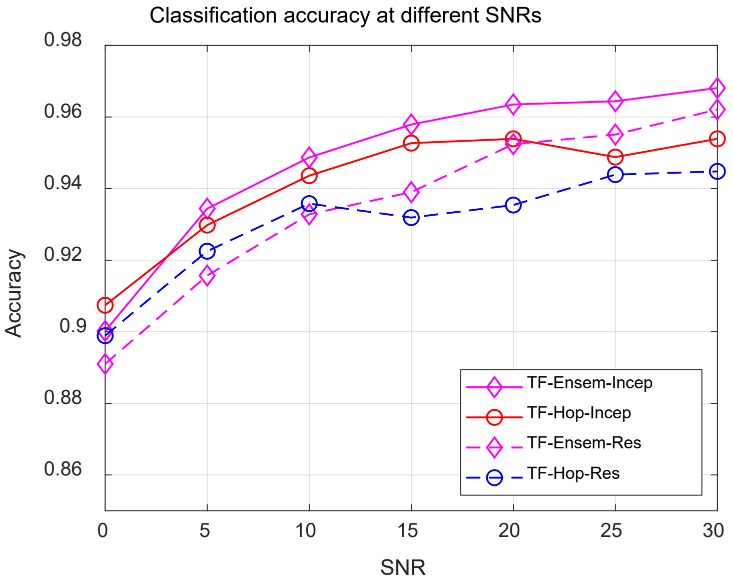
❖ Results : Hop signal approach vs Ensemble based approach

- The RT, SS and FT signals are extracted from Hop signal
  - The Question is :
    - ✓ The ensemble based approaches could outperform the direct usage of the hop signals?
- The results show that :
  - The ensemble approach shows better performance than hop signal approach for both feature extraction approaches.
  - The Inception block based model could effectively lean the signal fingerprints than ResNet based block.

Hop signal approach vs Ensemble approach

	Hop signal	Ensemble approach
	Mean Accuracy (%)	Standard Deviation
Spectrogram - ResNet***	94.4 ± 1.1	96.4 ± 0.7
Spectrogram - Inception [Ours]	95.1 ± 1.0	***97.0* ± *0.6***

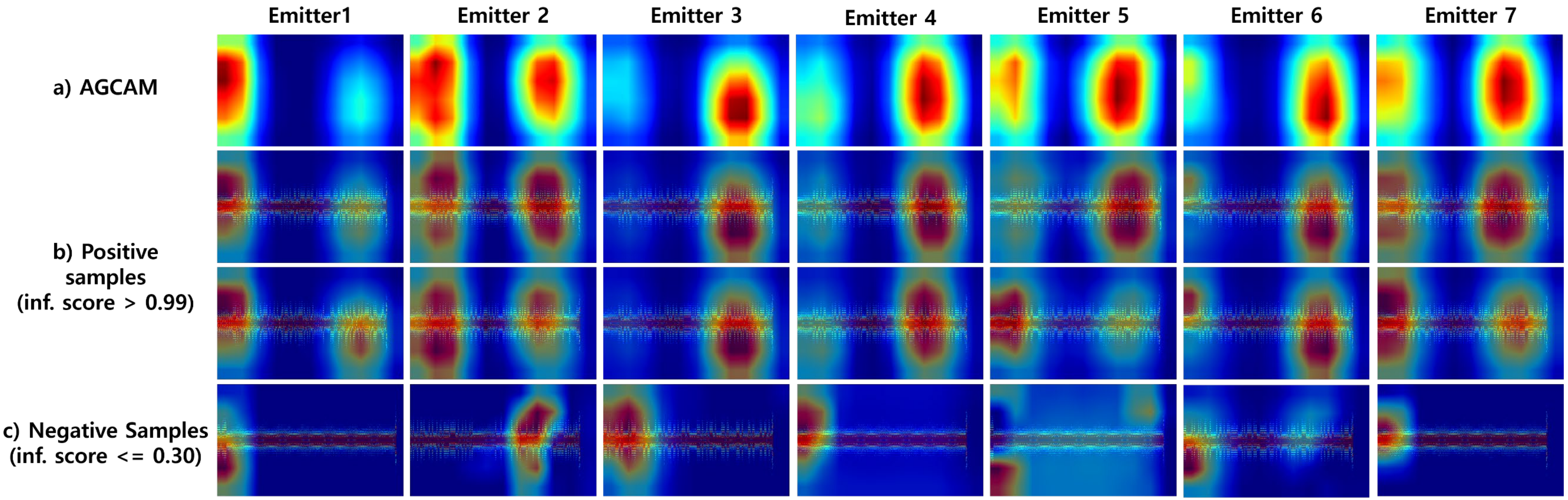
***: [Baseline 3] Spectrogram approach of [28]



