

Smartphones in a Microwave: Formal and Experimental Feasibility Study on Fingerprinting the Corona-Warn-App

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ABSTRACT

Contact Tracing Apps (CTAs) have been developed to contain the coronavirus disease 19 (COVID-19) spread. By design, such apps invade their users' privacy by recording data about their health, contacts, and—partially—location. Many CTAs frequently broadcast pseudorandom numbers via Bluetooth to detect encounters. These numbers are changed regularly to prevent individual smartphones from being trivially trackable. However, the effectiveness of this procedure has been little studied.

We measured real smartphones and observed that the German Corona-Warn-App (CWA) exhibits a device-specific latency between two subsequent broadcasts. These timing differences provide a potential attack vector for fingerprinting smartphones by passively recording Bluetooth messages. This could conceivably lead to the tracking of users' trajectories and, ultimately, the re-identification of users.

CCS CONCEPTS

• Security and privacy → Pseudonymity, anonymity and untraceability.

KEYWORDS

Anonymity, contact tracing, fingerprinting, privacy, pseudonymity

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1 INTRODUCTION

The coronavirus pandemic was the first pandemic in which we, i.e. humanity, had the means to observe its spread in real time. This wealth of information posed and continues to pose a challenge to societies around the world. More information allows to take the right decisions to slow the spread of a pandemic, one might conclude. Or does it though?

The greater goal, limiting the spread of the virus or at least slowing it down, is in conflict with individual freedom rights. In a first response, many governments opted to bring public live to a halt. This understandable and early response was not sustainable. Traditionally, one would aim to only isolate those who are infected,

but this approach was undermined by the fact that individuals with asymptomatic infection can also transmit the virus [13].

This has led to the first ever large-scale introduction of automatic contact tracing by means of Contact Tracing Apps (CTAs). Such apps record their users' contacts and alert them in case of a close encounter with an infected person. In 2020, Google and Apple integrated extensive contact tracing functionality into their respective mobile operating systems, and many national authorities worldwide deployed CTAs since then that have been used by millions of people, cf. [23] for more information on downloads and active usage in Europe.

CTAs inherently concern their users' privacy as they process personal contact and health data. The German Corona-Warn-App (CWA) [2] and numerous other CTAs operate by broadcasting a pseudorandom number (*pseudonym*) several times per second via Bluetooth Low Energy (BLE) to all nearby devices. Linking the pseudonym to a real person might allow an adversary to gain insights into their infection status or movement patterns. Developers have implemented basic privacy protection mechanism, but their effectiveness has not been proven. Due to this conceivable profound privacy threat, many legal frameworks, particularly the General Data Protection Regulation (GDPR) [11], hence require a Privacy Impact Assessment (PIA), which must be based on a thorough threat analysis. This PIA should happen in the light of article 9 GDPR which establishes a special protection of health data.

As the virus' spread slowed down and with the wide availability of vaccines, many CTAs are discontinued, i.e. infrastructure has been scaled down or switched off and maintenance of the apps has been brought to a hold. Therefore, imitate privacy risks of CTAs got reduced. However, two concerns remain: First, what happens to the contact tracing functionality implemented in the Android and iOS operating systems? Has this come to stay and pose a continuous threat to security? Second, while maintenance for e.g. the CWA has stopped, it is not actively removed from users' phones but considered to hibernate.¹ However, the semantics are unclear in many ways: Under which circumstances can such a hibernating app be woken up, i.e. which political and scientific process decides if a new pandemic is severe enough? What form of maintenance will be provided for such an app?

While the above questions are not subject of this paper, we observe that WHO epidemiologists expect that "COVID-19 will not be the last" pathogen with pandemic potential and the next one "could appear at any time" [25]. With this paper, we aim to

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¹The German Federal Minister of Health, Karl Lauterbach, says that as of June the German CWA will hibernate (<https://www.tagesschau.de/inland/innenpolitik/corona-warn-app-ende-100.html>).

contribute to the PIA if electronically aided contact tracing is reconsidered in the future.

Our contribution consists of two experiments. We used low-cost and off-the-shelf hardware to monitor the BLE sending behavior of smartphones with the German CWA installed. In our first experiment, we observed 15 smartphones in a shielded laboratory environment. It showed that the average latency between two successive broadcasts varies across devices and is stable over time. This characteristic acted as a fingerprint for some device and uniquely identified them among all tested phones. We were able to replicate our observations in a second experiment in busy public places in the city of Münster. To the best of our knowledge, our paper provides the first study investigating device fingerprinting of smartphones running a CTA. This in turn brings us to the conclusion that further investigations are needed.

