IoT Sentinel: Automated Device-Type Identification for Security Enforcement in IoT

Markus Miettinen
Ahmad-Reza Sadeghi
Technische Universität Darmstadt, Germany
Email: {markus.miettinen,ahmad.sadeghi}
@trust.tu-darmstadt.de

Samuel Marchal
N. Asokan
Aalto University, Espoo, Finland
Email: samuel.marchal@aalto.fi
asokan@acm.org

Ibbad Hafeez
Sasu Tarkoma
University of Helsinki, Finland
Email: {ibbad.hafeez,sasu.tarkoma}
@cs.helsinki.fi

***Abstract*—With the rapid growth of the Internet-of-Things (IoT), concerns about the security of IoT devices have become prominent. Several vendors are producing IP-connected devices for home and small office networks that often suffer from flawed security designs and implementations. They also tend to lack mechanisms for firmware updates or patches that can help eliminate security vulnerabilities. Securing networks where the presence of such vulnerable devices is given, requires a *brownfield approach*: applying necessary protection measures within the network so that potentially vulnerable devices can coexist without endangering the security of other devices in the same network. In this paper, we present IoT Sentinel, a system capable of automatically identifying the types of devices being connected to an IoT network and enabling enforcement of rules for constraining the communications of vulnerable devices so as to minimize damage resulting from their compromise. We show that IoT Sentinel is effective in identifying device types and has minimal performance overhead.**

I. Introduction

The proliferation of the Internet-of-Things (IoT) is an ongoing megatrend in computing with recent forecasts suggesting the number of IoT devices to reach 24 billion in 2020 [1]. More and more people install IP-enabled devices and household appliances in their homes in order to benefit from the improved ability to be informed about and control relevant features of their homes. Examples of emerging IoT systems include automated heating and air conditioning, security systems and home surveillance, lighting or traditional household appliances with added WiFi-connectivity.

Numerous device vendors are providing such connected products to users. Many of these firms are traditional household appliance manufacturers and do not necessarily have expertise in engineering systems with computer security in mind. As a result, there are many reports in the media about IoT devices being deployed in users' homes with security vulnerabilities that can be exploited by attackers (e.g., [2], [3]). There have been reports of a single software flaw affecting a full range of different products, as software components are reused for different device models, thereby placing thousands of Internet-connected IoT devices susceptible for attack [4].

Using vulnerabilities in insecure devices, adversaries can mount attacks against the user's home network. The preferred solution for dealing with device vulnerabilities would be to patch them in order to eliminate weaknesses. However, all too often device vendors are either unable (many users do not register their devices with the device vendor) or unwilling to provide such patches in a timely manner. Most IoT users do not have the skills or willingness to perform such tasks or they even forget unattended IoT devices previously installed in their network leaving them with outdated software versions.

Future security solutions for IoT will need to take into account that IoT devices with unpatched vulnerabilities may often be present in the user's network and co-exist with other devices during their whole device lifetime. The presence of insecure, unpatched legacy IoT devices mandates to accommodate a *brownfield* development approach for security designs: the security mechanisms must be able to co-exist with potentially insecure devices and software that users already have deployed or will deploy in their home networks.

Goals and Contributions. In this paper, we tackle this problem by presenting IoT Sentinel, a system capable of identifying the types of devices introduced to a network and enforcing mitigation measures for device-types that have potential security vulnerabilities. IoT Sentinel does so by controlling the traffic flows of vulnerable devices in order to protect other devices in the network from threats and prevent data leakage.

The contributions of this paper are the following:

- We present the design of IoT Sentinel, a security system (Sect. II) for managing the security and privacy risks posed by insecure IoT devices.
- We introduce a device-type identification technique tailored for IP-enabled IoT devices (Sect. III). Device-type identification, in conjunction with information from vulnerability databases can pinpoint vulnerable devices in a network.
- We demonstrate the accuracy and scalability of IoT Sentinel device-type identification using a large set of different real-world off-the-shelf IoT devices (Sect. V).
- We present a framework using software-defined networking for confining traffic flows of devices identified as vulnerable (Sect. IV).

II. Adversary and System Model

IoT Sentinel is targeted at a typical network setup found in homes and small offices, where devices are connected to

1063-6927/17 $31.00 © 2017 IEEE
DOI 10.1109/ICDCS.2017.283

a gateway router offering wireless and wired interfaces for connecting IP-enabled devices to the network. We assume that when IoT devices are initially connected to the target network they possibly have security vulnerabilities but are initially benign, i.e., uncompromised by the adversary. The adversary's goal is to exploit IoT devices to either a) exfiltrate data, security credentials or encryption keys, b) compromise other IoT devices in the network with the help of a compromised device, or, c) inject false or tampered information into the user's network.

The goal of IoT SENTINEL is to restrict communications in the network so that the adversary is either not able to connect to the vulnerable device to exploit vulnerabilities, unable to use a compromised device to attack other devices in the network, or, unable to exfiltrate data from compromised devices, thereby effectively mitigating attacks or limiting their impact.

