Who Is Charging My Phone? Identifying Wireless Chargers via Fingerprinting

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Abstract—With the increasing popularity of the Internet of Things (IoT) devices, the demand for fast and convenient battery charging services grows rapidly. Wireless charging is a promising technology for such a purpose and its usage has become ubiquitous. However, the close distance between the charger and the device being charged not only makes proximity-based and near field communication attacks possible, but also introduces a new type of vulnerabilities. In this paper, we propose to create fingerprints for wireless chargers based on the intrinsic non-linear distortion effects of the underlying charging circuit. Using such fingerprints, we design the WirelessID system to detect potential short-range malicious wireless charging attacks. WirelessID collects signals in the standby state of the charging process and sends them to a trusted server, which can extract the fingerprint and then identify the charger. We conduct experiments on 8 commercial chargers over a period of 5 months and collect 8000 traces of signal. We use 10% of the traces as the training dataset and the rest for testing. Results show that on the standard performance metrics, we have achieved 99.0% precision, 98.9% recall and 98.9% F1-score.

Index Terms—Wireless charging, hardware fingerprint, short-range security, machine learning

I. INTRODUCTION

As one of the most important technological changes in recent years, the Internet of Things (IoT) has stimulated market demand for smart home, intelligent vehicle, wearable device, smart city and other scenarios. A wide range of IoT devices supplying through wireless power is an attractive solution [1] [2]. As an energy source to power IoT devices, wireless charging technology has been a popular functionality, and wireless charging devices are also an important component of IoT system [3]. Infrastructure based on wireless charging will have a huge market share in the hardware of IoT. The global wireless charging market reached a value of US$ 6.9 Billion in 2018, growing at a CAGR (Compound Annual Growth Rate) of 24.6% during 2011-2018 [4]. Annual shipment volume is expected to top one billion units by 2020 and two billions by 2025 [5]. In order to facilitate charging, wireless charging facilities are widely deployed in different public IoT scenario, including airports, coffee shops, hotels, libraries, and other places. Although these charging facilities bring convenience to users, they also bring some security threats. Because wireless charging facilities in public areas are not controlled by users, it is likely that some devices for malicious attacks are installed at the same time.

Wireless charging technology requires a centimeter-level of proximity between the charger and the device to be charged. Like other short-range services, this opens doors to short-range attacks such as proximity-based attacks and near field communication (NFC) attack. For example, in the recently reported Tap’n Ghost attack [6], attackers can re-direct victim’s click on the smartphone to other options (such as connecting the phone to a malicious WiFi) by sending short-range signals to distort the electric field of the capacitive touch screen. As another example, by being close to the victim’s smartphone, attackers can obtain NFC UID without being noticed by the victim. The stolen NFC UID may cause many privacy problems.

Wireless charging scenario can be easily utilized by short-range attackers as it requires very close contact between the smartphone and the charger. Attackers may disguise the attacking device as a public charger or hide it underneath the charger to launch short-range attacks while the victim charges his smartphone. Moreover, wireless charging introduces new attacks such as battery security problems. By tampering with the charger, attackers can impact the lifetime of the battery and even exploit the surge to affect the circuit of the device. The left side of Fig. 1 illustrates one of such attack scenarios. Alice puts her smartphone on a wireless charger, then the malicious charger can perform attacks to cause various hazards. With the continuous development of IoT technology, this kind of security threat will continue to increase, because attackers can use IoT network to tamper and control wireless charger remotely. In addition, the existing work has carried on extensive research on the mobile phone wired charging attack. These works attack the side channel of the smartphone when it is charged by wire, which may also threaten the wireless charging security in the future. Some allow the attacker to identify the webpage loaded when the smartphone is charged [7], some are used by the attacker to infer the location of the mobile device [8], and even the attacker may steal the password of the lock screen and other privacy information [9].
Identifying and authenticating the wireless charger is a natural solution to defend against the above attacks. In the most commonly used cryptography-based device authentication method, mutual challenge-response is usually adopted, which requires information exchange between the smartphone and the wireless charger. However, the smartphone’s wireless charging module can only transmit battery information such as the amount of battery left. So the cryptography-based method cannot be used. In addition, authentication based on cryptography is computation-intensive and may not be the best solution for battery-starving devices. Finally, it is also vulnerable to various attacks such as violent cracking, side-channel or man-in-the-middle attacks. Therefore, it is critical to design a practical and effective authentication method for wireless chargers.

