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Robust Satellite Antenna Fingerprinting under Degradation using Recurrent Neural Network

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***Abstract*—Antenna fingerprinting is critical for a range of physical-layer wireless security protocols to prevent elevated identity attacks and authenticate legitimate users. However, many antennas suffer degradation especially in adversarial environments such as satellite antennas in outer-space. This is particularly a problem for nano-satellites, which are designed to operate for a short time span and are not currently afforded expensive protective coating. Current fingerprinting techniques only use convolution neural networks to take a snap-shot fingerprint at manufacturing, but fail to capture long term temporal variations. Here, we show how we can perform robust antenna fingerprinting (99.34% accuracy) up to 198 days under intense degradation damage using recurrent neural networks (RNNs). We are certain this can be improved and has real world impact on physical layer security of short-term nano-satellite antennas in adverse environments.**

***Index Terms*—RF Fingerprinting, deep learning**

I. Introduction

Physical security using RF fingerprinting has attracted significant attention. This is important especially in high value radio asset systems such as military and space applications. One of the critical issues currently facing wireless data is that most higher layer protocols are vulnerable to misuse and a variety of spoofing and denial of service attacks. For example, even though cryptographic digital signatures can achieve spoofing detection, they might be uneconomical due to the excessive cryptography overhead or inefficient for large-scale networks or challenging to reach transmitters (e.g. satellites) are involved. Replay attacks depend on protocol defects and are consequently even more challenging to detect.

Physical security in the form of RF fingerprinting can prevent attacks such as impersonation for elevated access status and forensic identification of malicious users [1]–[3]. In recent years, the development of Software-Defined Radios (SDRs) has facilitated the high-resolution exposure and extraction of features by providing high resolution bandwidth and Signal-To-Noise ratio. However, the discrimination between the noise of the radio signal and the required features is still a challenging factor for wireless radio fingerprinting, and this has led to the implementation of effective Deep Learning classification algorithms using the physical layer features.

A. State-of-the-Art

A key research objective is improving the distinctiveness of features rises from imperfections in the transmitter physical elements generated during the manufacturing process. Generally speaking, a variety of features can be leveraged: (1) location independent features (e.g., transient phase at the transmission onset, frequency and phase offsets, Radio Signal Strength RSS or Chanel State Information CSI) and (2) Location dependent features (e.g., position coordinates). Different features can be combined in order to perform accurate identification, however they should be characterised by uniqueness, universality and collectability, permanence and robustness.

Classification algorithms can be either unsupervised or supervised, depending on whether prior fingerprint information is available. Unsupervised Learning algorithms such as K-Means clustering and PCA are used when a labelled training dataset is not available, and the device fingerprints are similar. On the other hand, supervised methods such as Support Vector Machines are used for fingerprinting classification, but they are significantly less effective than Neural Networks that exhibit remarkable performance on noisy RF fingerprinting data. Convolutional Neural Networks (CNNs) [4] have been used to classify mobile devices using Differential Constellation Trace Figure (DCTF) features, achieving exceptional accuracy of 97-99%. There has also been work that exploit the spatiotemporal pattern of RSS features for mobile transmitters [5]–[8], but this does not consider antenna degradation.

In more realistic settings, the authors of [9] evaluate the accuracy of CNNs under several environmental conditions (in the wild and in an anechoic chamber) inspecting both ADS broadcast and WiFi, revealing that the wireless channel severely impacts the radio fingerprinting in low SNR, decreasing the fingerprinting quality by up to 85%. This limited performance of CNNs in low SNR and the risk of antenna material degradation over time [10], confirms the need for more effective classification methods.

B. Open Challenges in Satellite Fingerprinting

Among many volatile factors in space, the relatively high energy of the atomic oxygen (AO) [11] that exists at Low-Earth Orbit (LEO) altitude allows molecular bonds in materials to break. This can cause surface degradation to nano-satellite or CubeSat satellites [12] and their commercial off-shelf parts, such as their antennas. Current nano-satellites or CubeSats are not afforded expensive coating protection and are only designed to serve 300 days. However, even during this time the antenna parameters can decay and as the in-orbit time of satellites increases, this prolonged exposure to AO entails a high risk that, it could slowly alter the RF fingerprint over time to an extent that it cannot be identified. Therefore, the parameter of antenna decaying makes fingerprinting an even more challenging scenario that is currently unexplored.

