

# Secure, Usable and Practical Authentication for the Internet of Things

By

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PREVIEW

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## CONTENTS

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Contents iii

List of Tables v

List of Figures vi

Abstract xiv

<b>1</b>	<b>Introduction</b>	<b>1</b>
1.1	<i>Motivation</i>	2
1.2	<i>Objectives and Contributions</i>	4
<b>2</b>	<b>Background</b>	<b>7</b>
2.1	<i>Device authentication</i>	7
2.2	<i>Zero-interaction Authentication (ZIA)</i>	8
2.3	<i>Previous works on ZIA</i>	10
<b>3</b>	<b>ZIA for Mobile Devices</b>	<b>14</b>
3.1	<i>SYNCVIBE: Fast and Secure Device Authentication through Physical Vibration on Commodity Smart Phones</i>	14
3.1.1	System and Threat Models . . . . .	19
3.1.2	Proposed Approach . . . . .	20
3.1.3	Implementation and Evaluation . . . . .	26
3.1.4	Conclusion . . . . .	32
3.2	<i>ivPAIR: Zero-interaction Fast Intra-Vehicle Device Authentication for Secure Wireless Connectivity</i>	33
3.2.1	System and Threat Models . . . . .	35
3.2.2	Proposed Approach . . . . .	36
3.2.3	Implementation and Evaluation . . . . .	40
3.2.4	Conclusion . . . . .	47

<b>4</b>	<b>ZIA for Indoor IoT Devices</b>	<b>48</b>
4.1	<i>VOLTKEY: Continuous Secret Key Generation based on Power Line Noise for Zero-Involvement Authentication</i>	48
4.1.1	System and Threat Models . . . . .	53
4.1.2	Proposed Approach . . . . .	55
4.1.3	Implementation and Evaluation . . . . .	66
4.1.4	Conclusion . . . . .	86
4.2	<i>AEROKEY: Using Ambient Electromagnetic Radiation for Secure and Usable Wireless Device Authentication</i>	86
4.2.1	System and Threat Models . . . . .	92
4.2.2	Proposed Approach . . . . .	94
4.2.3	Implementation and Evaluation . . . . .	105
4.2.4	Conclusion . . . . .	126
<b>5</b>	<b>Balancing between Security and Usability in ZIA</b>	<b>128</b>
5.1	<i>Security and Usability of ZIA</i>	129
5.2	<i>Key Reconciliation Protocols</i>	132
5.3	<i>Analysis of Key Reconciliation Schemes</i>	135
5.4	<i>Conclusion</i>	142
<b>6</b>	<b>Future Works</b>	<b>143</b>
6.1	<i>Sensing Hardware Variation</i>	143
6.2	<i>Usability and Privacy of ZIA</i>	143
6.3	<i>Thorough Evaluation of the Security Properties of ZIA</i>	144
<b>7</b>	<b>Conclusion</b>	<b>145</b>
	<b>Bibliography</b>	<b>146</b>

## LIST OF TABLES

---

2.1	Physical context and sensors used in various ZIA works. . . .	10
3.1	Effective bit ratio, bit error rate, and expected authentication time. $L=150$ . . . . .	31
3.2	Expected authentication time and mean correlation coefficient before and after conditioning. . . . .	44
4.1	NIST test results of VOLTKEY ( $p\text{-value} \geq 0.05$ ) . . . . .	83
4.2	Overview of RECON stage between Devices A and B (Fuzzy commitment). . . . .	104
4.3	Measurement time required for varying $t_h$ in home and lab. .	121
4.4	NIST test results of AEROKEY ( $p\text{-value} \geq 0.05$ ) . . . . .	125
5.1	Error-correcting code based reconciliation (Fuzzy commitment) [33, 24, 43, 50, 51, 58] . . . . .	133
5.2	Compressed sensing based reconciliation [73, 46, 45, 71] . . .	134

