Domain-Agnostic Hardware Fingerprinting-Based Device Identifier for Zero-Trust IoT Security

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Abstract—Next-generation networks aim for comprehensive connectivity, interconnecting humans, machines, devices, and systems seamlessly. This interconnectivity raises concerns about privacy and security, given the potential network-wide impact of a single compromise. To address this challenge, the Zero Trust (ZT) paradigm emerges as a key method for safeguarding network integrity and data confidentiality. This work introduces EPS-CNN, a novel deep-learning-based wireless device identification framework designed to serve as the device authentication layer within the ZT architecture, with a focus on resource-constrained IoT devices. At the core of EPS-CNN, a Convolutional Neural Network (CNN) is utilized to generate the device identity from a unique RF signal representation, known as the Double-Sided Envelope Power Spectrum (EPS), which effectively captures the device-specific hardware characteristics while ignoring deviceunrelated information. Experimental evaluations show that the proposed framework achieves over 99%, 93%, and 95% of testing accuracy when tested in same-domain (day, location, and channel), cross-day, and cross-location scenarios, respectively. Our findings demonstrate the superiority of the proposed framework in enhancing the accuracy, robustness, and adaptability of deep learning-based methods, thus offering a pioneering solution for enabling ZT IoT device identification.

I. INTRODUCTION

In the ever-evolving landscape of intelligent and interconnected wireless systems, the comprehensive connectivity, enabled by massive Internet of Things (IoT) networks, and the surge in sophisticated cyber-attacks have highlighted the pressing need for a revolutionary approach to network security. Traditional approaches, built on the concept of a secure physical perimeter, are falling short of the increasingly demanding security measures as the key assumptions of these models no longer hold [1]. In response to this growing concern, the Zero Trust (ZT) model has emerged as a transformative paradigm, redefining the fundamental principles of network security [2]. Rooted in the philosophy of "never trust, always verify," the ZT model advocates for a proactive and dynamic approach to security, where trust is no longer assumed, but continuously verified throughout the entire network environment, and resource access is granted solely based on device and user credentials, irrespective of the user's network location. The new paradigm offers special attention to the identity authentication process as any misstep at this stage can jeopardize the integrity of the entire system. The foundational cornerstone within the ZT paradigm centers on the robust necessity for unequivocal device identity. This imperative encompasses an array of requisites including the hardware root of trust, passwordless authentication, renewable credentials, and device registry [3]. In accordance with these tenets, highlysecured devices possess a cryptographically-backed, unique, and unforgeable "onboarding" identity that is inseparable from the hardware and managed by an embedded security processor. They also enjoy a passwordless authentication process leveraging digital certificates signed and verified using private and public cryptographic keys. These certificates extend their efficacy to provide renewable and operational credentials for continuously secured operations. Lastly, it is crucial to have a device registry that stores the core attributes of the devices to facilitate and audit the access process. These requisites necessitate the incorporation of pivotal components including cryptographic engines, security processors, and secure storage [3]. However, this integration poses challenges for the vast number of microcontroller-based IoT devices, constrained by factors such as size, power, or cost limitations. With countless interconnected devices forming integral parts of expanding IoT ecosystems, the compromise of even seemingly innocent devices can catalyze escalating threats, encompassing data pollution, lateral movement, and denial-of-service attacks. Hence, safeguarding each individual device within the network attains paramount significance.

To bridge this gap, we propose a novel hardware device fingerprinting-based framework, named EPS-CNN, that builds a unique and unforgeable hardware-based identity for IoT device authentication. Hardware device fingerprinting technology serves as a powerful physical-layer security mechanism, enabling device identification through the extraction of unique device fingerprints embedded in the devices' transmitted signals [4], [5]. These fingerprints emerge due to inherent hardware manufacturing imperfections of various Radio Frequency (RF) circuitry components yielding signal distortions [6] that collectively shape distinctive device signatures.