2.7. RF Fingerprinting for FH signals - Results

❖ **Results : The Class Activation Map (CAM) of the classifier**

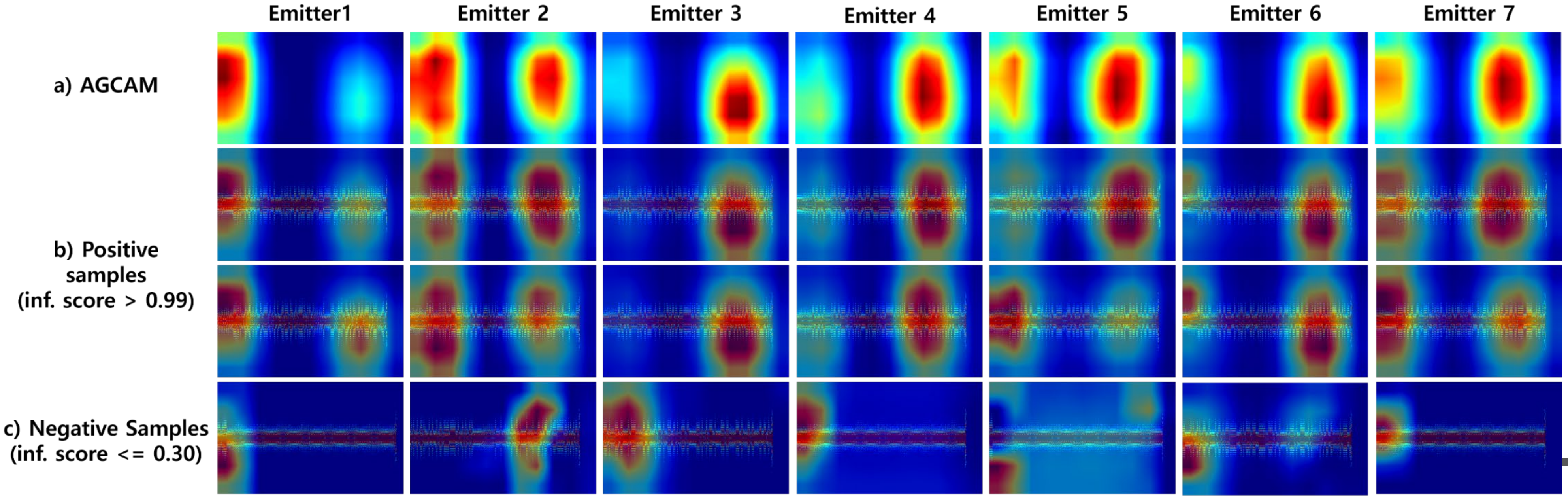
- The averaged Gradient-weighted CAM (Grad-CAM) for positive samples that produced the correct classification.
  - It is a feature visualization method that highlights the signal areas that offer positive information for class inference [54].



2.7. RF Fingerprinting for FH signals - Results

❖ **Results : The Class Activation Map (CAM) of the classifier**

- On the averaged Grad-CAM (AGCAM) results :
  - The CAM region is located on the header and tail of the input signal.
    - ✓ Usually, the control information, such as preamble or checksum data, is contained in these regions.
    - ✓ In literatures, the researches try to extract these control information, especially in preambles.
  - Our approach can automatically learn the signal region for correct emitter identification where the control information might be located.
    - ✓ This property can be used to alternate the pre-processing step for extracting control information,
    - ✓ The meaning for these CAM results will be studied further in future study.



2.8. RF Fingerprinting for FH signals - Conclusion

❖ **Conclusion**

- In this work, we aim to apply the RF fingerprinting algorithms targeting for identification of FH signal sources.
- As comparison the performance of algorithms at SAME dataset, the results shows that the Steady State signal based approaches was effective at the overall SNR ranges.
- Finally, we found that the Ensemble-based approach, using RT, SS, and FT at the same time, is more efficient than any other baselines.
- Also the activation maps of deep learning classifier are visualized to demonstrate the automatic feature-learning ability of the proposed algorithm.
- These results indicate that additional pre-processing steps, such as preamble extraction or data demodulation, are no longer required.
- The properties of the Grad-CAM results will be investigated as a future work.