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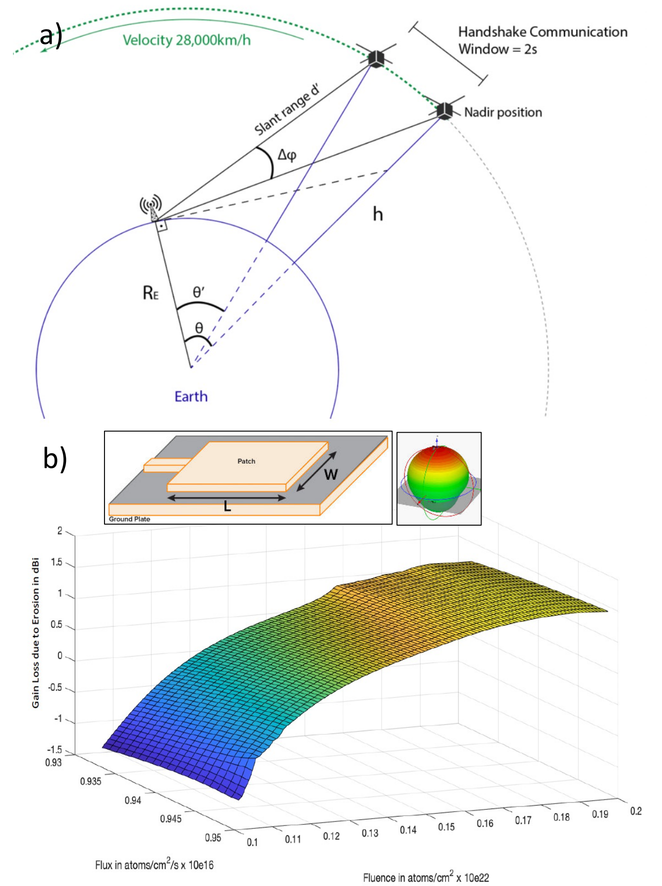


Fig. 1. **Antenna Fingerprinting for Satellites:** a) system model of LEO satellite and handshake window, b) typical patch antenna model, c) antenna radiation pattern, frequency dependent performance, and IQ maps, d) Space Atomic Oxygen (AO) impact on satellite antenna power gain as a function of Fluence (atoms/cm2) and Flux density (atoms/cm2/s), and e) satellite to ground downlink communication system.

C. Novelty & Contributions

The aim of this paper is to design the authentication framework that can support RF fingerprinting using RSS of CubeSat communication link with the ground station. We will implement effective Deep Neural Network classifiers that can address the challenge of the relative motion between the satellite and the Earth, whilst taking into account the following novel aspects:

- incorporate the satellites' antenna performance decay due to atomic oxygen (AO) impact
- robust classification of the long-term degradation fingerprint of satellite antennas using a Recurrent Neural Network (RNN)
- compare the performance of different deep learning algorithms on robust antenna classification under AO degradation in space

These are novel advances because it captures the limitations of current fingerprinting techniques that only use a CNN [4], [13] to take a snap-shot fingerprint at manufacturing, but fail to capture long term temporal variations.

TABLE I
SYSTEM MODEL PARAMETERS

Parameter	Value
LEO Orbit Altitude d	1804km (max)
Satellite Velocity	28,000km/h
Handshake Window	2s
Antenna Type	Patch 6x7.8x0.125cm
Polarization Loss L_{aml}	4.5dB
Polarization Loss L_{pol}	3dBi
Atmospheric Abs. Loss L_a	0.001dB/km
Tx Power & Gain	30dBm & 15 dBi
Frequency	S-Band 2.4-2.45GHz
Defect Tolerance	Impedance 0.04Ω
Data Samples	500 per Antenna

II. SYSTEM MODEL

A. Model Assumptions

As shown in Fig.1a-b, we consider LEO satellites orbiting at a slant range of 1804km, with a patch antenna gain of 15dBi and a transmit power of 30dBm. The pathloss model used is [14]:

$$L = L_a \left(\frac{4\pi d}{\lambda} \right)^2 L_{\text{aml}} L_{\text{pol}} L_{\text{AO}}, \tag{1}$$

where L_{aml} is the loss due to antenna misalignment, L_{pol} is the polarization loss due to misalignment between satellite and ground antennas, and L_a is atmospheric absorption loss. The AO degradation to antenna power L_{AO} is given empirically in [11], which we extrapolate to vary proportional to the predominantly Fluence (typical values of $0.2e^{22}$ atoms/cm2)) under a fixed flux rate of $9.5e^{15}$ atoms/cm2/s:

$$L_{\text{AO}} \approx a + b_1 \text{Fluence} + b_2 \text{Fluence}^2, \tag{2}$$

with a adjusted R2 of 0.995 fit to empirical data in [11], where the fit parameters are: $a = -8.2, b_1 = 1e^{-20}, b_2 = -2.8e^{-42}$.