In this paper, we propose to detect untrusted charger by exploiting wireless signal’s fingerprints, which are unique and hard to be tampered with. Based on such intrinsic fingerprints, we design WirelessID, a system consisting of a trusted cloud server, a wireless charger and a wireless charging receiver coil in a smartphone, as shown on the right side of Fig. 1. WirelessID system works as follows: before the wireless charging pad requests a connection, the system collects signals from the receiving coil and sends them to the trusted cloud server. The server will extract features (“fingerprint”) from the signal and match it with a database of trusted chargers. If a match is found, the charger is authenticated. Otherwise, the charger will be considered as untrusted and the system will warn the user about charging on the untrusted wireless charger.

The followings are our contributions in this paper:

- We propose a fingerprinting method for the wireless charger through the wireless charging signal in the charging circuit of the device being charged. To the best of our knowledge, this is the first fingerprinting approach for wireless charging scenarios.
- Based on the above fingerprint, we design the WirelessID authentication system which performs signal collection, feature extraction, and fingerprint matching to reliably and accurately identify wireless chargers.
- We validate WirelessID on 8 commercial wireless chargers. The results show that the proposed authentication system can achieve 99.0% precision, 98.9% recall and 98.9% F1-score.

The rest of this paper is organized as follows. Section II presents the basic principle of wireless charging and the related work on short-range security and hardware fingerprinting. The threat model and the wireless charging problem are demonstrated in Section III. Our solution and WirelessID system are detailed in Section IV, followed by the system evaluation in Section V. Section VI discusses the security of our system and the limitations. Finally, Section VII concludes the paper and looking forward to future work.

II. BACKGROUND

In this section, we introduce the principle and application of wireless charging followed by related work on short-range security and hardware fingerprinting.

A. Basic Principles of Wireless Charging Technology

Wireless charging, also known as inductive charging or cordless charging, uses an electromagnetic field to transfer energy between two objects via electromagnetic induction. Induction chargers use an induction coil to create an alternating electromagnetic field from within a charging base, and a second induction coil in the portable device such as a smartphone takes power from the electromagnetic field and converts it back into electric current to charge the battery. The two induction coils in proximity combine to form an electrical transformer [10]. The effective distance for commercial wireless charger products is generally within the range of 0.5cm to 3cm. The charging devices can be dock based, namely a charging pad, or surface based where multiple coils are used to provide a better user experience in terms of larger charging area and more flexible angles. The Qi wireless charging standard by the Wireless Power Consortium (WPC) alliance is the mainstream wireless charging standard [11]. Among the components of a wireless charger, the most important part is its inverter through which a charging board converts DC power supply into AC power, followed by energy transmission through the inductance coil which is depicted in Fig. 2.

With the wave of information industry set off by the Internet of Things, wireless charging plays an important role in it. Lai [3] proposed an IoT-Based wireless charging service for public. At the same time, Wireless charging provides a great solution for IoT devices whose lifetime is significantly limited by the Battery life [12] [13] [14] [15]. Besides, more and more wireless mobile chargers are introduced in wireless sensor networks to supplement the power of nodes to solve the key problem of limited energy [2] [16] [17].
Fig. 2. Composition of a typical wireless charger. The inverter module is the most important part as it converts DC power to AC form and then energy is transmitted by the inductance coil L wirelessly.

B. Related Work

Security vulnerabilities of short-range wireless service have been well-documented in IoT scenario. Bond et al. [18] illustrate attacks against EMV card with the flaw of EMV protocol. The security issues of RFID have been analyzed by many researchers such as [19] [20] [21]. Madlmayr et al. [22] and Eun et al. [23] study the security and privacy of NFC. White [24] designs a wireless charging system by using the resonant parameter as key so the charging board can authenticate smartphones, where the two parties are required to exchange keys constantly. The security problem of short-range acoustic communication in IoT network is studied in [25]. Zhang et al. propose a secure acoustic short-range communication system between IoT devices.

Intrinsic physical features of the device can be used as hardware fingerprints to identify different devices by utilizing the variations in hardware fabrication process. Many types of silicon physical unclonable functions (PUF) have been proposed for device authentication, secret key generation and other applications. Frequency discrepancy [26] [27] and clock skews [28] [29] are commonly used to identify wireless devices. Sensors on mobile device such as accelerometers [30], gyroscopes [31], microphones [32], speakers [33] and cameras [34] can also be used as fingerprint.