2 RELATED WORK

A large body of research exists on fingerprinting computing devices. Publications on fingerprinting typically fall into two categories: logical fingerprints and physical fingerprints. In the first case, devices are distinguishable due to differences in their software behavior; in the latter case, devices are different due to some physical process, e.g. manufacturing tolerances of a crystal which in turn influences the exact clock rate of a device.

Fingerprinting on Logical Behavior. Browser Fingerprinting aims to create fingerprints of web browsers to recognize returning visitors to a website. In 2009, Mayer [20] conducted a small-scale experiment and collected different information such as JAVASCRIPT objects (e.g. navigator, screen, Plugin, MimeType, among others) from 1328 web browser to generate a fingerprint.

Panoptlick [10] replicated and extended the former results in 2010 in a large-scale experiment with 470 162 browser fingerprints and additional features with Flash and Java. These studies marked the beginning of a discipline; since then, the scientific community has improved fingerprinting continuously, further aided by the introduction of new Application Programming Interfaces (APIs) by the World Wide Web Consortium (W3C) to provide rich multimedia content on web pages. Studies [3, 21] discovered that the Canvas API could be exploited to offer high-entropy attributes for a fingerprint. Further, a study [7] designed fingerprinting techniques based on the WebGL API. We refer interested readers to [19] for a detailed survey of browser fingerprinting.

Researchers [12, 16, 26] found that even complex network protocols such as Transport Layer Security (TLS) and OpenVPN are fingerprintable by the protocol handshake. Similarly for Bluetooth, Celosia and Cunche [8] showed that the GATT profile of the Bluetooth stack contains identifying characteristics. By connecting to nearby discoverable devices, they could collect complete GATT profiles to obtain fingerprints which are unique in many cases.

Fingerprinting Using Physical Attributes. Crystal oscillators are being used to generate the required frequency for any radio device. Due to small imperfections in production, their actual frequencies are slightly off target [24]; hence, devices have a unique frequency. It has been shown that this frequency offset can be used to distinguish devices [4, 14]. Similar results have been established using

the deviation of the device clock's speed from real-time [17, 18]. For Bluetooth, Huang et al. [15] exploited the frequency hopping behavior to extract a device's *clock skew* and use this as a fingerprint.

Our work falls between these two broad categories: We measure timing behavior which is partially influenced by the logic of the CWA, the logic of the underlying API by Google and Apple, and the logic of the operating system and particularly the BLE stack, but at the same time, our measurements are influenced by the accuracy of the underlying clocks.

3 TECHNICAL BACKGROUND

This section explains the technical foundation of the CWA which uses Bluetooth Low Energy for broadcasting the pseudonyms provided by the Google/Apple Exposure Notification (GAEN) API.

3.1 Bluetooth Low Energy

BLE [6] is a wireless communication standard introduced in 2010. Initially designed for battery-powered gadgets such as smartwatches and Internet of Things applications, it is nowadays supported by almost all modern devices. BLE uses 40 channels in the 2.4 GHz ISM band; 37 of these are used for data transfer while the other three *advertising channels* are reserved for devices to signal their presence. To do so, a device broadcasts *advertisement* frames to all nearby devices indicating e.g. its connectivity and characteristics. Moreover, this broadcast mechanism can be used to transmit small amount of data without establishing a connection between sending and receiving device.

The sender of a BLE message is identified by a 48 bit MAC address. For basic privacy protection, BLE introduced randomized MAC addresses: instead of broadcasting its globally unique MAC address, the device can generate a random number to be sent in place of the persistent identifier. Due to the length of this number, collisions occur extremely rarely so that the randomized MAC address is a unique identifier for its period of validity. The longevity and change is carried out by the device, the Bluetooth specification [6, Vol. 3, Part C, App. A] merely recommends to change it after at most 15 minutes.

3.2 Exposure Notification

In April 2020, Apple and Google jointly announced the integration of contact tracing directly into their respective mobile Operating System (OS), naming it *Exposure Notification* [1], or GAEN for short. When activated by the user, the OS generates pseudorandom 128 bit numbers (*pseudonyms*) which are changed every 10 min to 20 min according to the documentation [5]. GAEN frequently emits these pseudonyms with a recommended waiting time of 200 ms to 270 ms between two sendings, a delay which we refer to as Inter-Broadcast Latency (IBL). Additionally, the device listens to other smartphones' broadcasts and logs the pseudonyms it receives. An infected individual can decide to upload specific keys to a server which allow other phones to reconstruct their emitted pseudonyms. This key material is regularly fetched by every participating smartphones and employed to calculate a contagion risk for its user.