To protect the network against adversaries, IoT SENTINEL will 1) identify the device-types of new IoT devices introduced into the network, 2) make a vulnerability assessment of a device using its device-type, and, 3) constrain communication capabilities of the device accordingly. In this paper we focus on #1 and #3. The term *device-type* in this work is defined to denote the combination of *model* and *software version* of a particular device. Device-type identification in IoT SENTINEL is based on monitoring the communication behaviour of devices during the setup process to generate device-specific fingerprints which are mapped to device-types with the help of a machine learning-based classification model. For a given device-type, its potential vulnerability can be assessed by consulting an external information source as we briefly describe in Sect. II-B. Based on the vulnerability assessment, IoT SENTINEL protects the target network by limiting network communications of the vulnerable device accordingly. The design of our solution, shown in Fig. 1, consists of two major components: a *Security Gateway* located in the user's local network and an *IoT Security Service* operated by an IoT Security Service Provider (IoTSSP). A prototype implementation of IoT SENTINEL is presented in [5].

A. Security Gateway

The Security Gateway is a software-defined networking (SDN) based traffic monitoring and control component acting as a gateway router. Devices in the local network connect to the Security Gateway either through WiFi or an Ethernet connection.

Wireless devices use WiFi Protected Setup (WPS) to obtain device-specific credentials in the form of WPA2 Pre-Shared Keys (PSK) for authenticating with the wireless interface of the Security Gateway. This limits a local adversary's ability to impersonate other devices and eavesdrop on encrypted WiFi traffic in case the adversary can successfully compromise a device, as each device has a unique, device-specific PSK. For devices that do not support WPS, Security Gateway will provide a device-specific WPA2-PSK to be used in the setup process for WiFi authentication.

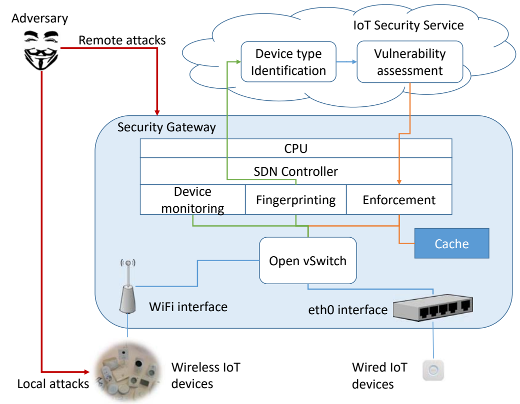


Fig. 1. IoT SENTINEL system design

The Security Gateway monitors and profiles the behaviour of individual devices and sends *device fingerprints* to the IoT Security Service for identification (Sect. III-B) and vulnerability assessment of individual devices. Based on this assessment, the IoT Security Service returns an *isolation level* (Sect. IV) to be enforced by the Security Gateway on the device.

B. IoT Security Service

Based on device fingerprints provided by Security Gateways, the IoTSSP uses machine learning-based classification models to classify devices according to their *device-type*. Ground truth information for training the models can be gathered by crowdsourcing device fingerprints from customers of the IoT Security Service. Contrary to traditional fingerprinting approaches utilising distinctive characteristics of particular data fields in protocol messages, our approach focuses on the behavioural characteristics of devices as discussed in Sect. III. This allows us to profile and classify devices without prior knowledge about the syntax of messages or data field values used by individual devices.

For each device-type in the training data, the IoTSSP performs a vulnerability assessment by querying repositories like the CVE database [6] for vulnerability reports related to the device-type. In case vulnerabilities exist, isolation level *restricted* (cf. Sect IV) is assigned. If no vulnerabilities for the device-type are reported, it is assigned the level *trusted*. Unknown devices will be assigned the level *strict*.

Using the trained classifiers, the IoTSSP identifies the device-types of any new devices by feeding their device fingerprints to the classifier. Based on each device-type's vulnerability assessment, the IoTSSP determines the appropriate isolation level required for the device and notifies the Security Gateway along with possible auxiliary information depending on the assigned isolation level. IoT Security Service does not store any information about its Security Gateway clients, it just receives fingerprints and returns an isolation level accordingly.

C. Mitigation Strategies

We apply following mitigation strategies that aim to maintain as much functionality as possible while minimizing the risk of harm. Their technical implementation is discussed in Sect. IV.

1) Network Isolation: The target of network isolation is to block a potentially vulnerable IoT device from communicating with other devices so that it cannot mount attacks against them. To this end, the Security Gateway divides the user's network into two virtual network overlays: an untrusted and a trusted network. Vulnerable devices are placed in the untrusted network and strictly isolated from other devices.

2) Traffic Filtering: The target of traffic filtering is to hinder adversaries from communicating with vulnerable devices and exploiting vulnerabilities or exfiltrating data. Traffic filtering is performed by the Security Gateway and can be targeted at particular protocols or endpoints so that the functionality of the vulnerable device is affected as little as possible.

3) User Notification: In some cases, network isolation and traffic filtering are not sufficient to provide adequate protection, e.g., if a vulnerable IoT device is equipped with an external communication channel like Bluetooth or an LTE data connection that cannot be controlled by the Security Gateway. Since a compromised device could use this channel for exfiltrating sensitive data, the only effective measure for securing the user's network is to manually remove devices at risk. We therefore envisage a mechanism by which the system notifies the user about devices with insurmountable security flaws, helps her to identify the device in question and make sure that it really is removed from the user's network.

III. IoT Device Identification

In this section we introduce fingerprints specifically designed to discriminate smart home device-types. A two-fold classification system fed with these fingerprints determines the type of unknown devices. The system is tailored for IoT scenarios being able to scale and adapt with minimal cost to a large and variable set of device-types.