Future work

- An Unified Framework of Out of Detection and Incremental Learning methods for Frequency Hopping Signals -

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3. Disclosed

- **It will be updated After the paper publications.**

Conclusions

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4. Conclusions

❖ Conclusions

- In this thesis, we aim to study about the RF fingerprinting application for military uses.
- As a researches :
  - We study about the RF fingerprinting algorithms and also categorizing the algorithms from the literatures.
  - Also we apply the RF fingerprinting targeting for highly secured signals, such as FH signals.
  - Finally, we try to consider the RF fingerprinting in Real-Word applications, i.e. Self-learning system.
- By completing the future works of these searches,
  - We could construct the emitter identification system for monitoring the enemy's RF emitter.
  - Also, by considering the position of eavesdropper's side,
    - ✓ We believe that this research will also have a great impart on a physical layer authentication system on IoT environments.
- Finally, we believe that our works could help understand how the distribution of trained data is working.

Thank You for Listening!

JuSung Kang, Ph.D. candidate,
School of Electrical Engineering and Computer Science,
Gwangju Institute of Science and Technology,
k92492@gist.ac.kr, https://infonet.gist.ac.kr

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Appendix

Jusung Kang

2021.02.17

in

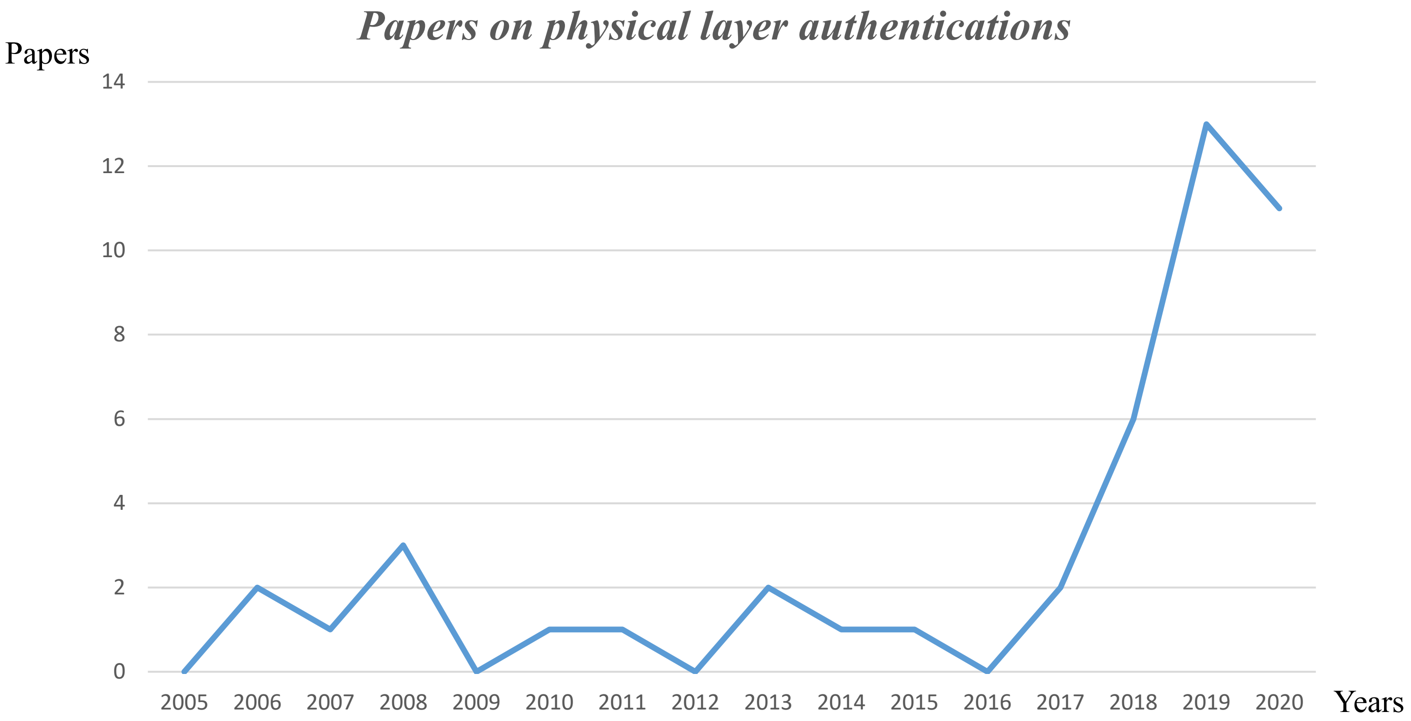
광주과학기술원

Gwangju Institute of Science and Technology

A.4. Literatures - Radio Frequency Fingerprinting

❖ The physical layer authentication – literatures

- In recent days, physical layer authentication receives great attention from researchers as **a pre-authentication process before verifying the encryption key**.
- [Search Keyword] Radio Frequency Fingerprinting, Specific Emitter Identification, Physical layer identification



A.4. Literatures - Radio Frequency Fingerprinting

❖ Related Literatures

Feature Signal	Approaches	Contents	References
Transient signals approach	Raw signal approaches	Transient signal, Instantaneous Amp. 에 PCA 적용 및 PNN / K-NN classifier	[1], Telatar 17, ELECO 17, 17.12
		Rising Transient, Steady State, Falling Transient에 FT, Concatenated feature 에 PCA , SRC Classifier 적용	[2], Lee 19, IEEE Comm. Letter, 19.05
	Feature Embedding approaches	Transient signal 에서의 inst. Amp 및 Phase 를 이용한 Quadratic feature를 정의하고, 여기서의 Difference 를 feature 로 사용	[3] Ureten 04, Can. J. Elect. Comput. Eng., 04.07
		Transient signal 에서의 TFED를 구하고, 13개 가량의 Statistic feature 를 계산, Classifier 수행	[4] Kara 19, IEEE Access, 19.05