## LIST OF FIGURES

---

1.1	Wide deployment environments of the IoT devices are categorized into two sectors: <i>consumer and industrial</i> . . . . .	1
1.2	The three design aspects of the proposed device authentication techniques. . . . .	5
2.1	In ZIA, co-located devices are autonomously authenticated based on the ambient contextual information which can only be observed within the close region. . . . .	8
3.1	The smart phone transmits authentication key to the target device through the vibratory channel using a vibration motor to bootstrap a high-bandwidth wireless connection. . . . .	16
3.2	Examples of envelopes of vibration pulses for different periods: 20, 50, 100, and 200 ms. Vertical lines denote the ideal pulse widths. . . . .	18
3.3	Example of bit errors due to the loss of synchronization in a long bit stream. . . . .	19
3.4	Modulation example. Synchronization marker is 001, $k = 4$ , vibration period ( $t$ ) is 10 ms, and long pulse period ( $t_1$ ) is 20 ms. . . . .	22
3.5	Demodulation and synchronization example for $k=8$ . After detecting consecutive bit 0's followed by a transition to 1, the number of samples in the corresponding segment is adjusted based on the measured slope and reference amplitude of the waveform. Segment boundary is adjusted from ① to ②. . . . .	24
3.6	Experimental setup. The transmitter (Galaxy S5) and the accelerometer (ADXL345) of the receiver under a constant pressure using a spring clamp. . . . .	26

3.7	(a) Authentication success rate for varying synchronization intervals ( $k$ ) between 10 and 50 bits and different vibration periods ( $t$ ) of 40, 50, and 60 ms. (b) Worst-case effective bit ratio for varying synchronization intervals ( $k$ ). . . . .	27
3.8	Authentication success rate (a) with and (b) without clock recovery. Note the different y-axis scale. . . . .	29
3.9	(a) Authentication success rate and (b) expected bps for varying vibration periods ( $t$ ) with two different protective cases: silicone case and TPU case. $L = 150$ . (c) Authentication success rate and (d) expected bps for varying vibration periods ( $t$ ) under two different noise conditions: walking motion and moving car vibration. $L = 150$ . . . . .	30
3.10	Passenger-owned mobile devices in the legitimate user's vehicle are authenticated to the vehicular computer (host), and the devices from the adversary are rejected to legitimate user's vehicular computer. . . . .	35
3.11	Overall protocol to extract identical keys on two devices to bootstrap high-bandwidth wireless connection. . . . .	36
3.12	Measured $Acc_y$ and $Acc_z$ , sample-wise error, and correlation coefficient $r$ between two devices (a) before and (b) after sampling frequency alignment using DTW. . . . .	37
3.13	Histogram of 14-bit key based on their number of bit 1s. . . . .	41
3.14	(a) Bit agreement rates and (b) success rate on sedan and SUV driven on different roads. . . . .	42
3.15	(a) Location of devices (H: host, 1–4: mobile devices). (b) Authentication success rate and bit agreement rate between pairs of devices. . . . .	43
3.16	Bit agreement rate achieved by the adversary under two different attack scenarios. . . . .	45

4.1	(a) Measurement of voltage signal on two colocated outlets using a USB DAQ at a sampling rate of 10 kSPS. Single period of 60 Hz signal (b) when the heat gun is off and (c) when it is on.	51
4.2	System and threat models of VOLTKEY. A number of IoT devices are installed in each home. WiFi range of each home can reach neighboring homes, potentially the adversary's.	53
4.3	(a) VOLTKEY's Analog front-end schematic. MCU's power regulation, debugger and serial communication circuitry is omitted for simplification purposes. (b) Frequency response of the twin-T notch filter used in the prototype. (c) Top-view of VOLTKEY prototype.	55
4.4	Overview of VOLTKEY's key establishment protocol. Solid lines denote plaintext messages exchanged on a public channel and dotted lines represent encrypted messages.	57
4.5	Mean of uniformly sliced signal at (a) $c = 1416$ SPP, (b) $c = 1419$ SPP, and (c) $c = 1422$ SPP. The correlation coefficient is highest when $c$ is equivalent to the actual SPS divided by 60.	59
4.6	VOLTKEY's time synchronization. Using the sliding window approach, Device B locates the most correlated segment between received preamble $S_{A,0}$ and discards the samples up to the offset $d$ .	61
4.7	Bit sequence extraction from the $p$ -th noise period with $n_b = 7$ . The largest absolute value of each bin is converted to a bit 1 if indexed value at $T_{p,b}$ is greater than the mean of the noise period, and a bit 0 otherwise.	62