III. THE SECURE WIRELESS CHARGING PROBLEM

Security issues are brought up by the trending wireless charging technique. We consider the following simple yet realistic scenario: Alice is at a public place and has her smartphone running low on battery. Luckily Alice has the option to charge her smartphone through the wireless charging services that are now available in more and more public IoT scenario, such as an attentive service restaurant(Fig. 3(a)), an airport(Fig. 3(b)), or a coffee shop(Fig. 3(c)). It could also be a wireless charger provided by a hotel(Fig. 3(d)) or third-party. However, Alice charges her smartphones with a public wireless charger that is not controlled by herself. However, is there any bad consequence for such wireless charging?

Just like using public WiFi could result in the loss of sensitive information, Alice will be exposed to many security threats the moment she puts her phone on a wireless charging board because various attacks can be launched if this charger is fully controlled by attacker Eve. For example, Eve can tamper with a trusted charger remotely from IoT network or build a malicious one and install it at the public place waiting for victims like Alice to charge their phones. When Alice starts charging her phone, because of the proximity of the phone and the malicious charger and the nontrivial amount of the charging time when this proximity needs to be maintained, Alice’s phone is subject to most if not all the proximity-based attacks such as the Tap’n Ghost attack [6] and the NFC attacks. When there are applications running on the phone, they might be vulnerable to side-channel attacks, which can identify the private information such as the webpage opened by the smartphone, the location, and the password of the lock screen. Furthermore, Eve can damage the battery of Alice’s phone by repeatedly charging-discharging-charging. What Alice needs is a way to convince herself that these attacks will not happen or very unlikely to happen.

In this paper, we propose WirelessID, a system supported by a trusted cloud server, to enable a user like Alice to secure the wireless charging process by identifying the untrusted chargers in public place. For Alice to use WirelessID, she only needs her device such as a smartphone to have a charging receiver coil, which is required for wireless charging, and the capability to communicate with WirelessID’s server. By identifying the public wireless chargers and only charging on trusted chargers, most of the aforementioned threats can be effectively mitigated.

Before we elaborate the design of WirelessID, we mention...
that it is designed to provide secure wireless charging in the following scenarios: (1) Eve leaves another attacking device close to a genuine charger (e.g. hiding it underneath the charger); (2) in the phone to phone wireless charging supported by companies like HUAWEI and SAMSUNG where one phone is malicious; or (3) the attacker only tampers with the software of the wireless charging device to obtain information such as the battery capacity of the smartphone. For case (1), the risk and damage do not come from the charger. In (2), a malicious phone is much more complicated and powerful than a wireless charger to launch attacks on the other phone. In (3), the attacker is not easy to tamper with the program of wireless charging device chip, and the threat of this attack is not great. These cases are out of the scope of this paper where we focus on identifying untrusted chargers to ensure the security of the wireless charging.

IV. IDENTIFYING CHARGER BY FINGERPRINTING

The basic idea of our solution to the secure wireless charging problem is to establish a fingerprint for each charger so before the charging starts, the phone can identify the charger and decide whether the charging will be safe or not. Our WirelessID system is based on this concept and will be elaborated in this section.

A. The Non-linear Distortion Effect of Inverters

In order to stimulate alternating magnetic field from DC power supply, inverters are the essential part for energy transmission. Power inverters employ switch devices such as Metal-Oxide-Semiconductor Field-Effect Transistor (MOSFET) and triode and MOSFET is dominant in nowadays wireless chargers to fulfill the transmission frequency requirement between 100 kHz to 200 kHz specified by the Qi standard.

Switching devices including MOSFET have been reported to have a non-linear distortion effect as MOSFET in essence is not ideal. We also conducted an experiment to verify the effect using three stand-alone MOSFET inverters, i.e., IRF530N-1/2/3. As shown in the Fig. 4, Vdc is the voltage between the drain and source of the MOSFET, and its change rate is non-linear during switching, either in the turn-off (Fig. 4a) or turn-on processes (Fig. 4b). Moreover, from Fig. 4 we can find that the non-linear distortions are distinct for different MOSFETs, even they are of the same model, e.g., the IRF530N series. This is reasonable because there are differences during the manufacturing processes for each MOSFET and the difference is a combination of multiple stochastic processes. This generation of the nonlinear distortion can be formalized in Equation 1

$$y(t) = x(t) * e(t)$$  \hspace{1cm} (1)

For simplicity, the output signal of the inverter $y(t)$ can be seen as the ideally linear signal $x(t)$ multiplied by a non-linear distortion parameter $e(t)$. When the DC power supply signal passes through an inverter, the resulted AC signal, i.e., the waveform after the processing of inverters and other components in the wireless charger, carries a fingerprint and hereafter we call it the wireless charger hardware fingerprint. At the receiver side, the received AC waveform signal can be analyzed to extract the fingerprint of a wireless charger. Details are presented in the following.