A. Device Fingerprint

Our fingerprint is based on passively observed network traffic. It leverages the specificity of smart home devices that need to be inducted into the home network and associated to the gateway by following a device/vendor specific procedure. This procedure is characterized by a distinguishable sequence of communications initiated by the inducted device, which our fingerprint attempts to capture. When a new device identified by a newly observed MAC address starts communicating with the gateway, the latter records n packets $\{p_1, p_2, p_3, \ldots, p_n\}$ received from it during its setup phase. The end of the setup phase can be automatically identified by a decrease in the rate of packets sent. We extract 23 features, giving a vector representation for each packet $p_i = \{f_{1,i}, f_{2,i}, f_{3,i}, \ldots, f_{23,i}\}$ where $i \in \{1, \ldots, n\}$. Hence, a device fingerprint is a $23 \times n$ matrix $\mathbf{F}$ with each column representing a packet received with order $i \in \{1, \ldots, n\}$ and each row representing a packet feature, see Eq. (1). Consecutive identical packets from our feature set perspective (i.e. $p_i = p_{i+1}$) are discarded from $\mathbf{F}$.

TABLE I
Description of the 23 packet features. Features are binary except those marked with "(int)", which are integer.

Type	Features
Link layer protocol (2)	ARP / LLC
Network layer protocol (4)	IP / ICMP / ICMPv6 / EAPoL
Transport layer protocol (2)	TCP / UDP
Application layer protocol (8)	HTTP / HTTPS / DHCP / BOOTP / SSDP / DNS / MDNS / NTP
IP options (2)	*Padding* / *RouterAlert*
Packet content (2)	Size (int) / Raw data
IP address (1)	Destination IP counter (int)
Port class (2)	Source (int) / Destination (int)

$$\mathbf{F} = \begin{array}{c} \\ \\ \end{array}\begin{array}{c} \begin{array}{ccccc} p_1 & p_2 & p_3 & \cdots & p_n \end{array} \\ \begin{pmatrix} f_{1,1} & f_{1,2} & f_{1,3} & \cdots & f_{1,n} \\ f_{2,1} & f_{2,2} & f_{2,2} & \cdots & f_{2,n} \\ f_{3,1} & f_{3,2} & f_{3,3} & \cdots & f_{3,n} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ f_{23,1} & f_{23,2} & f_{23,3} & \cdots & f_{23,n} \end{pmatrix} \end{array} \tag{1}$$

Features used for packet representation are presented in Table I, none of them rely on packet payload, ensuring that fingerprints can be extracted from encrypted traffic. A first set is composed of binary features set to 1 if some selected communication protocols are used. These 16 protocols were chosen because they are typically used during device association over WiFi. Two binary features represent the use of IP header options *padding* and *router alert*. The size of the packet (in bytes) and the presence of raw data is captured. The destination IP address, if any, is mapped to a counter starting from 1 and incremented each time a new destination IP address is observed. This feature denotes the count and order in which a device communicates with different entities during its setup procedure. The two last features represent the source and destination ports used, if any, mapped to network port class:

- no port $\Rightarrow f = 0$
- *well-known* port $[0, 1023] \Rightarrow f = 1$
- *registered* port $[1024, 49151] \Rightarrow f = 2$
- *dynamic* port $[49152, 65535] \Rightarrow f = 3$

Our fingerprints consider the temporal dimension of communication by representing the sequential order in which packets are sent by a device $p_1 \rightarrow p_n$. In contrast to techniques aggregating network traffic statistics over a period of time [7], [8], this extraction method raises some issues for comparison, since fingerprints have variable size n. To cope with this limitations we build a second fixed-size fingerprint $\mathbf{F}'$, composed of the 12 first unique vector packets p from $\mathbf{F}$, concatenated to produce a 276-dimensional feature vector (12 packets $\times$ 23 features):
$\mathbf{F}' = \{f_{1,1}, f_{2,1}, \ldots, f_{23,1}, f_{1,2}, f_{2,2}, \ldots, f_{22,i}, f_{23,i}\}$

Preliminary analysis concluded that 12 packets was a good trade-off for $\mathbf{F}'$ length: long enough to distinguish device-types and short enough to be fully filled with unique packets from $\mathbf{F}$. However, if $\mathbf{F}$ does not contain enough unique packets to fill $\mathbf{F}'$, a padding with 0 values is used to reach the size of 276 features.

B. Device-Type Identification

In order to be scalable and applicable for an evolving number of device-types, we propose a two-fold identification technique. First, we train a single classifier for each device-type. Each classifier provides a binary decision whether the input fingerprint matches the device-type or not. An unknown fingerprint can be accepted by several classifiers and thus match several device-types. In such cases, we break the tie between multiple matches by using an edit distance-based metric. While edit distance could be used alone to identify device-types, this procedure is more time consuming than classification as we will see in Sect V-B. The classification step can be easily applied to thousands of device-types, providing a limited set of device-types to tiebreak via edit distance, ensuring the speed and scalability of the approach.

1) Fingerprint Classification: The device classification is operated using the fixed length fingerprints $\mathbf{F}'$. Let's assume we have a set of fingerprints S for several device-types. We select the subset of n fingerprints $S_{D_i} = \{\mathbf{F}'_{1,i}, \mathbf{F}'_{2,i}, \dots, \mathbf{F}'_{n,i}\}$ for the device-type D_i. The remaining fingerprints of the set are for device-types $D_x \neq D_i$. These fingerprints belong to the complement of S_{D_i} in S: $S^c_{D_i}$. A classifier C_i is trained for identifying the device-type D_i, using all samples from S_{D_i} as one class and a subset of samples from $S^c_{D_i}$ as the other class. Only a subset from $S^c_{D_i}$ is selected for classifier training in order to avoid imbalanced class learning issues. C_i is then able to identify an unknown fingerprint as belonging to the type D_i or not. This process is repeated for each device-type in S in order to build one classifier per device-type. We use Random Forest classification algorithm [9] to build these models.