Deep Learning (DL) stands out as a powerful computational paradigm for embedding intelligence in IoT networks. It has been, recently, utilized for device discovery, vulnerability analysis, anomaly detection, and trust-based policy recommendations [7]. Although DL-based hardware device fingerprinting methods have demonstrated promising results in terms of device identification accuracy, several studies (e.g., [6], [8], [9], [10]) have revealed that many of these methods do not

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perform well when the testing data is collected under a *domain* that is different from that used during training. Here, the term *domain* refers to the network setting/environment (e.g., channel condition, device location, etc.) under which data is collected. This observation can be attributed to the prevalent use of raw In-phase/Quadrature (IQ) data representation as the input to the DL-based device identifiers [11]. However, within the context of fingerprinting, this representation contains an abundance of device-irrelevant information. Consequently, extracting meaningful fingerprints from this raw IQ data becomes akin to finding a needle in a haystack filled with numerous misleading needle-like objects.

To ensure a flawless authentication operation across various domains, the domain-resilient property becomes an indispensable attribute for any device identification framework aspiring to integrate seamlessly into the ZT architecture. Accordingly, our proposed identification framework introduces a novel RF signal representation, double-sided envelope's power spectrum, referred to as EPS for short, which significantly enhances the accuracy and robustness of DL-based hardware device fingerprinting methods against domain changes. Our EPS representation vividly captures the device's hardware impairments while suppressing device-irrelevant information. Specifically, it closely mirrors the impaired behavior of a key RF hardware component, the oscillator, whose impairment substantially contributes to the device's unique fingerprint and is proven resilient in the presence of variations in time, channel conditions, and/or location. The adoption of the EPS representation is pivotal in mitigating the impact of environmental changes on device identification, ensuring the reliability and stability of our approach.

To generate this EPS representation, we extract the outer shape or envelope of the IQ signal, thereby eliminating resultant amplitude offsets, and produce the double-sided envelope's power spectrum of the received burst, which serves as an effective input to machine learning classifiers. Leveraging EPS, we then propose the EPS-CNN device identification framework, which channels the output of the EPS extractor engine into a standard Convolution Neural Network (CNN) to create device-unique identities from received RF signals.

Through extensive evaluation on a testbed of 15 WiFi devices, we demonstrate the effectiveness of our EPS-CNN device identification framework in real-world scenarios. Notably, we show that our framework achieves an accuracy of over 99% in same-domain scenarios (i.e. training and testing are both done on same day/location), and more importantly, consistently sustains an accuracy that exceeds 95% for cross-location scenarios and 93% for cross-day scenarios.

The key contributions of this work can be summarized as:

- We propose EPS, a novel IQ representation that significantly enhances the performance of deep learning-based device identifiers. We demonstrate, through experimentation, the distinguishability and reliability of EPS under varying time, channel, and/or location domains.
- We propose EPS-CNN, an EPS-based device fingerprinting framework that substantially enhances the accuracy

and robustness of device identification in the presence of varying domains.

• We assess the effectiveness of EPS-CNN in identifying WiFi devices and showcase an exceptional cross-domain performance in real-world scenarios, achieving an average testing accuracy of 93% and 95% respectively for the cross-day and cross-location scenarios.

The rest of the paper is organized as follows. Sec. II studies the impact of the oscillator's carrier frequency inaccuracy and offset on the behavior of IQ signals. Sec. III presents the proposed IQ data representation approach, EPS. Sec. IV presents the proposed EPS-CNN identification framework along with its extensive evaluation under different scenarios. Finally, Sec. V concludes the paper.

II. UNDERSTANDING THE IMPACT OF OSCILLATOR'S FREQUENCY INACCURACY ON IQ SIGNAL BEHAVIOR

As highlighted earlier, recent studies [6], [9] have underscored a critical drawback in the performance of DL models that solely rely on IQ samples, revealing their struggles with maintaining consistency across diverse domains. Consequently, there arises a pressing need for novel RF signal representations that adeptly capture device-specific impairments. These representations are essential to refine the feature selection process within DL-based fingerprinting techniques and enhance their resilience to shifts in different domains. In this work, we propose a device identification framework based on a robust RF signal representation that accurately captures the impairments of oscillators, which serves as the foundation for identity generation.

To be able to design such efficient representations, it is important to begin by studying the impact of the carrier frequency inaccuracy caused by local oscillators on the behavior of the received IQ signals.