4.8	Illustration of key reconciliation process of the first seven bits using Hamming(7,4) code. ① Bit sequences extracted from both devices are divided into linear blocks of seven bits. ② Difference (exclusive or) between bits in the block and its corresponding codeword, denoted as $R_1$ , is transferred to Device B. ③ Using $R_1$ , Device B flips the bit differences with its own 7-bit block. ④ Result from the previous step is mapped to the codeword, and an additional bit flip with $R_1$ will reconcile the single-bit error between two devices. Subsequent blocks are reconciled in similar manner. . . . .	64
4.9	(a) 10-by-10 confusion matrix of average bit agreement rate between bit sequences generated by noise periods obtained by Device A and B. (b) Distribution of bit agreement rate between diagonal and off-diagonal pairs of noise periods. . . . .	67
4.10	(a) Bit agreement rate between all keys pairs generated within each hour over course of three consecutive days. (b) CDF of daily pattern and near time attack. . . . .	69
4.11	(a) Bit agreement rate between all keys pairs generated with nearby inductive electrical loads. (b) CDF of dominant noise attack using different loads. . . . .	71
4.12	(a) Experiment setup inside temperature chamber. (b) Success rate between legitimate devices with respect to different operating temperature. (c) CDF of passive attacks with different temperature. . . . .	72

4.13	(a) Location and distance between multiple VOLTKEY devices (not to scale). The power line is visible around the surrounding wall of the lab. The electrical distance from Device A to B, C, D and E is 1, 2.7, 12.8 and 24.8 m, respectively. (b) SPS of five different devices. (c) Bit agreement rate between devices with respect to the distance between authenticating devices. (d) Success rate of authentication attempts with respect to distance between authenticating devices. . . . .	75
4.14	(a) VOLTKEY prototype with circuit breaker attached on the hot line of power cable. (b) Bit agreement rate between devices with respect to the distance between authenticating devices. (c) Success rate of authentication attempts with respect to distance between authenticating devices. . . . .	77
4.15	(a) Floor plans of the one-bedroom apartment and office (not to scale). VOLTKEY devices are connected to different wall outlets to periodically authenticate themselves with Device A. (b) Bit agreement rate of devices with different $n_b$ before key reconciliation. . . . .	78
4.16	Successful authentication rate with multiple trials of authentication in apartment and office environment. . . . .	80
4.17	(a) CDF of bit agreement rate for passive attack ( $n_b=6$ ) on (a) one-bedroom apartment and (b) office. . . . .	81
4.18	Bit agreement rate of bit sequences generated by two colocated VOLTKEY devices with respect to different sampling rate. . . . .	85
4.19	(a) Raw ADC readings from two different locations (5 m apart) as a hair dryer (1875 W) switches on at 80 ms. (b) Spectrograms of the raw readings from two different locations. . . . .	88

4.20	(a) Measurement hardware with a conducting wire as an antenna. (b) Correlation heatmap of superimposed noise components between host and client devices within typical living room environment. (c) Correlation between devices located in the next room. (d) Correlation between devices located along the identical power line. . . . .	90
4.21	Five-stage pipeline of the AEROKEY protocol. . . . .	95
4.22	Synchronization of raw signals between Device A and B. Among three periods of Device B, the second period, $R_{B,c,2}$ , shows the minimum DTW distance against Device A's $R_{A,c,1}$ . . . . .	97
4.23	Two noise signals, $N_{d,c}$ , and their cross-correlations calculated from mean signals with (a) $n_p = 1$ and (b) $n_p = 50$ on two co-located devices. . . . .	99
4.24	(a) Relationship between $n_p$ and correlation coefficient between two noise signals. (b) Periodogram of noise signal, $N_A$ , and raw signal, $R_A$ . 60 Hz component is removed in the noise. (c) Spectral entropy of the noise signal, $N_A$ , and the raw signal, $R_A$ . (d) Correlation achieved between $R_{A,c,1}$ and $M_{A,c}$ , as well as $N_{A,c}$ . . . . .	100
4.25	In QUANT stage with $n_b = 8$ , the bits are only extracted from bins with slopes greater or less than the quantization threshold of 0.01: bins 1, 3, 6, and 8. . . . .	102
4.26	(a) BAR and (b) bit extraction rate between co-located devices for varying $n_b$ and $th$ . (c) Evidence bit length ( $m$ ) and (d) measurement time required for varying error tolerance rate. . .	107
4.27	(a) 10-by-10 confusion matrix of average BAR between evidence bits generated at different cycles. (b) Distribution of BAR between diagonal and non-diagonal element pairs. . . .	109