The rest of the system parameters are given in Table I, where the patch antenna designed operates at 2.4-2.45GHz (S-Band) and is attached to a ground panel of 12.5x12.5cm with air substrate of 0.0012491. Each cubesat antenna has slightly different input impedance to mimic the manufacturing defects within a tolerance window of 0.04Ω. Each antenna in a sample of $N = 21$ antenna variations has 500 RSS samples for training and out-of-sample validation split 70-30.

B. Atomic Oxygen Degradation to Antenna Fingerprint

Of primary novelty and concern is the modeling of erosion due to atomic oxygen (AO), which is formed by a photo dissociation process of oxygen molecules by ultraviolet (UV) radiation [11] - a particular problem for the Low-Earth Orbit environment. Thus, traditional satellite antennas are coated with a layer of geranium (expensive practice) to prevent any serious functional damages on their outer surface. AO exposure was not a designing constraint for a CubeSat mission, as it would stop functioning before the corrosive effect could cause any serious issues on its system [11]. However, the increase of CubeSat missions, and the advances of technology that enable

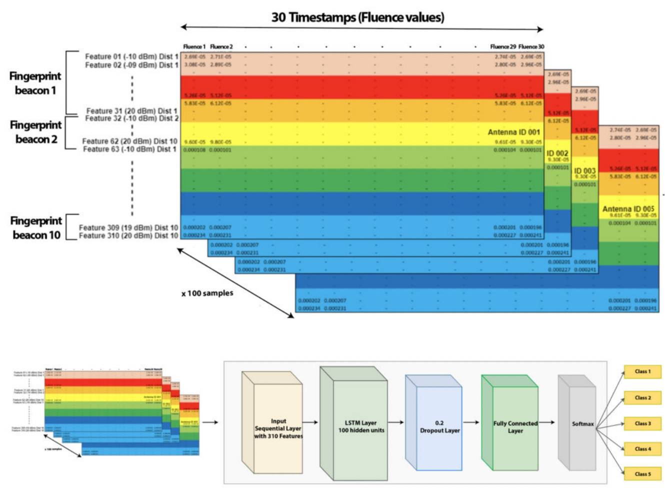


Fig. 2. **Antenna Feature Input Tensor and LSTM RNN Structure:** top) each antenna has 310 power and time samples related to degradation state, and bottom) LSTM structure.

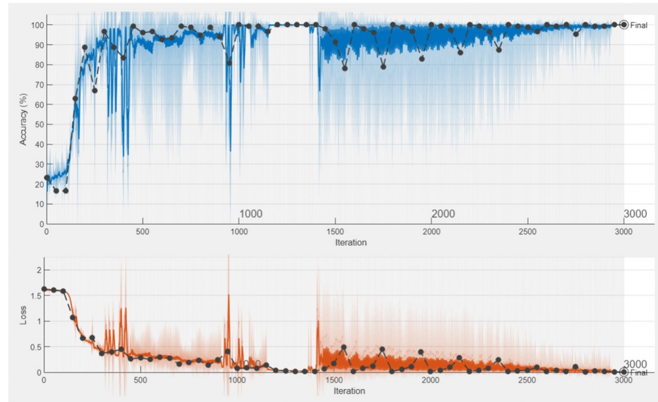


Fig. 3. **RNN Training Performance:** accuracy and loss function over training iterations.

them to stay longer on-orbit, means longer exposure in the harsh space environment.

The AO that exists in the LEO environment has a relatively high energy (at about 4.5 eV), which forces molecular bonds in materials of the satellite surface to break [11]. Even though, it may not limit the antenna performance, it could alter its RF Fingerprint over time to an extent that is not recognisable. A recent experimental research [11] has examined how AO erosion affects the performance of patch antennas for CubeSat applications. They exposed twenty-six S-Band patch antennas to AO in their laboratory equipment for 24 hours which correspond to roughly three months of on-orbit exposure and they quantified the erosion (mass loss) in Fluence and Flux - see Fig.1c. We use their data to drive the degradation model for our antennas.