Using this approach, every time the fingerprint of a new device-type is captured, a new classifier is trained without making any modification to the existing classifiers, avoiding a costly relearning process. This "one classifier per device-type" approach also enables the discovery of new devices since it does not force any fingerprint to belong to one learned class of a multi-class classifier. A fingerprint can be rejected by all classifiers and thus be identified as a new device-type.

2) Edit Distance Tiebreak: If an unknown fingerprint $\mathbf{F}'$ matches several device-types during the classification process, the corresponding full fingerprint $\mathbf{F}$ is compared to a subset of fingerprints from each device-type it got a match for. The fingerprint comparison is done by computing Damerau-Levenshtein edit distance [10], which considers the insertion, deletion, substitution and immediate transposition of characters. We consider the matrix $\mathbf{F}$ as a word with each character being a column of the matrix, i.e. a packet p_i. Character equality for edit distance computation is considered if all features f from a packet p_i are equal to those of another packet p_j. The obtained absolute distance between two fingerprints is divided by the length of the longest one to provide a normalized distance value bounded on $[0, 1]$.

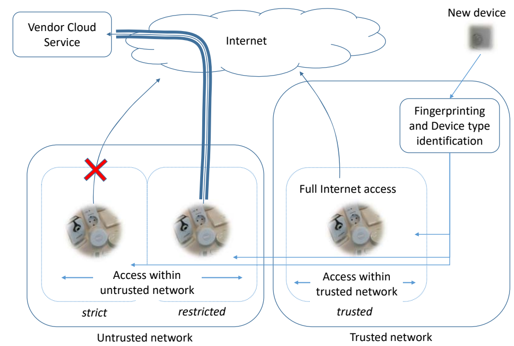


Fig. 2. After fingerprinting and device-type identification, new devices are assigned to isolation level *strict*, *restricted* or *trusted*.

The distance is computed between the fingerprint to identify $\mathbf{F}$ and a subset of five fingerprints from each device-type D_i it got a match for. Distances are summed up per device-type to get a global dissimilarity score $s_i \in [0, 5]$ of $\mathbf{F}$ with the type D_i. The lowest dissimilarity score s_i gives the final predicted device-type for $\mathbf{F}$.

IV. Enforcement

Security Gateway uses Software-defined Networking (SDN) to enable enforcement. We wrote a custom module for Floodlight SDN controller [11] to perform network monitoring tasks, fingerprint generation and to manage communications with IoT Security Service. This module is also responsible for generation and enforcement of restricted network access for connected devices.

When a new device connects to the network, Security Gateway generates a fingerprint from its network activity. This fingerprint is sent to IoT Security Service, which identifies the device-type, determines its required network isolation level and returns it to the Security Gateway. There are three different isolation levels for any device as shown in Fig. 2:

- ***Strict*** isolation level only allows the device to communicate with other devices in the untrusted network overlay with no Internet access for the device.
- ***Restricted*** isolation level allows the device to communicate with other devices in the untrusted network overlay as well as with a limited set of remote destinations on the Internet (e.g., the vendor's cloud service).
- ***Trusted*** isolation level allows the device to communicate with any other device in the trusted network overlay and unrestricted Internet access.

For the *Restricted* isolation level, the IoT Security Service provides to Security Gateway an additional set of IP addresses (or DNS names) with which communications are allowed. Security Gateway stores the received information in local cache and update it through regular queries to the IoT Security Service. Security Gateway uses this information to generate enforcement rules to enforce device-specific isolation level

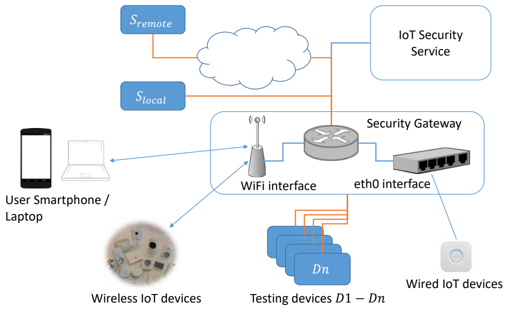


Fig. 3. Lab setup for IoT device monitoring and mitigation enforcement.

required in the network. We identify traffic to/from any device using device MAC addresses.

Network isolation at device level granularity ensures that no vulnerable device, when compromised, is able to infect other devices in the trusted network. Our custom module in the SDN controller intercepts all traffic flows in the network and ensures that they are filtered according to the required isolation level.

Our implementation extends the traffic filtering to make it more specific, up to the level of individual flows. To minimize latency, enforcement rules are stored in a hash table structure to minimize lookup times as the enforcement rule cache grows. Typically, the traffic between two wireless clients connected to same AP is bridged between the clients and does not go to the routing plane. To enable traffic filtering between wireless devices on the same AP, we use OpenWRT and Linux drivers to redirect traffic between wireless clients through Open vSwitch (OVS) for identifying the devices connected to the wireless interface. This allows us to manage device-to-device communications and maintain required isolation between wireless devices [12].

V. Evaluation

To evaluate our apprach, we developed a prototype system in an IoT laboratory environment shown in Fig. 3. We simulated the IoT device setup process and collected packets sent by each device during the setup process. The collected data were used to build classification models for IoT device identification as described in Sect. III.