A. The Carrier Frequency Offset (CFO)

Local oscillators are essential hardware components in the RF transceiver chain, primarily generating oscillating signals that serve as the foundation for establishing RF communication. Therefore, the accuracy of the oscillator, denoting the frequency offset from the specified target frequency, and its stability, which refers to the frequency dispersion around its operational value over time, are critical in RF applications, as they significantly impact the overall system performance [12]. Carrier Frequency Offset (CFO) is a hardware impairment that arises due to the mismatch between the receiver's local oscillating frequency and that of the sender. This mismatch often occurs due to various factors, including Doppler shifts, oscillator inaccuracies, or synchronization errors in communication systems [13].

B. The Impact of Oscillator's Frequency Inaccuracy

To investigate the impact of the oscillating frequency inaccuracy on the IQ signal behavior, we leveraged our testbed of 15 Pycom/IoT devices (shown in Fig. 5a) to analyze the IQ signals collected from multiple different (but identical in



(b) The Q component of the IQ signal of four devices

Fig. 1: The time-domain IQ signal behavior across four different Pycom/IoT devices.

hardware) off-the-shelf devices and captured using a USRP B210 receiver. This is done by having each of the 15 Pycom devices transmit the same IEEE 802.11b WiFi packets after being powered on for 12 minutes to ensure hardware stabilization. We want to emphasize here the importance of waiting until the end of the warm-up period of the devices' hardware before starting the data collection process to ensure robust and consistent measurements [14].

We show in Fig. 1 the behavior of both the I (in-phase, Fig 1a) and Q (quadrature, Fig. 1b) components of the time-domain IQ signals captured from four selected devices: Devices A, B, C, and D. We make a couple of key observations from the figure. First, both the I and Q signals showed a "sinusoidal" pattern in their envelopes, where the envelope of an oscillating signal is the smooth boundary function that outlines the extremes of the signal. More importantly, note that the number of "humps" of the envelope varied among the devices. It is worth mentioning that the reported sinusoidal behaviors of the IQ signal's envelopes are observed across all of the 15 tested Pycom devices, but with each device exhibiting a slightly different number of "humps".

Two pivotal questions now emerge: (i) what underlies the sinusoidal pattern seen in the IQ signal envelope, and (ii) what accounts for the varying count of "humps" among different devices? We proceed to show that the main cause behind such behavior is the CFO (carrier frequency offset) between the Pycom device's oscillating frequency and that of the receiver that exists due to the inaccuracy of the device's local oscillator. Specifically, we will next show that the number of humps in the sinusoidal envelope depends on the CFO value. This explains that the reason why different devices exhibit different numbers of humps is that each device presents a different CFO value, which varies across devices due to the device's oscillator



Fig. 2: Simulated time-domain I signal component.

hardware imperfections incurred during manufacturing.

C. What Causes the Observed IQ Envelope Behavior?

We utilized MATLAB simulations to validate that the CFO is responsible for the sinusoidal envelope behavior observed in the IQ signal of IoT devices. We constructed a complete WLAN 802.11b system which we manipulated to vary the CFO values between the transmitter and receiver. Various CFO impairments were introduced, including scenarios with 0 Hz (ideal device), 50 Hz, 100 Hz, and 200 Hz. The CFOimpaired transmitted signal is then first passed through an AWGN channel, and then down-converted and sampled by the receiver to generate IQ data samples. Then, we extracted the real (I) components of the signals and plotted them separately for CFO = 0 in Fig. 2a, CFO = 50Hz in Fig. 2b, CFO = 100Hz in Fig. 2c, and CFO = 200Hz in Fig. 2d. The simulated results clearly show the dependency between the CFO values and the number of observed "humps" in the I signal's Envelope, and that the CFO is what causes the observed envelope shape. The same trends were observed for the Q signal components as well, but we did not include them here to limit redundancy.

We want to mention that we also experimented with varying other hardware impairments, including IQ imbalance, Phase Noise, and DC offset, but did not observe any "sinusoidal" behavior of the envelopes. This confirms that other transceiver hardware impairments, though do manifest themselves in other types of distortions, do not yield the Envelope behavior we observed with the CFO impairment.