This functionality is implemented as an API on the OS level. Authorized apps like the CWA can access this API to provide a

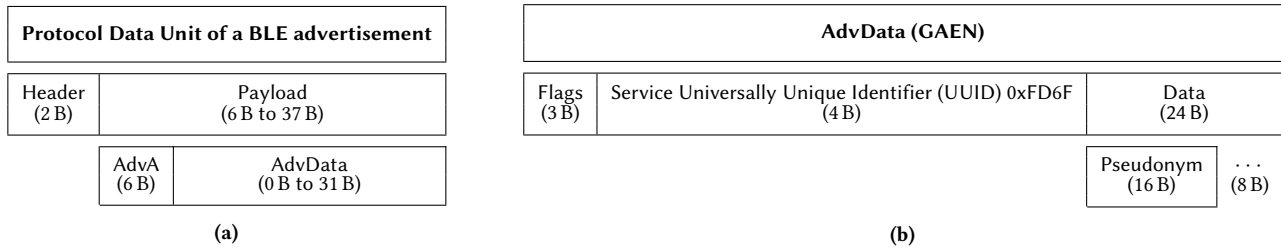


Figure 1: Structure and content of (a) the Protocol Data Unit of a `ADV_NONCONN_IND` type BLE advertisement [6, Vol. 6, Part B, Sec. 2.3] and (b) the `AdvData` field of a GAEN broadcast [5]

frontend to the user, but the underlying contact tracing function—especially the BLE broadcasting—is nevertheless not influenced by the app.

The GAEN API emits its information in the data unit of an `ADV_NONCONN_IND` type advertisement packet whose general structure is shown in Fig. 1a. It is comprised of a 2 byte header and a payload of variable size. The latter contains a field `AdvA` for the device’s (possibly randomized) MAC address as well as the `AdvData` whose content is variable. As can be seen in Fig. 1b, Google and Apple have defined it to contain two main ingredients:

- A UUID `0xFD6F` by which other smartphones can detect a GAEN broadcast among packets for other purposes.
- The pseudorandom 16 bit contact tracing pseudonym.

The MAC address is randomized in sync with the pseudonym as performing their change asynchronously would clearly annihilate the intended privacy protection.

The present, very frequent broadcasting is a design decision in favor of the app’s utility. While a lower broadcasting frequency would restrict the possibility of continuous device monitoring, it would also increase the risk of not detecting infectious encounters, eventually making the app less valuable from a medical perspective.

4 FORMAL BACKGROUND AND PRIVACY METRIC

In this section, we provide the terminological and mathematical background of analysing fingerprintability.

4.1 Pseudonym Types and Anonymity

In general, pseudonyms are identifying an entity in a given context. If the relation between the identity and pseudonym can be hidden from an adversary, a pseudonym can provide a certain level of privacy protection. The level of privacy protection pseudonyms can provide is depending on their usage; in particular, it depends on for how long and in which contexts they are used. For a systematic discussion on pseudonym types we refer to [22].

Following this terminology, GAEN pseudonyms are short term role pseudonyms, i.e. in its role as a participant of GAEN, an app user provides this pseudonym during interactions with other app users for a given time period. These pseudonyms are only used in the context of the app, hence by individuals in their role as app users. In the case of GAEN, users are broadcasting their pseudonym for 10 min to 20 min. During said period, all broadcast messages of the same user can be linked to each other. After said time period, users

will change their pseudonym, rendering it theoretically impossible to trivially *link* pseudonyms of different time periods. Here by *link* we mean that an adversary can distinguish if two or more pseudonyms belong to the same entity or not.

The way pseudonyms are used in GAEN allows a certain level of privacy protection: under the assumption that pseudonyms of different time periods cannot be *linked*, users’ trajectories cannot be reconstructed even if an adversary can observe broadcast messages at many locations and over longer periods of time. In other words, these pseudonyms provide a certain level of conditional anonymity.

4.2 Mathematical Treatment

To measure fingerprintability, we adapt the *degree of anonymity* model proposed by Diaz et al. [9]. The authors consider an adversary whose goal is to deanonymize the users of a system, e.g. a sender-recipient system. By observing the system, the adversary obtains probabilities about whether a user is the sender of a particular message. The normalized Shannon entropy of this probability distribution is then taken as a measure for the anonymity that the system provides.

Transferring this to fingerprinting, suppose an adversary observes n data points $X = \{x_1, \dots, x_n\} \subseteq \mathbb{R}$ over time originating from different entities and tries to group the data points according to their sources. For each entity, the data may vary and therefore can only be measured with some uncertainty $\varepsilon > 0$ even if the adversary has unrestricted measuring accuracy. A fingerprinting attack then is the attempt to partition X into subsets of data originated from the same entity. Such an attack is obviously more successful if the data are precise (i.e. ε is small) and admit high variation.