		Inst. Amp, Phase, DWT Coefficient 에 대한 15개 가량의 statistic feature 계산	[5] Kranakis 06, Int. Conf. on Comm. And Comp. Networks, 06.10
		Preamble 을 이용한 T.R. extraction, Amp, Phase 및 evolution time, tendency, profile rage 등 계산, PCA 사용 및 K-NN	[6], Valenzuela-Valdes 13, Elect. Letters, 13.10
		Transient signal 에서의 TFED, 15개 가량의 Statistic feature 계산	[7], Yuan 14, IET comm., 14.04
		Transient 에서의 Polyfiting 계산 및 Coefficient 에 대한 PCA, SVM	[8] Yuan 13, Progress In Elect. Reserch, 2013.08
		T.R. 에서의 Amplitude 및 Phase 정보에 대한 PCA	[9] Serinken 07, Can. J. Elect. Comput. Eng., 07.12

A.4. Literatures - Radio Frequency Fingerprinting

❖ Literatures Survey

Feature Signal	Approaches	Contents	References
Steady State signal approaches	Raw signal approaches	S.S. signal 에의 Segmentation 및, I/Q signal 을 LSTM에 넣은 논문	[10], Liu 18, Elect. Letters, 18.12
		S.S. signal 에서의 Error signal generation, Segmentation 을 통한 CNN approach	[11], Nousain 18, IEEE J. of Selected Topics in Sig. Processing, 18.02
		SS 에서의 Error signal, Segmentation 에 대한 CNN+ LSTM 구조	[12] Nousain 19, MILCOM 19, 19.11
		S.S., I/Q signal, Deep learning approach (DNN, CNN, LSTM)	[13] Qian 18, MILCOM18, 18.11
		SS 에서의 I/Q signal, + Deep learning approach	[14] Chris 18, IEEE J. of Radio Frequency Identification
		SS 에서의 preamble, FFT with bins (varied), Log spectral feature,	[15] Buddhikot 08, IEE Symp. On New Frontiers in Dynamic Specturm, 08.10
		SS 에서의 preamble, FFT, Log spectral feature,	[16] Buddhikot 08, IEEE VTC, 08.09
		SS + Error signal generation, + deep learning approach (GAN 영향)	[17] Nousain 19, MILCOM 19, 19.11
		SS + Error signal generation, + Deep learning approach (Receiver 영향)	[18] Nousain 19, GLOBCOM 19, 19.12
	Feature Embedding approaches	SS signal, Wavelet transform, Relief (weigh algorithm), PCA	[19], Wen 18, IEEE Conf. on CNS, 18.05
		SS Signal, Constellation domain 을 이용한 DCTF, Freq. Offset, CTF 로의 feature embedding 수행	[20] Yan 19, IEEE IOT J. 19.02
		SS signal, Preamble, Matched filter 를 이용한 Feature embedding method	[21] Russell 06, NDSS 06, 06.01
		SS, Preamble, Freq. Avg., Mutual Info. 로의 Feature embedding 수행	[22] Liu 10, Bell Labs Technical Journal,10.12
		SS, I/Q, Segmentation, Statistical Feature embedding	[23] Baldwin 15, IEEE Trans. On. Reliability, 15.03
		SS, Original data 에 대한 low-rank matrix 계산, Optimization 수행을 통한 classification	[24] Gan 17, IEEE Comm. Letters,17.08
		EPC code 에의 SS extraction (preamble), Wavelet transfer에 대한 higher order statistics feature	[25] Hinders 12, IEEE Trans. On Industrial Electronics, 12.12
		SS, I/Q Demodulation 단에서의 Feature embedding (Freq. offset, e.t.c.)	[26] Sangho Oh 08, MobiCom 08, 08.096

