LoFin: LoRa-based UAV Fingerprinting Framework

Maryna Veksler[1], David Langus Rodríguez[2], Ahmet Aris[2], Kemal Akkaya[1], A. Selcuk Uluagac[2]
1Advanced Wireless and Security Lab., [2]Cyber-Physical Systems Security Lab.
Florida International University
{mveks001, dlang029, aaris, suluagac, kakkaya} @fiu.edu

Overview

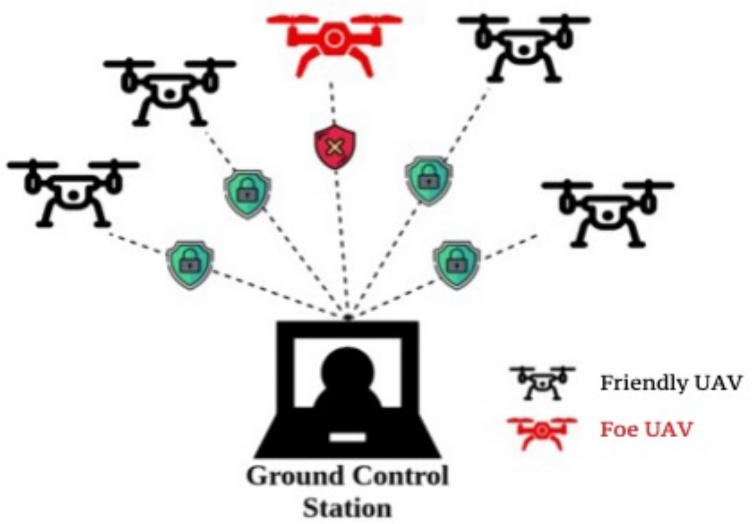
- Introduction
- Related Work
- Background
- LoFin Architecture
- Performance Evaluation
- Conclusions & Future Work

Introduction

- Unmanned Aerial Vehicles (UAVs) have become a world phenomenon:
  - Used for surveillance, reconnaissance, search & rescue missions
    - Intelligent decision making, mobility, and sensing capabilities
- UAV applications often involve long distance communications with the controller (GCS):
  - Reliable network channel for security and large transmission radius
- Long Range (LoRa) communication protocol:
  - Long-range and low-power technology
  - Consistent coverage across urban and rural areas

Motivation

- UAV applications require strong security:
  - Impersonation attacks
  - Attack may steal sensitive information
  - Mission infiltration
  - Communication disruption
- Intrusion Detection system is required:
  - No sniffing tools developed for UAV communicating via LoRa
  - Radio frequency (RF) analysis not effective due to channel interference and reconfiguration of LoRa channel



Related Work

- **Device Fingerprinting is an effective technique to detect the device impersonation attack**
  - LoRa fingerprinting:
    - Analysis of physical (PHY) layer radio frequency (RF) using deep learning (DL) [1, 2]
    - Challenges: varying configurations of LoRa protocol
  - UAV fingerprinting:
    - RF statistical analysis [3,4]
    - Challenges: affected by signal-to-noise (SNR) ratio
- **Our Contribution → LoFin:**
  - Do not require analysis of physical layer communications:
    - Resistant to changes in (1) RF signals due to external factors, (2) LoRa parameters
  - Passive fingerprinting:
    - No processing overhead
  - Encryption immunity with preserved data security

Background

❑ LoRa Stack

- ❖ LoRa physical layer – chirp spread spectrum (CSS) radio frequency modulation system
- ❖ LoRaWAN communication protocol and network architecture of upper layers
- ❖ LoRa provides flexibility to configure multiple transmission parameters for improved data rate:
  - Spreading factor (SF), bandwidth (BW), coding rate (CR) and carrier frequency (CF)
  - Adjusted based on the payload size and transmission range
- ❖ LoRaWAN provides two methods for device activation:
  - Over-the-air-activation (OTAA) provides dynamic assignment of device addresses and session keys.
  - Activation-by-Personalization (ABP) requires hardcoding of device addresses and session keys

❑ LoRa-based UAV Communications:

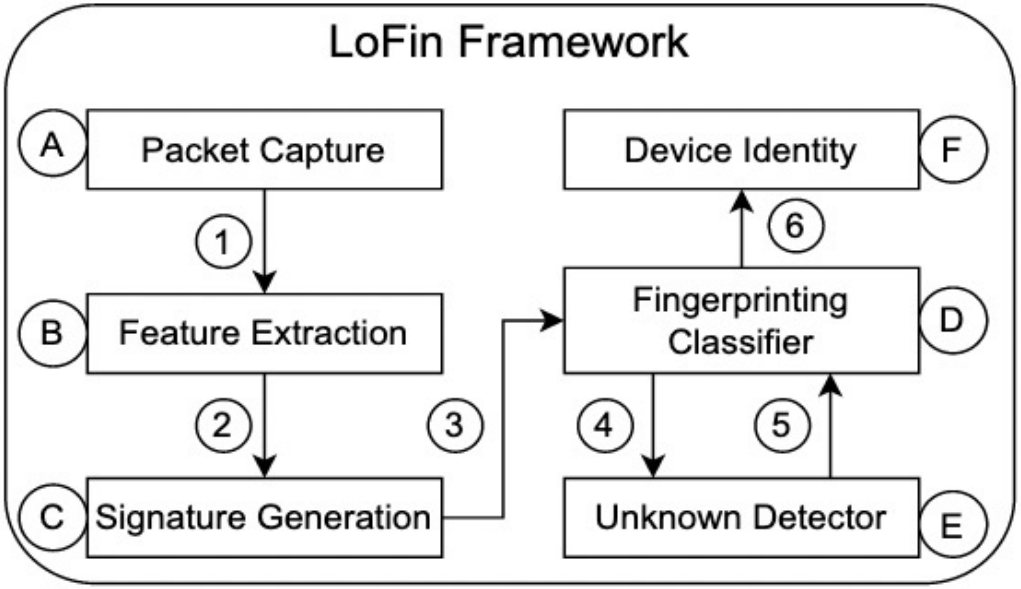
- ❖ Real-time quality monitoring system [5]
- ❖ Marine coastal environment monitoring [6]
- ❖ UAVs as end-node and gateway devices in LoRa network [7]

Threat Model & Assumptions

- Assumptions:
  - Network consists of multiple LoRa-based UAVs and sensors
  - LoFIN set up on the centralized server to passively capture network traffic
- Attacks & scenarios considered:
  - Passive Impersonation:
    - Network infiltration to mimic the behavior of legitimate UAV
  - Active attack
    - Disrupt functionality of the device identification tool and network communications
  - LoRa Configurations:
    - Periodic changes of the protocol configuration may impact accuracy of proposed detection mechanism

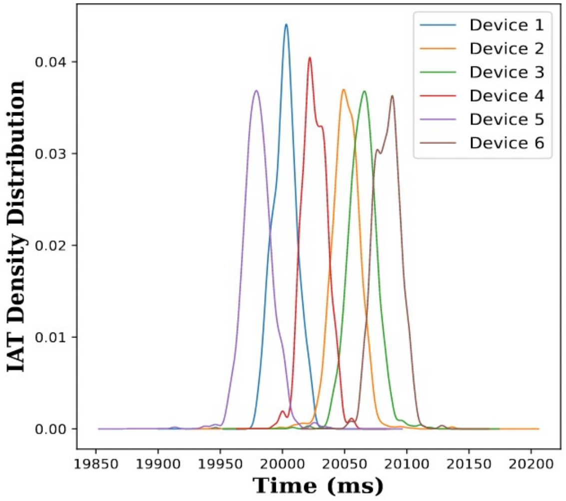
LoFin Architecture - Overview

- Overview:
  - Passively collects network traffic
  - Extract device-specific features
  - Generate device signature
  - Classification process & detection of unknown device signatures
  - Devices identify – a foe or a friend



LoFin Architecture - Components

- **4 major components:**
  - *feature extraction, signature generation, classifier, and unknown detector*
- **Feature Extraction:**
  - Considered features:
    - Payload length, device address, SNR, and combination of LoRa configuration parameters
  - Selected inter-arrival time (IAT) for device signature generation
    - Manufacturing defects introduce unique noises to the data transmission process, resulting in fixed time overhead
  - IAT for LoRa is affected by Time on Air (ToA):
    - Represent the time it takes a signal to travel from sender to receiver
    - ToA is directly affected by spreading factor (SF) and bandwidth (BW) L:oRa parameters
  - $\boldsymbol{IAT = (t_i - t_{i-1}) - ToA_i}$



LoFIN Architecture – Components contd.