The amount of information that the adversary gains from the observed characteristic X can be quantified as follows: By grouping the data set X into k bins $1, \dots, k$ of width ε , we obtain the histogram of a discrete probability distribution. The probability p_i of bin $i = 1, \dots, k$ is given by the number of elements in that particular bin divided by the number of total data points n . Practically, elements in the same bin can be considered indistinguishable by the adversary as their distance is at most the uncertainty ε . Hence, the maximum information the adversary can obtain from their observations is quantified by the Shannon entropy of that histogram:

$$H(X) = - \sum_{i=1}^k p_i \log_2(p_i) \quad (\text{where } 0 \log_2(0) = 0)$$

Technically, note that the probabilities p_i depend not only on ε but on the location of the bins on the x -axis as well which we

did not define. The above term $H(X)$ is understood to be the maximum of the right hand side over all (finitely many) probability distributions for different bin locations. Even an adversary with unlimited background knowledge could not gain more than $H(X)$ information from their observations.

If data precision and variation are high, then $k > n$ and p is the uniform distribution $p_i = \frac{1}{n}$ which results in a maximum entropy of $\log_2(n)$. On the other hand, a low precision or variation leads to data points from different entities in the same bin and in the most extreme case of $p_i = 1$ for one bin i to $H(X) = 0$.

Similar to [9] we say that the data set X with precision ε provides a *fingerprinting anonymity* of

$$A(X, \varepsilon) = 1 - \frac{H(X)}{\log_2(n)} \in [0, 1].$$

Note that our definition is almost literally the same as the *degree of anonymity* given in [9], but in our case, the attacker knowledge is represented by the histogram entropy $H(X)$ instead of $\log_2(n) - H(X)$. The fingerprinting anonymity reaches its minimum and maximum if

$$\begin{aligned} A(X, \varepsilon) = 0 &\Leftrightarrow H(X) = \log_2(n) &&\Leftrightarrow \text{high precision and variation,} \\ A(X, \varepsilon) = 1 &\Leftrightarrow H(X) = 0 &&\Leftrightarrow \text{low precision or variation.} \end{aligned}$$

5 EXPERIMENTAL METHODOLOGY

This section presents the results of our two performed experiments. The first experiment was conducted on a small scale in an isolated environment: we collected temporal broadcasting data of 15 smartphones which had the CWA installed and running. After finding device-specific differences in the IBLs, we proceeded in a second experiment and measured smartphones in multiple public places. This yielded insights into the IBL distribution across an estimated 121 smartphones. We used this distribution data to evaluate the privacy breach of the IBL differences in terms of the fingerprinting anonymity.

5.1 Software and Hardware Setup

Processing BLE broadcasts is feasible with little programming expertise and cheap hardware. All our measurements were performed using a Python script which operates as follows: collect BLE advertisements every 50 ms and filter GAEN broadcasts by their UUID 0xFD6F; group incoming BLE broadcasts by their MAC address as such advertisements originate from the same device; for each device, calculate the latencies between its successive broadcasts and store those between 220 ms and 350 ms.

The decision to group BLE broadcasts by their MAC address instead of their GAEN pseudonym was made in order to process as little personal data as possible: in contrast to the MAC addresses, the pseudonyms could potentially leak the Covid infection status of a participant at a later time. Since MAC address and pseudonym are changed in sync, both identify a broadcast's source equally well.

As for Bluetooth receiving hardware, we used a Lenovo Idea-pad 510S laptop running Fedora Linux. However, we subsequently verified that the measurements could be carried out identically on a Raspberry Pi 4B with 4 GB of RAM (cf. Fig. 2). The attack is thus feasible without significant hardware requirements.

The above methodology was applied in two experiments:

```

Covid Sniffer
File Edit Tabs Help
Listening to Exposure Notification Broadcasts
Started on 04.05.2023 at 17:35:37.370925
Sampling every 50 milliseconds
Stops
  automatically after 600 seconds (04.05.2023, 17:45:37.370925) or
  if key 'q' is pressed.
Stopped at 04.05.2023 at 17:45:37.398264: scanning time over
Seen devices: 7
MAC Address      First seen      Last seen      Number      Mean (ms)
56:1b:67:fe:3b:d7 17:35:37.990458 17:41:39.935547 319         283.5
1a:1b:ce:1d:87:d9 17:35:37.990697 17:36:16.315645  50         278.3
4c:ce:57:a0:f6:e7 17:35:38.101237 17:45:37.385148  386        284.9
2f:93:34:05:33:6b 17:36:05.425530 17:45:36.769489  66         272.8
2a:d0:13:2a:7b:40 17:36:06.785513 17:38:59.296982  88         276.7
1d:95:f9:05:4b:ad 17:36:17.938546 17:45:35.328494  616        275.6
47:c6:74:be:2e:87 17:41:33.810816 17:45:36.610692  103        283.0
procyon@raspberrypi:~$

```

Figure 2: A screenshot of the script running for ten minutes on a Raspberry Pi 4B

5.2 Laboratory Experiment

In the first experiment, we measured the IBL of the 15 smartphones in Table 1 in an isolated environment. At the time of testing, all phones were personal devices in everyday use, meaning that a variety of apps other than the CWA were installed, custom settings were made, and some phones could be measured for a longer time and contribute a greater number of pseudonym cycles than others.