III. DISTINGUISHABLE IOT DEVICE IDENTIFICATION THROUGH NOVEL RF SIGNAL REPRESENTATION

In this section, we begin by presenting a novel RF signal representation extracted from the oscillator's envelope shape that substantially improves the robustness of device fingerprinting to domain changes and variations. Next, we assess



Fig. 3: The EPS representation of 10 devices.

the performance of the suggested feature design concerning its capability to effectively serve two main purposes: (i) *distinguish between devices* and (ii) *withstand* domain changes by maintaining high accuracy performance under varying domains.

A. The Proposed Double-Sided Envelope's Power Spectrum (EPS) Representation

To generate the proposed signal representation, we utilized a sequence of operations that compose the EPS generator. The procedure involves creating an analytic signal by initially processing the IQ values of the received frame, denoted as r(t), through an FIR Hilbert transform filter based on the Parks-McClellan algorithm [15]. This filtered output is then scaled by $\sqrt{-1}$ and combined with the time-delayed original signal. Incorporating a delay is crucial due to the inherent delay introduced by the FIR filter implementation of the Hilbert transform, equating to half the filter's length. Subsequently, the signal's envelope, denoted as e(t), is derived by computing the absolute value of the analytical signal. This envelope is characterized by a lower frequency compared to the original signal. Consequently, we downsample the signal by a factor of 15 and then subject it to a lowpass filter to effectively mitigate ringing and smoothen the envelope. Once the envelope is extracted, we center its amplitude around zero before proceeding to generate the corresponding normalized doublesided envelope's power spectrum, i.e., the EPS representation, utilizing a power spectrum estimator. The EPS representations of various Pycom/IoT devices are visualized in Figure 3. This representation possesses critical attributes in terms of both distinctiveness and robustness, rendering it the suitable foundation for generating strong device identities.

B. EPS Distinguishability Across Different Devices

In the context of device identification, a signal representation that exhibits distinctive device-specific characteristics is indispensable. The proposed EPS representation possesses this property, as it captures the local oscillator's behavior, which is affected by the oscillator's unique hardware impairments. To validate this hypothesis, we conducted an experimental evaluation using a testbed consisting of 15 Pycom devices, running the IEEE802.11b protocol and a USRP B210 receiver.



(b) Location Domain

Fig. 4: EPS representation resiliency across the channel and location domains

Our results depicted in Fig. 3 reveal that the EPS representation is indeed unique for each device, as evidenced by the discernible differences, across the 10 studied devices, in the shape and location of the main sideband and its harmonics. This will be further validated through experimental results that are presented later in Sec. IV-B.

C. EPS Robustness to Domain Changes

Displaying distinctive features that are unique to each device is a crucial aspect, but it alone isn't enough for a representation to serve as a solid foundation for generating device identities. When a representation of a device exhibits random variations as the network's context shifts, it becomes incapable of providing a dependable fingerprint. Consequently, it cannot be employed as an input for a reliable device identification system. Therefore, having demonstrated the distinctiveness of the proposed representation through our testbed, our focus now shifts to evaluating its resilience across three different domains: time, channel, and location.

1) Channel-Agnostic Fingerprinting: To thoroughly investigate how the wireless channel impacts the stability and consistency of EPS, an extensive experiment was conducted within an indoor environment. In this experimental arrangement, devices were consistently positioned at a fixed distance of 1 meter from the receiver, in both wired and wireless setups. Over three consecutive days, packets were captured and analyzed. The objective of this investigation was to compare the EPS representations of packets corresponding to each individual device across both the wired and wireless channels over time, thereby discerning the influence of channel variations over time. Fig. 4a presents the graphical representations of the EPS representations obtained from four distinct devices under both wired and wireless channel conditions. Notably, the figures demonstrate that the EPS representation of each device remains unaltered regardless of the underlying channel

characteristics. This observation is consistent across all 15 devices, providing strong empirical support for the robustness and efficacy of our proposed representation in mitigating sensitivity to channel variations during device identity generation.

2) Location-Agnostic Fingerprinting: Changing the location and distance between the transmitting devices and the receiver after training can also lead to a drastic drop in performance. To evaluate the robustness of the EPS representation to such distance and location changes, we captured data at three different locations with the devices being placed 1m-away (Location A), 2m-away (Location B), 3m-away (Location C), and randomly deployed within a radius of 3m-away (Location D) from the USRP receiver; this is shown in Fig. 5b. The plots in Fig. 4b manifest the stability of the EPS feature representation over the four studied location scenarios as the signal representations at the four locations completely overlap. Our findings confirm the stability of the EPS representation in scenarios in which the location, distance, and time of the training and testing sets are different, making the proposed EPS representation a more reliable and robust input for wireless device identification.