A. Device Fingerprint Collection

Measurement collection was implemented with a Linux Laptop running Kali Linux. The software package `hostapd` was used to set up a WiFi access point on the laptop emulating the WiFi interface on a WiFi AP. Similarly, an external Ethernet interface was connected to the laptop for emulating the Ethernet ports typically present on APs. The packet capture module was implemented by using `tcpdump` on the monitored WiFi and Ethernet interfaces so that all network traffic visible to the Security Gateway on both wireless and wired network interfaces could be recorded and forwarded to the fingerprinting module. Data collection was controlled by a scripted UI showing the test person performing the device setup process the necessary step-by-step instructions required to complete the connection of each device to the network. The test scripts were manually compiled following the printed or on-line user manual of each device. The setup process of most of the examined IoT devices was facilitated with a smartphone app or in a few cases a PC application. For such devices, the corresponding app was installed on a testing smartphone or laptop and used in the setup process according to the provided instructions.

1) Tested devices: A representative set of IoT devices targeted for regular consumers that were available in the European market during Q1 2016 was selected for our experiments. These covered most common device classes related to smart lighting, home automation, security cameras, household appliances and health monitoring devices. Most of the tested devices were connected to the user's network via WiFi or Ethernet, but some devices used other IoT protocols like ZigBee or Z-Wave to connect to the network indirectly through an Ethernet or WiFi hub device. For such devices, we focused on monitoring the indirect traffic generated by the hub device acting as a gateway towards the user's network. The detailed list of tested devices is available in a full technical report [13].

For each tested device, the typical device setup process was repeated $n = 20$ times in order to generate sufficient fingerprints for classification model training. After each testing round, a hard reset of the tested device was performed to return it to its default factory settings. Typically, a setup procedure for a device involved activating the device, connecting to the device directly over WiFi (the device sets up an ad-hoc WiFi access point) or Ethernet with the help of a vendor-provided app and transmitting WiFi credentials to the user's network over this connection to the device. After this, the device would typically reset and connect to the user's network using the provided credentials. During this setup procedure, all network traffic visible to the Security Gateway was recorded and provided to the fingerprinting module for further processing. The fingerprints generated were then transferred to the IoT Security Service for off-line training of the classification model. The dataset collected from our evaluation setup is publicly available for research use [14].

B. IoT Device Identification

The fingerprints $\mathbf{F}$ and $\mathbf{F}'$ were extracted from the traffic captures following the technique introduced in Sect. III-A to obtain a dataset of 540 fingerprints representing 27 device-types. The IoT device identification method was evaluated through a stratified 10-fold cross-validation process using this dataset. At each fold, we used the training data to learn one classification model per device-type taking all the n fingerprints $\mathbf{F}'$ of the targeted type as one class and *10*n* randomly selected fingerprints $\mathbf{F}'$ from the rest to represent the other class. The testing data were subjected to the 27 learned models to get a prediction from each. In case of positive decision from several classifiers, edit distance tiebreak was performed using fingerprints $\mathbf{F}$ randomly selected from

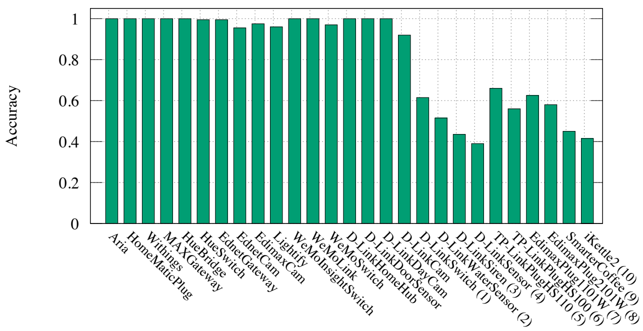


Fig. 4. Ratio of correct identification for 27 device-types

the training data as described in Section III-B. The cross-validation was repeated 10 times to generalize the results.

The ratio of correct identification for each device-type is reported in Fig. 4. The accuracy of identification is over 0.95 for 17 devices, most of them reaching 1. However, we can see that 10 devices are correctly identified with an accuracy around 0.5, which is lower but still good considering a random type assignment that would give $1/27 = 0.037$ accuracy. The global ratio of correct identification over the 27 devices is 0.815. To better understand why the 10 aforementioned devices got identified with lower accuracy than others, Table II depicts their confusion matrix. We can see that the misidentification occurs between similar devices from same vendors, i.e., a set of similar D-Link devices (1-4), two models of smart plugs from TP-Link (5-6) and Edimax (7-8) and a coffee machine (9) and water kettle (10) from the same vendor. In contrast, Fig. 4 shows that our identification technique is able to distinguish devices from same vendor with different purposes, e.g., D-Link camera, hub and sensors, WeMo devices, Edimax camera and plug, etc. From a system point of view, the misidentified devices are very similar: D-Link water sensor (2), siren (3) and sensor (4) have identical hardware and firmware version, as TP-Link plugs (5-6) do. Hence, these devices are likely to share vulnerabilities, if any and this specific misidentification issue is not a concern for our purpose of identifying vulnerable devices.