While being measured, the phones did not perform any resource-intensive tasks. Moreover, we isolated the phone and receiver in a common microwave to reduce the influence of other environmental Bluetooth devices. Considering the full ISM band, a microwave oven is not a Faraday cage. It still blocks 2.4 GHz RF communication sufficiently which is the relevant frequency range for our experiment. We were able to verify the effectiveness of our isolation by observing that the Python script recorded only a single BLE source once the microwave door was closed.

5.3 Field Experiment

In the second experiment, we collected the IBL of unknown smartphones carried around by present people in public places. We conducted this experiment in multiple spots in Münster, Germany, in April, July, and August 2022. Since a pseudonym change could result in a smartphone contributing twice to our data, we limited each measurement to ten minutes. Subsequently, we rejected entries with less than 50 data points.

6 RESULTS

This section is divided into two parts. We begin by presenting the main qualitative observations we made in the two experiments. Afterwards, we evaluate the fingerprinting information leakage by the IBL in terms of the privacy metric introduced in Section 4.2.

6.1 Key Findings

The IBL data collected in the laboratory experiment are presented in Table 1. For each device, the IBLs of a pseudonym cycle were averaged to give the IBL mean for this particular pseudonym. The columns *mean* and *double standard deviation* were then derived from these values. Hence, when talking about a phone's overall IBL (*mean*), we refer to the average of its pseudonyms means.

- (1) The IBL distribution can vary strongly between different devices.

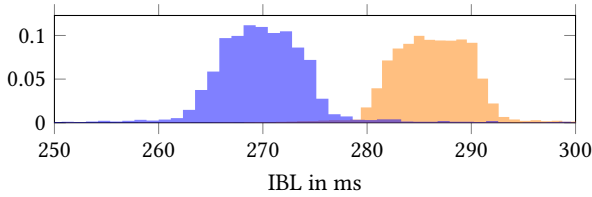


Figure 3: Distribution of all IBL data of the OnePlus Nord 2 (blue, left, 3598 data points) and the OnePlus Nord (orange, right, 17681 data points)

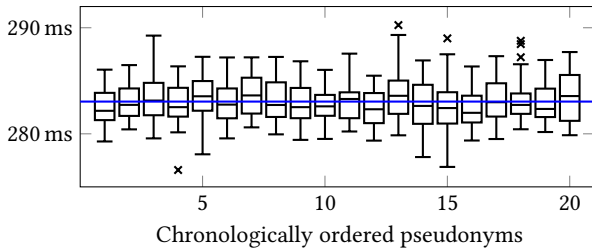


Figure 4: Boxplots of the IBL for the first 20 observed pseudonyms of the Huawei Mate 10. The blue horizontal line indicates its overall IBL mean of 283.04 ms. The data contain outliers which are not present in an appropriate choice of the y-axis range.

For example, Fig. 3 plots the IBL distributions of the OnePlus Nord and the OnePlus Nord 2. Both distributions have evidently little intersection and are separable by a visual inspection with the naked eye. More comprehensively, the means in Table 1 range from roughly 262 ms to 286 ms among all observed devices. While some smartphones in our test set (such as the Huawei P10 Lite) are uniquely identifiable by this characteristic, others share a similar IBL (e.g. all iPhone 13 Mini or Huawei Mate 10 & Samsung Galaxy J7). We will discuss possible influences on this attribute later in Section 7.

- (2) For each device, the IBL mean varies little between different pseudonym cycles.

The rather small standard deviations in Table 1 indicate little variation of the IBL mean between pseudonym cycles. For instance, the IBL means per pseudonym in Fig. 4 narrowly fluctuate around the Huawei Mate 10’s overall IBL mean of 283.04 ms.

- (3) The results from the isolated experiment are reflected in observations of public spaces.

All means from Table 1 also arise in the histogram of the roughly 121 observed pseudonyms in public (cf. Fig. 5). Regarding the fact that we did not prevent phones from possibly contributing twice to our measurements—i.e. the 121 pseudonyms could potentially originate from only 110 devices—the distribution of the IBLs must be taken with caution. However, it shows that the sample of phones in Table 1 is not considerably different from what an adversary would observe in public spaces.