IV. EPS-BASED FINGERPRINTING FRAMEWORK FOR DOMAIN-AGNOSTIC DEVICE IDENTIFICATION

Addressing the device identification challenges arising from domain shifts remains a formidable task. This has hindered the practical adoption of deep learning-aided fingerprintingbased device identification approaches in real-world scenarios. In this section, we present our proposed device identification framework, built upon the novel EPS feature representation, and show its effectiveness in overcoming such domain-shift challenges by enhancing the resiliency of device identification when faced with changes in the channel condition, device location and/or time of data collection.

A. An Overview of the Proposed EPS-CNN Framework

Designing an architecture for integrating our EPS-CNN into a zero-trust IoT network involves several components and considerations. At its highest level, the operation flow can be described as follows. New IoT devices are enrolled in the network through a secure enrollment/registration process, during which each IoT device undergoes hardware device fingerprinting. The fingerprinting of these devices, via the EPS generator, is initiated by taking the complex-valued IQ representation of a received frame, r(t), as an input (with a dimension of 1x25170) and then processing the I and O components separately. For each frame, the EPS generator first extracts the envelope of the signal, e(t), and then generates the EPS representation of the two components: EPS(I) and EPS(Q). Refer to Sec. III-A for details about the EPS representation generation. These two EPS representations are then combined into a tensor of size 2x4096, which plays a central role in training the CNN model serving as the device identifier. Our device identifier encompasses a structured arrangement of six convolutional blocks, which



(a) 15 Pycom transmitting devices

(b) Location Setup

Fig. 5: IoT Testbed consisting of 15 Pycom transmitting devices and a USRP B210 receiving device

extract the fingerprint from the EPS representation, three fullyconnected layers with LeakyReLUs in between, and a concluding Softmax layer, which makes determinations regarding the device's identity. Each convolutional block includes 2D-Convolutional, BatchNormalization, LeakyReLU, and Max-Pooling layers. The device identifier's primary function is to discern patterns within the EPS input and make precise predictions about the corresponding device's identity. This completes the enrollment/registration phase.

Subsequently, when an IoT device attempts to access the network, it goes first through a rogue device detection to confirm its legitimate affiliation with the network. This is followed by identity verification, which employs the hardware fingerprint EPS and leverages the device identifier to accurately establish the device's identity. For robust security, continuous authentication is implemented on the packet level using the device's received RF signal during its interaction with the network. Any deviation from the established EPS fingerprint triggers an alert for further investigation.

B. Performance Metrics

To assess the effectiveness of EPS-CNN, we considered two key performance metrics: same-domain accuracy and crossdomain accuracy. Same-domain accuracy measures the ability of the device identifier to identify devices accurately when the testing data/packets are drawn from the same training domain. On the other hand, cross-domain accuracy evaluates the models' ability to generalize across different domains, such as different locations, channels, or days. To ensure robust results, we utilized the 5-fold cross-validation technique, dividing each device's data into five non-overlapping partitions of equal size. Furthermore, we compared the performance of our proposed EPS-CNN with the same CNN framework fed with a typical IQ representation as an input (referred to as IQ-CNN).

C. Device Identification Results and Analysis

1) Robustness to Fixed-Location Changes: We begin by assessing the robustness of EPS-CNN to changes in device locations, meaning that training and testing are done on data collected on different (but fixed) locations. For this, we leveraged our 15-device testbed, shown in Fig. 5a, to collect



Fig. 6: EPS-CNN performance: the testing accuracies under the location and time scenarios

WiFi 802.11b data for three different locations, Loc A, Loc B and Loc C, with devices being placed 1-meter, 2-meter and 3meter away from the USRP receiver, respectively (see Fig. 5b).