A.5. Literatures – Tracking the FH signals

❖ Related literatures – blind estimation methods for FH signals

- On the attacker side, many researchers have investigated blind estimation methods to extract useful information from frequency hopping (FH) signals, such as dynamic programming [48] and autoregressive moving average [49].
- These methods were designed to estimate parameters for accurate signal tracking, such as hopping timing and frequency.
- But, the signal demodulation and decryption of the packet load are required to extract useful details about the transmitter, such as its identification (ID) information.

Paper	*Summary*	*Publisher*	*비고*
[48]	Dynamic programming modulated wideband converters에 기반한 도약 주파수 추적 및 분류 방법을 제안함. 추적을 위해 시간 축에서의 ***power estimation method***를 제안하였으며, 분류를 위한 ***dynamic programming*** 기반 feedback control algorithm 제안함.	***MDPI***	***2019***
[49]	도약 주파수 신호에 대한 ***Autoregressive moving average (ARMA) model*** 및 ***FFT, multi channel clustering***을 기반으로 하는 도약 주파수 추정 알고리즘을 제안함.	***2019 ICSPCC***	***2019***
[50]	Multiple sensor에 기반한 Multi-channel 환경에서, Overlap 되는 주파수 도약 신호를 ***ARMA 모델***을 통해 모델링하고, 도약하는 주파수를 감지하고 추적하는 방법을 제안함.	***IET Communications***	***2012***
[51]	Cognitive Radio 환경에서, Secondary User 의 Spectrum sensing 환경을 ***Sparse Represented FH signal 로 모델링***하고, Learned Exemplar Dictionary 를 구성하여 느리게 도약하는 주파수에 대한 Spectrum sensing 방법을 제안함.	***2014 SPCOM***	***2014***

A.6. Categorizations - Radio Frequency Fingerprinting

- **Categorization of the Literatures**
  - **Signal Fingerprints**

Feature Signal type	Sub type	References
Transient signals approach	***Transient Signals***	1, 2, 3, 4, 5, 6, 7, 8, 9,
Steady State signal approaches	Preambles	2, 15, 16, 21, 22, 24, 25, 26
	I/Q (with Nyquist Sampling)	X
	I/Q (with Over Sampled & Data information)	10, 11, 12, 13, 14, 17, 18, 20, 23,
	S.S signals (언급 X)	19,
Falling Transient signals approaches	***Falling Transient signals***	2,

A.6. Categorizations - Radio Frequency Fingerprinting

- **Categorization of the Literatures**
  - **Feature Extraction approach - Signal Profile**

Feature Signal type	Signal Profile Type	References
Transient signals approach	***Instantaneous Amplitude***	1,3,4, 5, 6, 7, 9,
	Instantaneous Phase	3, 4, 5, 6, 7, 9,
	Instantaneous Frequency	4, 7,
	Frequency info (FT)	2,
	Wavelet Transform coefficient (DWT)	5,
	Time-Frequency info (TFED)	4, 7,
Steady State signal approaches	***Frequency info (FT)***	2, 15, 16, 21, 22,
	Error sig. generation (with Data information)	11, 12, 17, 18,
	Wavelet Transform	19, 25,
	Instantaneous Amplitude	23,
	Instantaneous Phase	23,
	Instantaneous Frequency	23,
Falling Transient signals approaches	Frequency info (FT)	2,