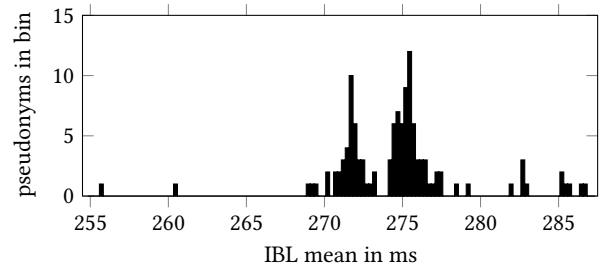


Figure 5: Histogram of observations in the field experiment

Table 1: Isolated IBL measurements of 15 smartphones

Device	OS	Pseudonyms	Mean	Double stdev.
Google Pixel 4a (5G)	Android 12	10	286.38	0.41
Huawei Mate 10	Android 10	38	283.04	0.24
Huawei P10	Android 9	11	283.02	0.3
Huawei P10 Lite	Android 8	4	261.92	0.21
iPhone 13	iOS 15	3	274.98	0.19
iPhone 13 Mini ^a	iOS 15	4	274.96	0.12
iPhone 13 Mini ^b	iOS 15	5	275.36	0.06
iPhone 13 Mini ^c	iOS 15	4	275.05	0.16
iPhone X	iOS 15	8	271.74	0.24
OnePlus Nord	Android 12	28	286.28	0.2
OnePlus Nord 2	Android 11	7	270	0.44
Redmi Note 11 Pro	Android 12	9	286.01	0.67
Samsung Galaxy A51	Android 11	7	286.11	0.31
Samsung Galaxy A6	Android 10	3	283.1	0.1
Samsung Galaxy J7	Android 9	3	282.96	0.12

- (4) This behavior is not consistent with the GAEN documentation which specifies an IBL of 200 ms to 270 ms [5].

Although this may not be crucial, it raises the questions as whether and how the specification can be adapted to improve privacy and how smartphones can be made to follow this specification.

6.2 Quantification of Fingerprintability

We apply fingerprinting anonymity as a privacy metric to the above data in order to quantify the information provided by the IBL. Therefore, we first need to determine the precision ε with which an adversary can observe the IBL mean. As each device d apparently targets the same IBL during different pseudonym cycles, one can reasonably argue that the pseudonyms’ IBL means are normally distributed around the device’s IBL μ_d . Consequently, 95% of pseudonyms’ IBL means would lie within the range $\mu_d \pm 2\sigma_d$ of two standard deviations. By averaging the values from Table 1, we obtain a *precision* of

$$\varepsilon = \frac{1}{15} \sum_{\substack{d \text{ device} \\ \text{in Table 1}}} 2\sigma_d = 0.251\bar{3} \approx 0.25.$$

This value determines the bin width of the histogram in the fingerprinting anonymity quantification.

The histogram shown in Fig. 5 is already the result of dividing the field experiment data into a histogram of bin width ε with a maximal entropy of $H(X) = 4.88$. Theoretically, these 4.88 bits of information suffice to distinguish $2^{4.88} \approx 29$ devices. This number must be noted cautiously for different reasons. On the one hand, we

cannot exclude the possibility that our measurements overestimate the real entropy of the IBL which would make more devices indistinguishable than assumed. On the other hand, a real adversary could exploit additional heuristics such as asynchronous pseudonym changes or signal strength to link pseudonyms efficiently.

The IBL mean thus provides a fingerprinting anonymity of

$$1 - \frac{H(X)}{\log_2(121)} = 0.29.$$

With lower values implying less privacy protection, one might consider this result as a warning and call for a closer investigation whether users of the CWA are exposed to a disproportional privacy risk. However, this warning needs to come with a caveat: Fingerprinting anonymity—like the degree of anonymity [9] from which it is derived—should be interpreted as a relative measure which is meant to compare different scenarios. Hence, our calculations here are merely setting a baseline for further investigations that might help fine-tuning parameters towards an optimal balance between privacy protection and utility of the CWA.

7 DISCUSSION AND FUTURE WORK

GAEN-based apps such as the German CWA turn smartphones into continuous radio wave emitters and raise questions about their users' privacy. The privacy protection of GAEN relies on the assumption that a smartphone's broadcasted pseudonyms cannot be linked. If this fails to be the case, various attacks such as trajectory reconstruction could arise. Against this background, unlinkability of randomized pseudonyms should not be taken for granted but must be ensured and verified.

Our results indicate that the temporal differences in the broadcast behavior can potentially be exploited to link pseudonyms of the CWA. To illustrate how an adversary could proceed, observe that the Huawei Mate 10 from Table 1 is present in the screenshot in Fig. 2. The first and last entry are clearly similar in terms of their mean and much different from all other observed pseudonyms. Moreover, the last pseudonym in the list was observed for the first time just a few seconds after the first one stopped broadcasting. In various scenarios, these information may be enough to link these two pseudonyms. We quantified the information provided by the IBL to be 4.88 bits which is theoretically enough to distinguish 29 devices. As pointed out, this quantitative result is subject to some uncertainty due to the small sizes of our experiments.