Our findings, depicted in Fig. 6(a)-(c), demonstrate remarkable identification enhancements of EPS-CNN over IQ-CNN in cross-location scenarios, where training and testing are done on different locations. For instance, when training is done in Loc A but testing is done in Loc C (see Fig. 6(a)), the average testing identification accuracy achieved under EPS-CNN exceeds 95%, whereas that achieved under IQ-CNN is below 30%. Similar significant enhancements are also seen when training is done in Loc B (Fig. 6(b)) or Loc C (Fig. 6(b)) but testing is done in different locations. To the best of our knowledge, this is the highest performance achieved by deep learning-based device fingerprinting methods when training and testing are done on different domains.

In addition to improving robustness to location changes remarkably, EPS-CNN does achieve exceptional testing accuracy when testing and training are done at the same location, whether Loc A, Loc B, or Loc C. Observe that the average same-location testing accuracy achieved under EPS-CNN at Loc A, Loc B, and Loc C are 100%, 99.6%, and 96.7%, respectively. It is worth mentioning that in the case of samelocation scenario, IQ-CNN too achieves high performances, as shown in Fig. 6.

2) Robustness to Random-Location Changes: We now turn our attention to evaluating the effectiveness of EPS-CNN under random placement of devices. For this experiment, during training (also referred to as enrolment or registration), all devices transmit from a fixed location, 1m away from the receiver, but during testing, the devices transmit from random locations all within 3m from the USRP receiver. Fig. 6d shows that EPS-CNN achieves high average cross-domain testing accuracies of 93% and 98%, respectively, when trained on Loc A and tested under two random-location deployments 1 and 2. In contrast, IQ-CNN's performance deteriorates when tested under random-location placements, whose achieved average testing accuracies are only 40% and 58% under randomlocation deployments 1 and 2, respectively.

3) Robustness to Time Changes: We now evaluate the resiliency of EPS-CNN under the cross-day scenario, where training and testing are done on data collected on different days. For this, we collected WiFi datasets over three consecutive days, where all devices were placed 1 meter away from the receiver, and present the results of this experiment in Fig. 6(e). The first observation we draw here is that the sameday testing accuracies (both training data and testing data are collected on the same day) under EPS-CNN and IQ-CNN were found to be 100% and 99%, respectively. More interestingly, Fig. 6(e) shows that EPS-CNN (and IQ-CNN to a lesser degree) maintains remarkable accuracy for the cross-day scenario, where the average testing accuracies of EPS-CNN are 93% (compared to 88% for IQ-CNN) and 92% (compared to 89% for IQ-CNN) when tested on Day 2 and Day 3 data, respectively. Similar significant enhancements were obtained when trained on Days 2 and 3 and tested on the other days.

In recap, our findings shown in Fig. 6 demonstrate the superiority of our EPS-CNN framework compared to the conventional IQ-CNN framework in overcoming cross-location generalizability and adaptability.

D. Other Security Benefits

In addition to enhancing security, EPS-CNN preserves privacy by minimizing the transmission of device credential information during network access operations. Moreover, it eliminates the need for error-prone manual upkeep of MAC Authentication Bypass/allow lists, as security policy rule recommendations are automatically derived from EPS-CNN's output.

The durability of our framework inherently depends on the aging rate of hardware components, especially the quality of the crystal oscillator, and the intra-distance between different fingerprints in the latent space. Consequently, it varies between deployments. In our current evaluation, we have concentrated on showcasing the resiliency of our framework against shortterm aging, a standard practice in the assessment of newly proposed device fingerprinting techniques. This short-term analysis, conducted over a month, forms a robust foundation for understanding initial performance. However, we acknowledge the necessity to explore the model's behavior under prolonged aging circumstances, spanning months or even years, aligning with the typical lifespan of IoT devices.

V. CONCLUSION

In conclusion, this article addresses security challenges posed by limitations in resource-constrained microcontrollerbased devices, hindering their integration into the ZT security paradigm due to insufficient capabilities for robust identitybased access authentication. We present EPS-CNN, an innovative wireless device identification solution tailored for ZT architecture, emphasizing resource-constrained IoT devices. At its core is the unique EPS representation, overcoming domain challenges and establishing a robust foundation for device identity. Rigorous empirical validation demonstrates the practical viability of our approach, contributing to the advancement of secure IoT networks in an era marked by cyber threats and sophisticated attacks.

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