A.6. Categorizations - Radio Frequency Fingerprinting

❖ Categorization of the Literatures

- **Feature Extraction approach - for T.R. approach**

Feature Signal type	***Future Extraction Method***	References
Transient signals approach	***PCA***	1, 2, 6, 9,
	Difference on Amplitude-Phase trajectory	3
	Lower order Statistical feature (mean, variance, e.t.c.)	4, 5,
	Higher order statistical features (Kurtosis, Skewness)	7,
	Entropy of signals	4, 7,
	Polyfitting coefficients info.	4, 8,
	Diff. on a DWT coeff.	5,
	Duration of transient signals	6,
	Tendency (1st, 2nd, order of derivatives)	6,
	Sum of energy	4, 7,
	Centre of distribution	7,

A.6. Categorizations - Radio Frequency Fingerprinting

❖ Categorization of the Literatures

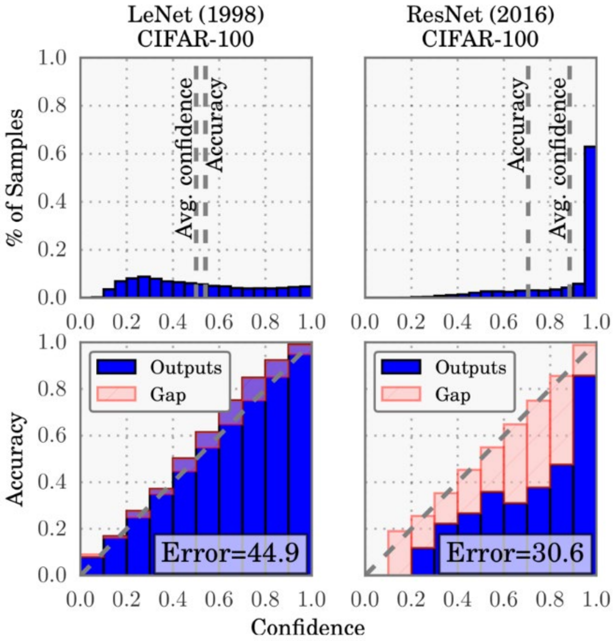
- **Feature Extraction approach - Signal Profile for S.S. approach**

Feature Signal type	***Future Extraction Method***	References
Steady State signals approach	Log spectral energy features	15, 16,
	Relief	19,
	PCA	19,
	Differential Constellation Trace	20
	Frequency Offset Feature	20
	Contellation Tract figure features	20
	Matched filter coefficient	21
	Mutual info. For freq.	22,
	Lower order Statistical feature (mean, variance, e.t.c.)	23, 25,
	Higher order statistical features (Kurtosis, Skewness)	23, 25,
	Low Rank Representation	24,
	Entropy of signals	25,
	Maximum Cross Correlation results	25
	Phase, mag, error vector magnitude error	26
	I/Q origin offset, Frequency / Sync error	26

A.7. Self-Studying system for RF Fingerprinting – Mismatch Problem

❖ **[ODIN] : ‘Enhancing the Reliability of Out-of-distribution Image Detection in Neural Networks’ [57]**