TABLE II
CONFUSION MATRIX FOR 10 DEVICES WITH LOW IDENTIFICATION RATE (DEVICE INDEX FIND CORRESPONDING NAMES IN FIG. 4)
A= ACTUAL TYPE / P= PREDICTED TYPE

A\P	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
1	123	23	28	26	0	0	0	0	0	0
2	0	103	42	55	0	0	0	0	0	0
3	4	55	87	54	0	0	0	0	0	0
4	8	65	49	78	0	0	0	0	0	0
5	0	0	0	0	132	68	0	0	0	0
6	0	0	0	0	88	112	0	0	0	0
7	0	0	0	0	0	0	125	75	0	0
8	0	0	0	0	0	0	84	116	0	0
9	0	0	0	0	0	0	0	0	90	110
10	0	0	0	0	0	0	0	0	117	83

From a performance perspective, Tab. III reports the time taken for device-type identification. We see that most of the time is spent on cases where tiebreak using edit distance was required. During experiments, 55% of the analyzed fingerprints matched more than one type and needed a tiebreak step that involved between two and five types. On average, seven edit distance computations were needed per device. The average time for device-type identification is around 150 ms. For comparison, the time taken for device setup was between one and two minutes, the packet collection was performed in parallel of this operation. The classification with Random Forest takes very little time (<1 ms) and grows linearly with the number of types to identify. This shows that IoT SENTINEL can easily scale to thousands of device-types while keeping classification time below 100 ms and type identification likely below 1 second.

TABLE III
TIME CONSUMPTION FOR DEVICE-TYPE IDENTIFICATION. TIME FOR SINGLE STEPS IS PRESENTED AT THE TOP AND TIME FOR AN AVERAGE TYPE IDENTIFICATION IN OUR LAB SETUP IS PRESENTED BELOW.

Steps	**Mean (±StDev)**
1 Classification (Random Forest)	0.014 ms (±0.003)
1 Tiebreak (edit distance)	23.36 ms (±24.37)
Fingerprint extraction	0.850 ms (±0.698)
27 Classifications (Random Forest)	0.385 ms (±0.081)
7 Tiebreaks (edit distance)	156.5 ms (±170.6)
Type Identification	**157.7 ms** (±171.4)

C. Mitigation Measures Enforcement

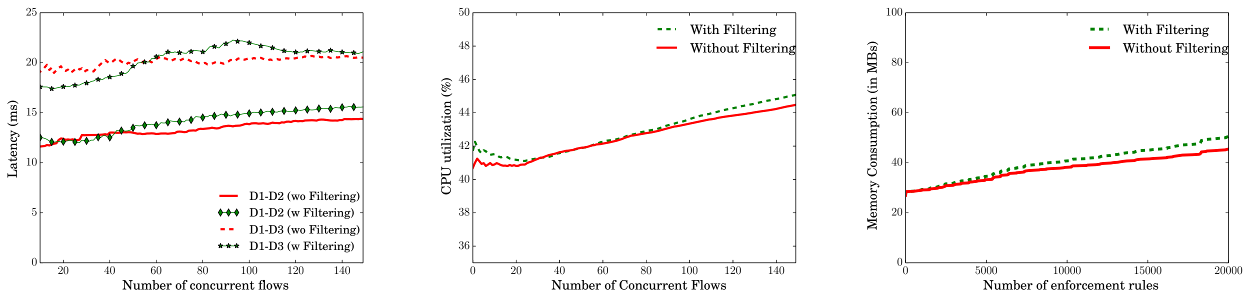
Fig. 3 shows the lab setup used for testing enforcement mechanism employed by Security Gateway. We used a Raspberry PI 2 (R-Pi II) running both OVS and the SDN controller to take the role of Security Gateway in the network. An external USB WiFi dongle and `hostapd` was used to emulate the wireless interface on R-Pi II.

For each experiment, we performed 15 iterations for each measured device pair. We measured the latency experienced between devices $D_1 - D_n$ connected to Security Gateway wireless interface, as well as between devices and servers, where S_{local} is in the local network and S_{remote} is a remote server deployed in Amazon EC2. Table IV shows that the enforcement mechanism employed for traffic filtering by Security Gateway does not impact the latency experienced by the user. Fig. 5a shows the impact on latency experienced by devices regarding the total number of concurrent flows in the network. The results show that the increase in latency for up to 150 concurrent flows is insignificant to affect user experience or device operations.

We also measured the memory and CPU overhead of our enforcement mechanism. Fig. 5b shows that there is very little overhead in terms of CPU utilization due to traffic filtering mechanism. The overall CPU utilization

TABLE V
OVERHEAD DUE TO FILTERING MECHANISM.

Case	**Overhead Mean (± StDev)**
$D1D2$ Latency	+5.84% (±4.76%)
$D1D3$ Latency	+0.71% (±5.88%)
CPU utilization	+0.63% (±1.8%)
Memory usage	+7.6% (±4.6%)



(a) **Latency increase relative to concurrent flows.** (b) **CPU utilization for Security Gateway.** (c) **Memory utilization of Security Gateway.**

Fig. 5. **IoT Sentinel Performance evaluation for Raspberry PI based deployment of Security Gateway.** *There is only minimal increase in CPU and memory utilization of Security Gateway with filtering mechanism enabled. Additionally, the increase in latency experienced relative to increasing number of concurrent flows in the network is insignificant in terms of user experience.*

TABLE IV
LATENCY (MS) EXPERIENCED BY USERS WHERE $D1 - D4$ ARE USER DEVICES CONNECTED TO SECURITY GATEWAY (SGW) AND S_{local} AND S_{remote} ARE SERVERS.