B. System Design

The WirelessID system is composed of four modules, i.e., signal collection, signal processing, device verification and trusted database management, as shown in Fig. 5. The signal collection module collects wireless signals before the charging process begins. The signal processing module processes the collected signals and extracts fingerprint features for further verification. The verification module then queries the trusted database in the cloud to verify whether the wireless charger is trusted, i.e., whether the fingerprint is pre-registered. The trusted database management module manages and updates trusted fingerprints.

1) Signal Collection: According to the Qi standard, during a normal wireless charging process, there are in total three stages: a standby signal stage for a to-be-charged device detection, a connection signal stage, and a power transmission
signal stage. We choose the first stage for fingerprint extraction because the charger and the smartphone are not connected yet to avoid any risks as well as the last two stages are not stable enough. For each collection, the collected signal lasts for 50 ms with a sampling requirement of 500 kHz (the wireless charging signal is 100-200 kHz). In our prototype, we use a software radio USRP for signal collection. In practice, the signal collection function should be achieved on smartphones and we discuss the implementation details in Section VI.

2) Signal Processing: In this step, the collected signal trace is processed to obtain the fingerprint for the wireless charger.

**Signal segmentation and pre-processing.** The collected standby signal is composed of active period signals and inactive period signals as shown in Fig. 6. So we can slice the received signal to obtain the active period signal. In this part, we intercept the 50 millisecond signal as a trace for every device. In order to remove the interference from high frequency noise, we utilize a digital Butterworth low-pass filter. We also normalize the raw signal strength to eliminate random disturbance.

**Feature extraction.** For each processed signal trace, we extracted 40 scalar features in the time domain and frequency domain. To further determine key features, we exploit FEAST toolbox [36], which is a feature ranking tool commonly used in machine learning, to choose important features. From the results, we obtain a feature set as the fingerprint for each signal. The feature set includes Linear-Trend [37] in 5, 10, 50 chunks, on which remarkable distinctions can be observed in Fig. 4. These features match the nonlinear switching process of MOSFET.

3) Verification: The verification module is at the cloud sever side and exploits supervised learning to classify each extracted fingerprint. The verification module compares the uploaded fingerprint with existing ones in the database and verification passes, i.e., the represented wireless charger is trusted if the fingerprint matches with one of the registered fingerprints in the database. For the sake of high classification accuracy and robustness over a single classification algorithm, we employ the Extra Trees algorithm.

**Algorithm training.** During the training process, for a specific device, we use $k$ traces from it as a positive class, and $k$ traces from all other devices as a negative class to train a binary classifier. The cloud server trains the corresponding model for each device and stores it in the cloud. In real-world deployment, we may need to extend our system when a new device comes and registers. We extract features and train set of the new device, generate a new two classifier without the need of retraining the original classifiers. Then we combine the new classifier with the existing classifier to form a new classification system.

4) Trusted Database Management: The trusted database is a whitelist of verified wireless chargers. It supports user queries for verification and updates. Whenever a new trusted wireless charger should be added to the database, the classification model should be re-trained. In this paper we only demonstrate the possibility of fingerprinting wireless chargers and leave the model training on large scale devices in the future work.

V. EVALUATION

A. Experiment Setup

Fig. 7 shows the experiment setup. We have conducted experiments with 8 wireless chargers covering the mainstream brands on the market in the lab environments.

**Wireless chargers.** The 8 wireless chargers used in our experiment are from 4 different manufacturers and of 6 different models, as shown in Table I. Note that #1, #2 and #3 are from the same manufacturers but different models while #4 and #5 are exactly of the same model, as the case for #7 and #8.

**Collection device.** We use a receiver coil from a smartphone and the coil is connected to USRP N210 equipped with a LFRX daughterboard. The USRP is driven by compatible software GnuRadio in Linux platform. We tune the sample rate to be 500 KHz in all the following experiments especially evaluation the influence from sampling rate.
Trusted server. We utilize a ThinkPad T440p laptop as the server to perform training and classification. The laptop is with Intel i5 4200M CPU, 4G RAM, and Intel 7260 BGN wireless network adapter.