It is of particular interest for future studies to investigate which factors have an influence on the IBL. As we did not conduct any reverse engineering, we cannot answer this question definitely but may discuss various approaches. Overall, our observations lead us to the conjecture that a smartphone's IBL is mostly affected by two factors:

- *Its hardware stack.* By design, the GAEN API frequently accesses the phone's Bluetooth hardware and is thus influenced by the physical characteristics of the device. For example, our experiment included three iPhone 13 Mini as well as two phones from different manufacturers sharing the same chipset (the Google Pixel 4a and the OnePlus Nord have a Qualcomm Snapdragon 765G built in), and the devices exhibited similar IBLs in both cases.

- *Its usage and multitasking.* Whenever two processes demand hardware resources at the same time, they are granted access by the operating system's scheduler in a specific order. The mentioned frequent access to processor and Bluetooth consequently causes a waiting time for the GAEN process if the demanded resources are already allocated. If this waiting time has a notable influence on the IBL, then the latter might change with a varying usage. During our experiments we found subtle hints that the IBL may be slightly prolonged when another app heavily uses Bluetooth, but we could not examine this any further. If it turns out to be the case, an active adversary could disturb phones (e.g. the processor via network queries) and observe changes in their IBLs to gain further information about which phone broadcasts which pseudonym.

Moreover, we expect that this behavior is not limited to the German CWA but also appears in the context of other GAEN apps.

8 CONCLUSION

This exploratory study demonstrated that the German CWA is vulnerable to device fingerprinting. Smartphones with installed CWA target a device-specific latency between two subsequent Bluetooth broadcasts. This latency can potentially identify a smartphone, among others, and can be measured with no more than a few minutes of passive Bluetooth observation. Contrary to public assurances, regular pseudonym changes—as implemented today—are not enough to disguise a user reliably.

Our work contributes to the costs and effectiveness of CTAs by indicating that the CWA's privacy impact could be higher than expected. This becomes more significant since passive Bluetooth sniffing attacks are virtually unpreventable, and the affected OS-level code cannot be easily removed from the users' smartphones. Hence, any non-negligible risk of device fingerprinting needs to be considered in the evaluation and further development of CTAs.

Given that medical experts do expect the next similar pandemic soon, the time is now! We should work to reduce the fingerprintability of continuously sending BLE devices. As a side effect, a more privacy-friendly version of pseudonym-changing protocols with BLE or other wireless technologies might open up opportunities for other, more mundane uses of such technologies.

REFERENCES

- [1] 2020. *Exposure notifications: Helping fight covid-19*. <https://google.com/covid19/exposurenotifications/>
- [2] 2020. *Open-Source Project Corona-Warn-App*. <https://coronawarn.app/en/>
- [3] Gunes Acar, Christian Eubank, Steven Englehardt, Marc Juarez, Arvind Narayanan, and Claudia Diaz. 2014. The Web Never Forgets: Persistent Tracking Mechanisms in the Wild. In *Proceedings of the 2014 ACM SIGSAC Conference on Computer and Communications Security*. 674–689. <https://doi.org/10.1145/2660267.2660347>
- [4] Florian Adamsky, Tatiana Retunskaja, Stefan Schiffner, Christian Köbel, and Thomas Engel. 2018. Poster: WLAN Device Fingerprinting Using Channel State Information (CSI). In *Proceedings of the 11th ACM Conference on Security & Privacy in Wireless and Mobile Networks (Stockholm, Sweden) (WiSec '18)*. ACM, New York, NY, USA, 277–278. <https://doi.org/10.1145/3212480.3226099>
- [5] Apple and Google. 2020. *Exposure Notification - Bluetooth Specification*. https://blog.google/documents/70/Exposure_Notification_-_Bluetooth_Specification_v1.2.2.pdf
- [6] Bluetooth Special Interest Group. 2021. *Bluetooth Core Specification v5.3*. <https://www.bluetooth.com/specifications/specs/core-specification-5-3/>