C. RF Fingerprinting using Deep Learning

We use 3 deep learning frameworks premised on both current literature's state-of-the-art, and our own innovation on combating long-term AO degradation effects to the antenna:

- Baseline Neural Network: feed-forward NN (FF DNN) with 3 hidden layers comprised of N neurons in first layer, followed by 64, 128, 256, and N in final layer. Activation functions are ReLu in hidden layers and Softmax at the representation layer, with 0.0001 learning rate and a batch size of 500. The hyper-parameters were optimised with the adaptive learning algorithm (Adam) with SGD to be efficient in the face of noisy data.
- State-of-the-Art Convolution Neural Network (CNN): CNN network published in 2020 [4], [9] to exploit cross-feature feature signals in antenna: with I/Q constellation maps used that are 125x125 in resolution and a sub-sampling of 62x62 is followed by 2 convolution layers.
- Recurrent Neural Network (RNN) for Degradation: LSTM network (see Fig.2) with 310 input features (31 power levels x 10 time samples across AO flurence degradation states), 100 hidden LSTM units, 0.2 dropout layer, and a fully connected softmax representation layer. Initial learning rate is 0.00001, batch size is 256, and Adam optimized with gradient decay factor is 0.9.

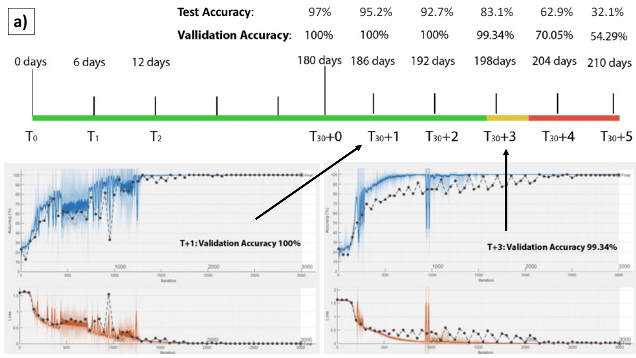
For this brief paper, we only show our proposed RNN training performance in Fig.3 which shows good convergence in accuracy and loss function after 3000 iterations.

III. Results

For our results in Fig. 4, we highlight the robustness of our proposed RNN fingerprinting capability over the first 200 days. Here, we show that for the first 198 days, the accuracy across the different antennas remain above 99%, before falling off dramatically. This cannot be said for the state-of-the-art CNN framework which examines a richer IQ map and sees a steady decline in performance over time due to the lack of recurrent training, which means the accuracy drops from 91% after 190 days to 64% after 200 days. The feed-forward DNN is the simplest baseline which performs very well at beginning but rapidly loses accuracy with AO degradation onset as it neither benefits from convolution properties of richer features nor the longitudinal recurrent data training. These results are reasonably robust to different frequency in S-Band and LEO altitudes as shown in Table II, where we varied the frequency and altitude slightly. In general, we advice against using feed-forward DNNs with a basic RSS signal classification. IQ or DCTF maps [4], [9] tends to be far more robust, but their accuracy also falls off after 5-6 months into the operation due to AO erosion. As such a RNN has more promise extending accurate classification to 200 days with above 97% accuracy.

IV. Conclusions & Future Work

Antenna fingerprinting is critical for a range of physical-layer wireless security protocols to prevent elevated identity attacks and authenticate legitimate users. However, many antennas suffer degradation especially in adversarial environments such as in outer-space. This is particularly a problem for nano-/cute-satellites, which are designed to operate for a short time span and are not currently afforded expensive protective coating. Current fingerprinting techniques only use CNNs to



b)

Test Results at 50dB	0 days	190 days	198 days	200 days
Feedforward DNN for RSS	99.9%	82.7%	59.2%	34.9%
CNN for DCTF/IQ Maps	99.8%	91.3%	80.0%	64.6%
RNN for AO Degradation	100%	93.2%	83.1%	75.2%

Fig. 4. **RNN Validation Results over Degradation Time of 210 Days:** top) RF fingerprinting performance summary, bottom) accuracy and loss function examples for time frames of 186 days and 198 days.

TABLE II
RESULTS SUMMARY

Parameter	Robust Classification Duration (97%)
2.39 GHz, 1700km	
FF DNN with RSS	7 days
CNN with IQ Map	156 days
RNN with RSS	198 days
2.49 GHz, 1800km	
FF DNN with RSS	7 days
CNN with IQ Map	170 days
RNN with RSS	202 days

take a snap-shot fingerprint of the I/Q map at manufacturing, but fail to capture long term temporal variations due to degradation.

Here, we showed how we can perform robust antenna fingerprinting (99.34% accuracy) up to 198 days under severe space degradation damage using RNNs. As it currently stands, this work has the promise to improve RF fingerprinting for nano-/cube-satellites which do not benefit from expensive anti-degradation coating, and are expected only to operate for a maximum of 300 days. Here, we can ensure robust RF fingerprinting for 200 days and this can be improved by combining RNN and CNN.

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