Dataset description. Under the above hardware setup, we collect 1000 traces for each of the 8 wireless chargers. Each trace is 50ms long after processed. The data collection period is 5-month long. To train and evaluate the classification model, we evenly select 1000 traces from the 8000 traces and leave the rest 7000 traces for testing.

### TABLE I

SPECIFICATION OF THE WIRELESS CHARGERS USED IN THE EXPERIMENTATION.

| No. | Manufacturer | Model | No. | Manufacturer | Model |
|-----|--------------|-------|-----|--------------|-------|
| 1   | Torras       | CDRZ17| 5   | Baseus       | BSWC-08|
| 2   | Torras       | CDRZ21| 6   | Mophie       | 110-02961-A|
| 3   | Torras       | CDRZ25| 7   | UGREEN       | CD134 |
| 4   | Baseus       | BSWC-08| 8   | UGREEN       | CD134 |

B. Performance Metrics

Given a fingerprint from a wireless charger, WirelessID verifies whether it belongs to the category that it claims to be in. That is, a classifier is maintained for each registered device. For each classifier $i$, we define $TP_i$ as the true positives for classifier $i$, which means that a device is classified correctly, $FN_i$ refers to the number of devices that are wrongly considered the malicious devices and $FP_i$ refers to the number of fingerprints that are wrongly accepted as $i$, respectively. We define the standard classification metrics for each classifier $i$ as: $Pr(i) = \frac{TP_i}{(TP_i+FP_i)}$, $Re(i) = \frac{TP_i}{(TP_i+FN_i)}$, and $F1-Score(i) = \frac{2 \times Pr(i) \times Re(i)}{Pr(i)+Re(i)}$. The final precision, recall and F1-Score for WirelessID are the average of all evaluated wireless chargers.

C. Micro-benchmark Evaluation

In this subsection, we evaluate the impact of classifier choices and sampling rate. All devices from Table I are chosen for the micro-benchmark evaluation.

a) Classifier choice: We compare 10 most commonly used supervised learning algorithms, including 1) Logistic Regression, 2) Gaussian Naive Bayes, 3) K-Nearest Neighbors, 4) Linear Discriminant Analysis, 5) Quadratic Discriminant Analysis, 6) Decision Tree, 7) Support Vector Machine, 8) Extra Trees Classify, 9) Random Forest, and 10) Gradient Boosting. We utilize the default threshold and employ the 10-fold cross validation to evaluate the classifier performance.

We randomly choose 100 traces from each device, feed them into the classifiers and record the corresponding accuracy. The results in Fig. 8(a) show that 3) K-Nearest Neighbors, 7) Support Vector Machine and 8) Extra Trees Classify are the top 3 classifiers in terms of precision, recall, and F1-score. Therefore, we chose Extra Trees Classify as our candidate classifier.

b) Sampling rate: We also set the sampling rate of the collection device from 500kHz to 1MHz, 2MHz, 4MHz and 8MHz respectively. At each sampling rate, we collect 50 traces for each device for training and testing. The resulting precisions and recalls are shown in Fig. 8(b) from which we can observe that there is little change for the three metrics. At all sampling rates, the precision, recall, and F1-score of the system is higher than 98.6%. In order to minimize overhead, WirelessID selects 500 kHz as the sampling rate.

c) Confusion matrix: To evaluate the influences from manufacturers and models, we plot the confusion matrix in terms of classification accuracy. Each cell such as $(i, j)$ in the matrix represents the possibility of classifying $i$ to $j$. The confusion matrix is shown in Fig. 8(c). The results illustrate that all 8 devices are almost classified correctly. There exists slight classification errors between #1 and #2, #4 and #5. We will further improve the accuracy in the future by selecting...
more robust features.