- [7] Yinzhi Cao, Song Li, and Erik Wijmans. 2017. (Cross-)Browser Fingerprinting via OS and Hardware Level Features. In *Proceedings of the Network and Distributed System Security Symposium (NDSS) 2017*. <https://doi.org/10.14722/ndss.2017.23152>
- [8] Guillaume Celosia and Mathieu Cunche. 2019. Fingerprinting bluetooth-low-energy devices based on the generic attribute profile. In *Proceedings of the 2nd International ACM Workshop on Security and Privacy for the Internet-of-Things*. 24–31.
- [9] Claudia Díaz, Stefaan Seys, Joris Claessens, and Bart Preneel. 2003. Towards measuring anonymity. In *Privacy Enhancing Technologies*. Springer Berlin Heidelberg, 54–68. https://doi.org/10.1007/3-540-36467-6_5
- [10] Peter Eckersley. 2010. How Unique Is Your Web Browser?. In *Proceedings of the 10th Privacy Enhancing Technologies Symposium (PETS 2010)* (Berlin, Heidelberg). Springer Berlin Heidelberg, 1–18. https://doi.org/10.1007/978-3-642-14527-8_1
- [11] European Union. 2016. Regulation (EU) 2016/679 of the European Parliament and of the Council of 27 April 2016 on the protection of natural persons with regard to the processing of personal data and on the free movement of such data, and repealing Directive 95/46/EC (General Data Protection Regulation). <https://eur-lex.europa.eu/eli/reg/2016/679/oj>
- [12] Sergey Frolov and Eric Wustrow. 2019. The use of TLS in Censorship Circumvention. In *Proceedings 2019 Network and Distributed System Security Symposium (NDSS)*. Internet Society. <https://doi.org/10.14722/ndss.2019.23511>
- [13] Xi He, Eric HY Lau, Peng Wu, Xilong Deng, Jian Wang, Xinxin Hao, Yiu Chung Lau, Jessica Y Wong, Yujuan Guan, Xinghua Tan, et al. 2020. Temporal dynamics in viral shedding and transmissibility of COVID-19. *Nature medicine* 26, 5 (2020), 672–675. <https://doi.org/10.1038/s41591-020-0869-5>
- [14] Jingyu Hua, Mr Hongyi Sun, Mr Zhenyu Shen, Zhiyun Qian, and Dr Sheng Zhong. 2018. Accurate and Efficient Wireless Device Fingerprinting Using Channel State Information. In *Proceedings of the IEEE International Conference on Computer Communications (INFOCOM)*. 9.
- [15] Jun Huang, Wahhab Albazraqoe, and Guoliang Xing. 2014. BlueID: A practical system for Bluetooth device identification. In *IEEE INFOCOM 2014-IEEE Conference on Computer Communications*. IEEE, 2849–2857.
- [16] Martin Husák, Milan Čermák, Tomáš Jirsík, and Pavel Čeleda. 2016. HTTPS traffic analysis and client identification using passive SSL/TLS fingerprinting. 2016, 1 (2016), 6. <https://doi.org/10.1186/s13635-016-0030-7>
- [17] Suman Jana and Sneha Kumar Kasera. 2009. On Fast and Accurate Detection of Unauthorized Wireless Access Points Using Clock Skews. In *Proceedings of the 14th ACM international conference on Mobile computing and networking*. 104–115. <https://doi.org/10.1109/TMC.2009.145>
- [18] Tadayoshi Kohno, Andre Broido, and Kimberly C Claffy. 2005. Remote physical device fingerprinting. *IEEE Transactions on Dependable and Secure Computing* 2, 2 (2005), 93–108. <https://doi.org/10.1109/TDSC.2005.26>
- [19] Pierre Laperdrix, Natalia Bielova, Benoît Baudry, and Gildas Avoine. 2019. Browser Fingerprinting: A survey. (2019). arXiv:1905.01051 <http://arxiv.org/abs/1905.01051>
- [20] Jonathan R Mayer. 2009. “Any person... a pamphleteer.” Internet Anonymity in the Age of Web 2.0. Bachelor Thesis.
- [21] Keaton Mowery and Hovav Shacham. 2012. Pixel Perfect: Fingerprinting Canvas in HTML5. In *Proceedings of W2SP 2012*. 12.
- [22] Andreas Pfitzmann and Marit Hansen. 2010. A terminology for talking about privacy by data minimization: Anonymity, unlinkability, undetectability, unobservability, pseudonymity, and identity management.
- [23] Alexandra Prodan, Strahil Birov, Viktor von Wyl, and Wolfgang Ebbers. 2022. *Digital Contact Tracing Study — Study on lessons learned, best practices and epidemiological impact of the common European approach on digital contact tracing to combat and exit the COVID-19 pandemic*. European Commission.
- [24] Yoke Leen Sit. 2017. *MIMO OFDM Radar-Communication System with Mutual Interference Cancellation*. KIT Scientific Publishing.
- [25] Maria D Van Kerkhove, Michael J Ryan, and Tedros Adhanom Ghebreyesus. 2021. Preparing for “Disease X”. *Science* 374, 6566 (2021), 377.
- [26] Diwen Xue, Reethika Ramesh, Arham Jain, Michalis Kallitsis, J. Alex Halderman, Jedidiah R. Crandall, and Roya Ensafi. 2022. OpenVPN is Open to VPN Fingerprinting. In *31st USENIX Security Symposium (USENIX Security 22)*. USENIX Association, Boston, MA, 483–500.