Source	Destination	Filtering Mean (± StDev)	No Filtering Mean (± StDev)
$D1$	$D4$	24.8 (±1.4)	24.5 (±1.4)
	S_{local}	18.4 (±1.3)	18.2 (±1.3)
	S_{remote}	20.6 (±3.3)	20.3 (±3.1)
$D2$	$D4$	28.5 (±1.7)	28.2 (±1.6)
	S_{local}	17.2 (±1.2)	17.0 (±1.2)
	S_{remote}	20.0 (±2.9)	19.8 (±3.1)
$D3$	$D4$	27.6 (±1.6)	27.5 (±1.6)
	S_{local}	15.5 (±1.2)	15.4 (±1.1)
	S_{remote}	20.6 (±3.2)	19.9 (±3.2)

measurements also shows that Security Gateway does not require high processing power to perform network operations.

Similarly, Fig. 5c shows the amount of memory utilized by Security Gateway with and without using filtering mechanism is almost similar. The amount of memory used for storing enforcement rules can be controlled by limiting the size of enforcement rule cache and removing unused enforcement rules (for the devices that are no longer connected to the network) from the cache. The percentage increase in memory, CPU utilization as well as latency experienced by user due to filtering mechanism is given in Table V. These results show that the overhead on memory and CPU utilization is low. Fig. 5 also shows that a small form factor PC such as Raspberry Pi II provides sufficient computational resources for a typical environment hosting, e.g., a hundred IoT devices generating the same number of concurrent flows and requiring as many enforcement rules.

VI. Related Work

A. Securing IoT Device-to-Device Communications

Authentication schemes tailored for resource constrained devices [15] are primarily used to control communications between IoT devices. Zenger et al. [16] proposed a vicinity based pairing mechanism that delegates trust from one node to another based on physical proximity. Messaging between devices can be authenticated using multiple communication channels (e.g. Bluetooth + NFC) to ensure secure pairing [17]. However, these schemes require some implementation on all devices of the system to be applicable, failing to cope with the IoT brownfield of legacy devices already deployed.

At run time, communications between IoT devices can be restricted based on high level user requirements that a system, namely SIFT [18], translates to low level access control policies. Fully automated techniques to identify malicious communications rely on intrusion detection systems tailored for IoT scenarios [19]. Verification of data sent from a given device can be based on measurement correlation with other devices to identify malicious nodes attempting to pollute measurements [20]. The main difference between IoT Sentinel and these techniques is that the former is preventive, mitigating the threat of vulnerable devices when they are inducted in the system and before any malicious communication is initiated.

B. Device Fingerprinting

Early work in 802.11 wireless communication fingerprinting targeted the identification of hardware and driver specific characteristics. Cache [21] used 802.11 frames' duration field that only takes few discrete values depending on driver implementation to identify WiFi drivers. Passively recording 802.11 probing frames inter-arrival time from a device, Franklin *et al.* [7] were able to classify 17 WiFi drivers with an accuracy ranging between 77% and 96% using a Bayesian classification method. While relying on passively captured network traffic as we do, these techniques build hardware/driver specific fingerprints that are too coarse-grained for our purpose of identifying device-types. Low cost IoT devices are likely to use identical cheap WiFi interfaces and corresponding drivers leading to aggregate a wide range of device-types in the same class using these techniques.

On the other hand, the fingerprinting of specific users is achieved using network features such as packet destination, SSID probes, broadcast packet size and MAC protocol fields [8] or web transaction characteristics [22]. Hardware specific characteristics such as clock skew [23] or radio-frequency signature [24] can be used to identify a unique network interface card, mostly for rogue wireless Access Point detection purposes. IoT-specific techniques target mostly high-end devices, leveraging mobile device configuration [25], or sensor specific features [26]. However, sensor data analysis only addresses the identification of a limited class of devices actually reporting such information. All these methods build fingerprints able to uniquely identify a device, which is too specific to identify an unknown device as belonging to one type. Our technique is positioned between the former and latter approaches, providing the right granularity to identify device-types from passive traffic captures.

Gao *et al.* [27] similarly introduced a passive technique to identify device-types using the fact that a type of device modifies a packet in a unique way, due to its internal architecture, while processing it. Capturing incoming and outgoing packets and applying wavelet analysis, they were able to discriminate device-types. This technique only applies to devices processing and forwarding packets such as routing devices but is not applicable to end point IoT devices that we target in our work.

GTID [28] also addresses device-type identification. GTID builds a feature vector composed of inter-arrival time of packets sent by a device for a specific type of traffic (e.g. Skype, ICMP, etc.). Feature vectors are used in a neural network predicting as many classes as there are device-types to identify. The main difference with our work is that our fingerprints are not specific to a type of traffic sent at high rate over a significant period of time. In contrast to devices used for GTID evaluation, i.e., smartphones and tablets, most IoT devices generate little traffic with little diversity limiting this approach to high-end devices. Our technique has a wider scope, applying to wireless and wired traffic. In addition, using a single multi-class neural network model in GTID requires full model relearning when one new type is identified while our "one classifier per type approach" does not.

VII. Future Work

In this work, we defined a device-type to denote the combination of a device's model and software version. In our set of test devices, only a few devices offered the possibility for a software update during our experimentation period, so we were not able to comprehensively investigate the impact of updates. For three devices for which updates were applied, they led to generate distinguishable fingerprints between software versions of these devices. In our future work we expect to be able to investigate this further, as we expect over time software updates to become available for more devices.

Acknowledgments: This work was supported in part by the Academy of Finland (grant 274951) and Intel Collaborative Research Center for Secure Computing (ICRI-SC). We would also like to thank Tommaso Frassetto and Igor Braun for their support in the implementation of the IoT Sentinel system.