**D. Overall Performance**

a) **Impact of time:** We trained the classifier with the data collected in first month and tested the classifier with the data collected in the second, third, fourth and fifth months. Fig. 9 shows that the three metrics have no correlation with time. That is, the fingerprint is stable and does not change with time.

b) **Impact of environment:** To investigate the impact of environments, we test WirelessID in the office, laboratory and conference room environments. As shown in Fig. 10, WirelessID’s average precision, recall rate and F1-score can all exceed 98%.

c) ** Scalability:** In real-world deployment, WirelessID needs to identify alien devices which are not trained beforehand. We randomly choose 7 devices for training and the rest one serves as alien device. For each device we randomly choose 50 traces to assess whether the alien device is classified as the 7 devices. We repeat the experiment for 20 times to eliminate randomness errors. We plot the miss rate, i.e., the alien device is classified as a registered one and plot the CDF in Fig. [11]. The results reveal that WirelessID hardly misses the alien device with an average probability of only 0.9%.

d) **Impact of other factors:** We also evaluate the receiving distance of the wireless signals from the chargers. Although the receiving distance affects the strength of the received signal, after normalization, the strength of the received signal should not have any affect on the classification performance. Besides, we test different placement angles on the charger. At present, both the transmitting coil and the receiving coil are circular coils, so the change in the placement angle does not matter.

**VI. DISCUSSION**

**A. Security Analysis**

We assume that attackers are aware of the WirelessID system, but cannot compromise the trusted server and the classifiers. This represents the most realistic scenario where attackers have full control of the wireless charger but not the cloud. The goal of the attackers is to fool WirelessID to classify a malicious device as legitimate. Under extreme circumstances, an attacker can record the signal from a legitimate charger and then replay it to confuse WirelessID system, for example, as WirelessID detects only a small segment of the signal located in the head. the attack should fail because the hardware fingerprint of the replay device itself is introduced and the resulted fingerprint is not recognized. Another case is that the attacker may disassemble the inverters from a legitimate wireless charger and then install them on its malicious device. Although the hardware fingerprint of the inverters plays a key role in the signal analysis and authentication, as shown in the figure, LC filter circuit of the wireless charging board and transmitting antenna coil will also contribute to the hardware fingerprint. It is extremely difficult assembly a wireless charger with characteristics identical to another one. Further more, we compared hardware security measures such as PUF and security chip with our WirelessID system. Although these measures can achieve the same hardware certification effect, they require changes to the wireless chargers’ hardware under current standards, so it is not possible to certify existing devices on the market. Attackers can steal exploit the wireless charger already on the market to evade security certification. Compared to These measures, WirelessID does not require additional processing to the device hardware of wireless chargers, nor does it require changes to the existing wireless charging transport protocol (Qi standard). Therefore, WirelessID can certify existing wireless chargers on the market.

**B. Limitations**

The WirelessID system has several limitations to be addressed in the future.

**Implementation on the smartphones.** In our current prototype, we used USRP N210 to collect wireless signals. Since the wireless charging module of smartphones fail to transmit the received charging signals to the OS, WirelessID cannot be directly applied to the existing smartphones. In addition, the extraction of hardware fingerprint requires kHz-level sampling rate. Therefore, we need to add an extra AD sampling chip on a smartphone for signal collections.

**The affect of multiple coils.** Some wireless chargers, e.g., surface charging desk, use multiple induction coils to accommodate different charging locations. According to Qi standard, multiple coils are connected in parallel in the circuit and they share the same inverter. This will be a challenge to WirelessID because different coils plus the identical inverter result in different fingerprints. We can train all the coil+inverter combinations to cope with this situation.

**Software tampering attack.** If an attacker can just tamper with a legitimate wireless charger’s software program to achieve some kind of attack (although most of the currently known attacks require hardware changes), then our WirelessID system may not recognize this kind of attack. So our WirelessID system is focused on identifying and detecting hardware tampering attacks which can pose a greater threat.

**VII. CONCLUSION AND FUTURE WORK**

In this paper, we propose WirelessID, an effective wireless charger fingerprinting system utilizing the non-linear distortion effects of inverters, to detect potential short-range malicious wireless charging attacks. We prototype WirelessID and use it to conduct experiments on 8 commercial wireless charging boards. The results show that WirelessID can achieve 99.0% precision, 98.9% recall and 98.9% F1-score. Moreover, we evaluate factors such as time, environment, sampling rate and location that may affect our system.
In the future work, we will further expand the number and types of tested devices, timely study new wireless chargers, optimize the existing classification model, and improve the generalization ability. We will do more in-depth research on wireless charging attack based on software tampering, and research on wireless charging process protection from more aspects of signal characteristics. Furthermore, we consider the security of mobile reverse wireless charging. The application of reverse wireless charging technology may bring some threats to mobile data and personal privacy, which needs further research.

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