Signature Generation

- Time-series extraction
  - Extract time-series of length *l* for each set of IAT values
  - Extracted features split into N shorter series

$$time\_series = [IAT_1, IAT_1, IAT_2, ...IAT_n].$$

- Statistical Analysis
  - Using tsfresh obtained 816 distinctive features
  - Selected 367 significant features based on p-score and relevance table

Fingerprinting Classifier

- Machine Learning classifiers: KNN, RF, GaussianNB, and SVM)
- Produces probability vector, V_p indicating similarity value for known device
- V_p is passed to ***unknown detector,*** to filter out unknown devices:
  - Then classification results for known devices are interpreted to determine device identity

LoFIN Architecture – Components contd.

Unknown Detector

- Responsible for identifying potentially adversarial devices within LoRa network
- Intermediate stage of ***fingerprinting classifier***
  - Applies probability measures to filter out suspicious devices
  - Threshold approach to spot samples yielding low closeness in regard to known devices

Effectiveness Metrics

- Accuracy (ACC) to measure overall system performance

$$ACC = \frac{TP + TN}{TP + FP + TN + FN}$$

- Precision & Recall
  - Accuracy for specific device class and indication of the number of mishits for a given class

$$Precision = \frac{TP}{TP + FP} \qquad Recall = \frac{TP}{TP + FN}$$

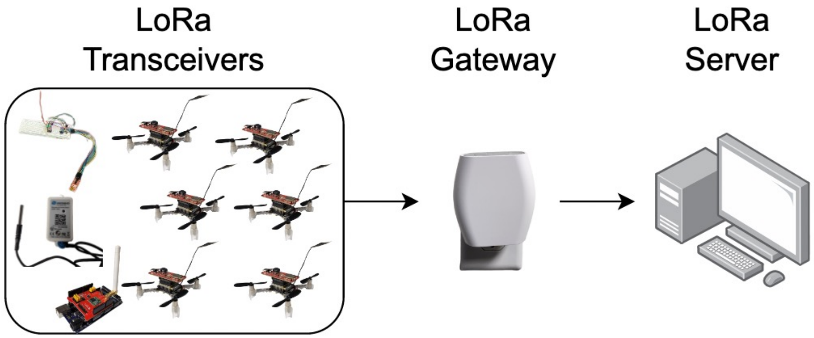
Performance Evaluation - Testbed

❑ Devices Summary

Device	Device Type	Quantity
CrazyFlee with Arduino expLoRaBLE	Drone Telemetry	6
Arduino Mega	LoRa Transceiver 1	1
Arduino Mini	LoRa Transceiver 2	1
Dragino LHT65	Temperature Sensor	1

❑ Testbed Setup:

- ❖ CrazyFlie drones programmed using Bitcraze library [8]
- ❖ Arduino expLoRaBLE as telemetry
- ❖ MAVLink protocol



❑ Data Collected:

- ❖ Total of ≅ 24,000 network packets
- ❖ 1,200 packets for each device
- ❖ Additional data collected to implement adversarial random delay scenario
- ❖ 70% of data used to train LoFin classifier

Performance Evaluation - Experiments

- **Devices setup:**
  - Drone Telemetry devices configured for a synchronized mission of data collection
  - Rest of the devices transmit independently
- **LoFin Configurations:**
  - Extracted 40 time series vectors consisting of 30 consecutive IAT values for each device
  - Selected optimal ML algorithm for fingerprinting classifier
    - RF with 10 trees, *entropy function* as quality measure of a split, and random split of 42
    - KNN with "ball_tree" algorithm for nearest neighbors computation
  - 5 K-Fold cross validations
    - Optimal model fitting