References

[1] J. Greenough, "How the 'Internet of Things' will impact consumers, businesses, and governments in 2016 and beyond," http://www.businessinsider.de/how-the-internet-of-things-market-will-grow-2014-10, Business Insider, [Accessed: 2016-07-18].

[2] Core Security, "AVTECH DVR multiple vulnerabilities," http://www.coresecurity.com/advisories/avtech-dvr-multiple-vulnerabilities, Aug. 2013, [Accessed: 2016-03-29].

[3] D. Lodge, "Hacking a Wi-Fi coffee machine – part 1," https://www.pentestpartners.com/blog/hacking-a-wi-fi-coffee-machine-part-1/, 2015, [Accessed: 2016-03-29].

[4] Senrio. 400,000 publicly available IoT devices vulnerable to single flaw. [Accessed: 2016-07-07]. [Online]. Available: http://blog.senr.io/blog/400000-publicly-available-iot-devices-vulnerable-to-single-flaw

[5] M. Miettinen *et al.*, "IoT Sentinel Demo: Automated device-type identification for security enforcement in IoT," in *Proc. 37th IEEE International Conference on Distributed Computing Systems (ICDCS 2017)*. IEEE, Jun. 2017.

[6] MITRE Corporation. Common vulnerabilities and exposures. [Online]. Available: https://cve.mitre.org/data/downloads/index.html

[7] J. Franklin *et al.*, "Passive data link layer 802.11 wireless device driver fingerprinting," in *USENIX Security Symposium*. USENIX, 2006.

[8] J. Pang *et al.*, "802.11 user fingerprinting," in *Proceedings of the 13th Annual ACM International Conference on Mobile Computing and Networking*, ser. MobiCom '07. ACM, 2007, pp. 99–110.

[9] L. Breiman, "Random forests," *Machine Learning*, vol. 45, no. 1, pp. 5–32, 2001.

[10] F. J. Damerau, "A technique for computer detection and correction of spelling errors," *Commun. ACM*, vol. 7, no. 3, pp. 171–176, Mar. 1964.

[11] Big Switch Networks, "Project floodlight - floodlight OpenFlow controller," http://www.projectfloodlight.org/floodlight/, Oct. 2016, [Accessed: 2016-09-17].

[12] S. Hätönen *et al.*, "Off-the-shelf software-defined Wi-Fi networks," in *ACM SIGCOMM*. ACM, 2016, pp. 609–610.

[13] M. Miettinen *et al.*, "IoT Sentinel: Automated device-type identification for security enforcement in IoT," *CoRR*, vol. abs/1611.04880, 2016. [Online]. Available: http://arxiv.org/abs/1611.04880

[14] ACRIS, "IoT devices setup captures (IoT Sentinel experiments)," https://research.aalto.fi/files/11504588/captures_IoT_Sentinel.zip.

[15] J. L. Hernández-Ramos *et al.*, "Toward a lightweight authentication and authorization framework for smart objects," *IEEE Journal on Selected Areas in Communications*, vol. 33, no. 4, pp. 690–702, 2015.

[16] C. T. Zenger *et al.*, "Authenticated key establishment for low-resource devices exploiting correlated random channels," *Computer Networks*, pp. –, 2016.

[17] V. Mora-Afonso *et al.*, "Strong authentication on smart wireless devices," in *Second International Conference on Future Generation Communication Technologies (FGCT)*, 2013, pp. 137–142.

[18] C.-J. M. Liang *et al.*, "SIFT: Building an internet of safe things," in *Proceedings of the 14th International Conference on Information Processing in Sensor Networks*. ACM, 2015, pp. 298–309.

[19] S. Raza *et al.*, "SVELTE: Real-time intrusion detection in the internet of things," *Ad Hoc Networks*, vol. 11, no. 8, pp. 2661 – 2674, 2013.

[20] S. Gisdakis *et al.*, "SHIELD: A data verification framework for participatory sensing systems," in *Conference on Security & Privacy in Wireless and Mobile Networks*. ACM, 2015, pp. 16:1–16:12.

[21] J. Cache, "Fingerprinting 802.11 implementations via statistical analysis of the duration field," *Uninformed*, vol. 5, 2006.

[22] R. Tomšů *et al.*, "Profiling users by modeling web transactions," in *IEEE International Conference on Distributed Computing Systems*, 2017.

[23] T. Kohno *et al.*, "Remote physical device fingerprinting," *IEEE Trans. Dependable Secure Comput.*, vol. 2, no. 2, pp. 93–108, April 2005.

[24] V. Brik *et al.*, "Wireless device identification with radiometric signatures," in *International Conference on Mobile Computing and Networking*. ACM, 2008, pp. 116–127.

[25] A. Kurtz *et al.*, "Fingerprinting mobile devices using personalized configurations," *Proceedings on Privacy Enhancing Technologies*, vol. 1, pp. 4–19, 2016.

[26] T. Van Goethem *et al.*, "Accelerometer-based device fingerprinting for multi-factor mobile authentication," in *Symposium on Engineering Secure Software and Systems*, 2016, pp. 106–121.

[27] K. Gao *et al.*, "A passive approach to wireless device fingerprinting," in *Proceedings of the 2010 IEEE/IFIP International Conference on Dependable Systems Networks (DSN)*. IEEE, 2010, pp. 383–392.

[28] S. V. Radhakrishnan *et al.*, "GTID: A technique for physical device and device type fingerprinting," *IEEE Trans. Dependable Secure Comput.*, vol. 12, no. 5, pp. 519–532, 2015.