4.28	BAR, TAR, and bit extraction rate with respect to varying distance between authenticating devices within (a) home and (b) lab environment. . . . .	110
4.29	(a) Four different regions of deployed device pairs. (b) Confusion matrix and (c) distribution of BAR between all evidence bit sequence pairs. (d) BAR and (e) bit extraction rate of devices within four locations with respect to different hours of the day.	112
4.30	BAR achieved from passive, replay, replay injection, active injection and ML attacks. Six most effective attacks (high BAR) are highlighted in gray columns. . . . .	116
4.31	Raw ( $R_{A,c}$ ) and noise ( $N_{A,c}$ ) signals extracted from the same location at different time instances with an operating temperature chamber nearby (replay injection attack). . . . .	116
4.32	Measured and predicted raw signal using trained ML-model with ( $R_{A,1,1}$ ) as an input (ML-raw attack). Two signals exhibit high correlation of $r = 0.97$ . . . . .	117
4.33	(a) Signal generator (Hewlett-Packard audio oscillator 200AB) outputting 34.87 V AC signal. (b) Noise signal, $N_A$ , observed from the victim device as the signal generator is turned off and on ( $\sim 2000$ Hz). (c) BAR achieved from the devices located in different distances from the generator signaling different frequency components. . . . .	118
4.34	(a) Resulting EER from six most effective passive attacks. (b) EER from varying $th$ by passive attack within home environment.	119
4.35	(a) Total authentication time measured on four different devices. (b) Execution time of each AEROKEY stages on Arduino Due (log scale). . . . .	122

4.36	(a) BAR and (b) bit extraction rate under varying sampling rate between two closely located devices. (c) BAR and (d) bit extraction rate under varying wire length between two closely located devices. . . . .	123
5.1	General pipeline of ZIA techniques between two Devices: A (Client) and B (Host). . . . .	129
5.2	Framework to determine reconciliation parameter given three user inputs: authentication range, bit error model (optional), and target EER. . . . .	131
5.3	(a) Success rate for ECC-based scheme varying $T$ and required BAR between devices to achieve 5%, 50% and 95% success rate in (b) independent and (c) simple Gilbert model with $r=0.2$ and (d) $r=0.1$ . . . . .	136
5.4	(a) Success rate for CS-based scheme varying $M$ and required BAR between devices to achieve 5%, 50% and 95% success rate in (b) independent and (c) simple Gilbert model with $r=0.2$ and (d) $r=0.1$ . . . . .	137
5.5	Entropy of the final key, $K$ , using (a) ECC-based and (b) CS-based reconciliation schemes. . . . .	139
5.6	Number of executed instructions under (a) ECC-based and (b) CS-based reconciliation schemes. . . . .	140

## ABSTRACT

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The explosive growth in the number of connected and Internet-of-Things (IoT) devices (e.g., smart speakers, lights, and thermostats) today calls for more convenient and yet secure ways to establish wireless connection between devices. Unfortunately, current device authentication method between typical IoT devices heavily involves manual human interaction by requiring the user to type in a pin or password to establish credentials between two devices. Considering highly distributed and heterogeneous nature of today's connected environment, this unwieldy authentication process particularly degrades the overall usability of IoT systems, which often causes device users to perform poor security practices such as choosing weak passwords or even reusing them. To overcome this usability challenge that leads to various security vulnerabilities, researchers have devised zero-interaction authentication (ZIA) technique which allow devices to autonomously authenticate with each other through common secret extracted from environmental contexts to prove co-existence of devices.

In this dissertation, I present series of works on designing and building novel ZIA techniques for spontaneous authentication of IoT devices based on their deployment environments. More specifically, I first propose two techniques named *SYNcVIBE* and *ivPAIR*, leveraging readily available accelerometer to sense physical vibration in the ambient environment and authenticate closely located wearable and mobile devices in various portable scenarios. Secondly, I present two authentication techniques named *VOLTKEY* and *AEROKEY*, designed to seamlessly and continuously associate indoor IoT devices using ubiquitously observable power line noise and ambient electromagnetic radiation as a secret to authenticate co-located devices in a fully autonomous manner. Specifically tailored towards emerging mobile and resource-constrained IoT devices, the proposed works effectively result in higher overall security and usability than

traditional authentication approaches while maintaining high practicality to be directly applicable to today's already deployed devices. In addition, to address generic challenges and limitations that exist in the current state-of-the-art ZIA works, I present a framework to automatically determine proper key reconciliation parameters that provide optimal balance between security and usability.