Performance Evaluation - Experiments

- Experiment 1 – Isolated Environment
  - All devices are known and isolated from the adversary
  - Accuracy: **100%** for RF classifier and **99.2%** for KNN
- Experiment 2 – Different Configuration Scenarios (Table 1)
  - LoFin is trained for devices transmitting using **SF7**
  - Set LoRa SF configuration to **SF10** for 4 devices and apply LoFin framework

Device	RF		KNN	
	Precision	Recall	Precision	Recall
Drone Telemetry 1*	1.0	1.0	1.0	1.0
Drone Telemetry 2*	1.0	1.0	1.0	1.0
Drone Telemetry 3	1.0	1.0	0.89	1.0
Drone Telemetry 4	1.0	1.0	0.88	1.0
Drone Telemetry 5	1.0	1.0	1.0	1.0
Drone Telemetry 6*	1.0	1.0	1.0	1.0
LoRa Transceiver 1*	1.0	1.0	1.0	0.67
LoRa Transceiver 2	1.0	1.0	1.0	1.0
Temperature Sensor	1.0	1.0	1.0	1.0
Average Accuracy	1.0		0.972	

Table 1. Results for experiment 2

Performance Evaluation - Experiments

Experiment 3 – Impersonation Attack (Table 2)

- 6 identical drone telemetry devices;
  - 1 is selected to represent an **adversary**
- Evaluated unknown detector ability to detect foe's traffic
- ***Unknown detector*** cannot be used with KNN:
  - Requires probability vector
- **100%** classification and true negative rate;
  - False negative rate **below 10%**

Devices	Precision	Recall
Drone Telemetry 1	1.0	1.0
Drone Telemetry 2	1.0	1.0
Drone Telemetry 3	1.0	1.0
Drone Telemetry 4	1.0	1.0
Drone Telemetry 5	1.0	1.0
Drone Telemetry 6*	N/A	N/A
Average Accuracy	1.0	
True Negative Rate	1.0	
False Negative Rate	0.082	

Table 2. Results for experiment 3

Performance Evaluation - Experiments

❑ Experiment 4 – Random Delay Attack (Table 3)

- ❖ Implemented artificial delay to 1 drone telemetry device
  - Used built-in probabilistic random() library to design random delay algorithm
- ❖ Overall accuracy is **95%** for RF-based fingerprinting classifier
- ❖ Unknown detector trade-off
  - Benign traffic may be marked as potentially adversarial

```
p=0; d=0, counter=0;
while(True):
   select p from [30,70] and d from [1,5]
   if  counter == p:
      wait d and transmit
      p=0; d=0, counter=0;
   else:
      transmit
          counter += 1
```

Device	RF		KNN	
	Precision	Recall	Precision	Recall
Drone Telemetry 1*	1.0	0.86	1.0	0.57
Drone Telemetry 2	1.0	1.0	1.0	1.0
Drone Telemetry 3	1.0	1.0	1.0	1.0
Drone Telemetry 4	1.0	1.0	0.86	1.0
Drone Telemetry 5	1.0	1.0	1.0	1.0
Drone Telemetry 6	0.92	1.0	0.91	0.91
LoRa Transceiver 1	1.0	1.0	1.0	0.67
LoRa Transceiver 2	1.0	1.0	1.0	1.0
Temperature Sensor	1.0	1.0	1.0	1.0
Average Accuracy	0.991		0.964	

Table 3. Results for experiment 4

Conclusion & Future Work

- **LoFin:**
  - 1st framework to passively fingerprint LoRa devices using MAC layer information
  - 100% precision and recall for majority of the scenarios
  - Resistant to changes in LoRa configurations
  - 100% detection of unknown devices with false-negative rate below 10%
  - Not influenced by changes in PHY layer
- Future Work:
  - Increase number of devices and its diversity
  - Improve LoFin robustness against random delay attack

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Thank you! Q&A


THANK
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GRACIAS
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SHUKURIA
GOZAIMASHITA
EFCHARISTO
JUSPAXAR
DANKSCHEEN
TASHAKKUR ATU
YAQHANYELAY
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