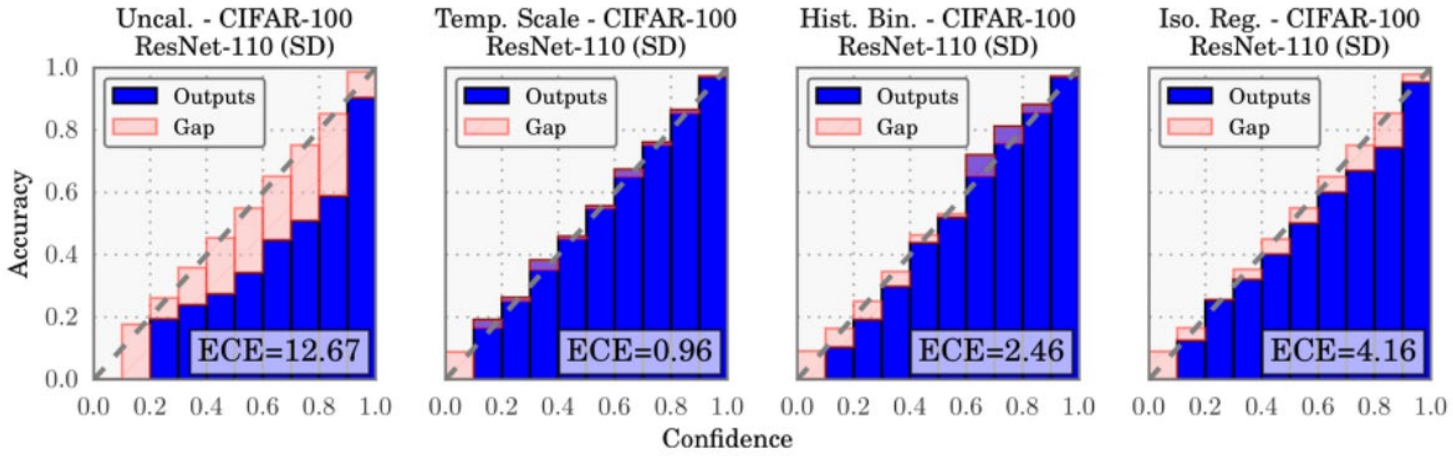
- **Core Idea :**
  - Temperature Scaling [58]
    - ✓ [목적] : Classification task 속 Confidence score 를 calibration 하기 위함.
    - ✓ [방법] : (Training) T = 1, (Testing) T = N
    - ✓ [효과] In-distribution 및 Out-of-Distribution 간의 score 차이를 크게 만들 수 있음.



Temperature scaling

temperature scaling parameter

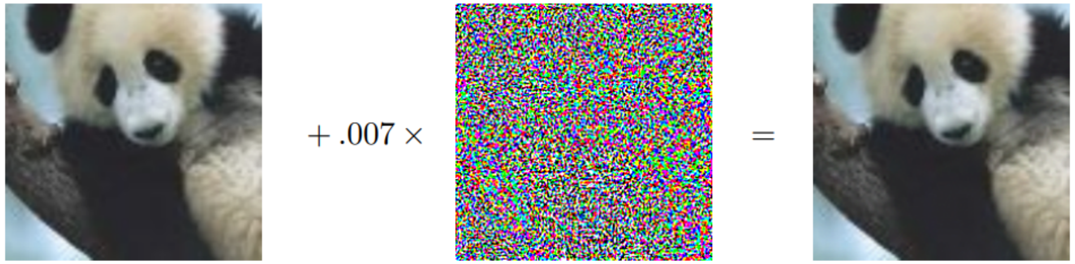
$$S_i(\boldsymbol{x};T) = \frac{\exp(f_i(\boldsymbol{x})/T)}{\sum_{j=1}^{N}\exp(f_j(\boldsymbol{x})/T)}$$



A.7. Self-Studying system for RF Fingerprinting – Mismatch Problem

❖ **[ODIN] : 'Enhancing the Reliability of Out-of-distribution Image Detection in Neural Networks' [57]**

- **Core Idea :**
  - 'Input Preprocessing' := Adversarial attack
    - ✓ [목적] : In-distribution 에 대한 Confidence Score 를 높여주기 위함.
    - ✓ [Reference] Adversarial attack, 'Fast Gradient Sign Method (FGSM)' [59]
      - 극소량의 perturbation 을 Ascent(i.e. loss 를 증가시키는) 방향으로 더해줄 경우, input class 에 대한 Softmax score를 낮출 수 있다.
    - ✓ [방법] : Perturbation 을 Descent(i.e. loss를 감소시키는) 방향으로 더해줄 경우, Input class 에 대한 Softmax score를 높일 수 있다.
    - ✓ [효과] : In-distribution 및 Out-of-Distribution 간의 score 차이를 크게 만들 수 있음.



x
"panda"
57.7% confidence

$\text{sign}(\nabla_x J(\theta, x, y))$
"nematode"
8.2% confidence

$x + \epsilon\text{sign}(\nabla_x J(\theta, x, y))$
"gibbon"
99.3 % confidence

Input Preprocessing

different with FGSM

$$\tilde{x} = x - \varepsilon\text{sign}(-\nabla_x \log S_{\hat{y}}(x;T))$$

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