PREVIEW

## 1 INTRODUCTION

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The number of connected and Internet-of-Things (IoT) devices has been experiencing explosive growth, driven by emerging applications and advanced technologies, coupled with the active standardization of connected ecosystems. It is predicted that by the end of year 2024, there will be around 84 billion connected devices throughout the world, which is more than double the number of devices that existed in 2020 [63]. According to a former chief futurist of Cisco, there are around 127 newly introduced devices that are being connected to the internet every second [62].

With this overwhelming growth in its numbers, there are various environments in which these IoT devices are being deployed. As Figure 1.1 illustrates, the deployment environments can generally be categorized into two major sectors: *consumer and industrial*. In the consumer sector, personal, wearable, and home IoT devices, such as smart watches, smart

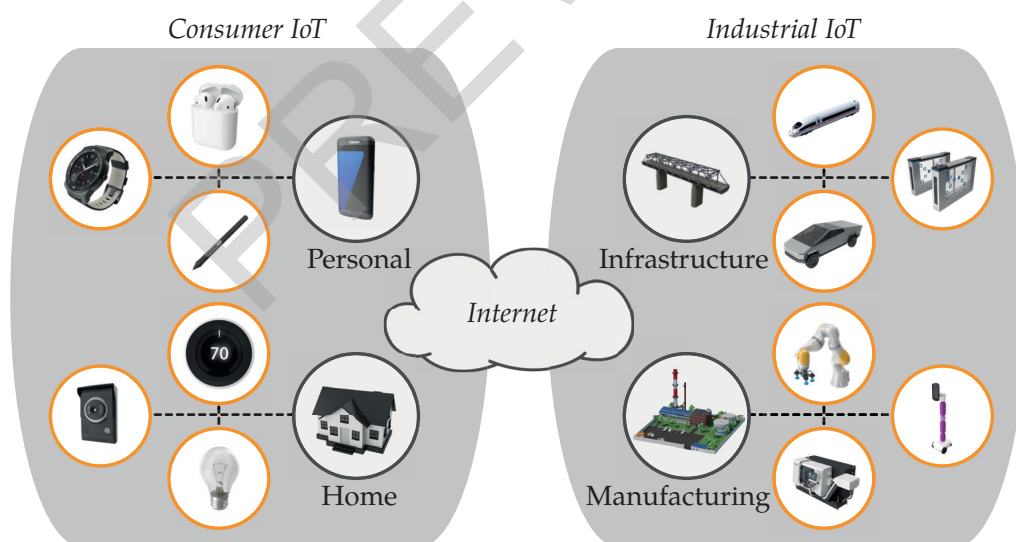


Figure 1.1: Wide deployment environments of the IoT devices are categorized into two sectors: *consumer and industrial*.



earbuds and speakers make our daily lives more efficient, effective, and healthy. On the other hand, devices deployed in the industrial sector, such as smart sensors and machines deployed in cities, warehouses, and manufacturing plants ensure higher level of automation to maintain good air quality, efficient traffic managements, and faster package deliveries. As the awareness of connected efficiency grows in the market, every industry and businesses of all sizes are thinking of ways to adopt IoT into their day-to-day activities. However, while this increased connectivity brings far too many benefits to our lives, adaptation of proliferating IoT devices leads to scalability challenges much like any other technology systems.

## 1.1 MOTIVATION

One of the most paramount scalability challenges that has continued to vex researchers is the question of how to quickly, securely, and seamlessly verify the authenticity between connecting devices. Unfortunately, conventional device authentication methods profoundly rely on manual human involvement. For example, Bluetooth pairing activity or connecting a wireless device to an access point in a WiFi network require human verifiers to type in a pin or password to verify that associating devices are trustworthy. Compared to traditional computing systems, this process can be considered particularly more labor-intensive and usability degrading when applied to current IoT systems for two reasons: i) Stringent constraints in the cost and the form factor have forced the manufactures to build IoT devices with limited or no usable interfaces such as touchscreens or keyboards (i.e., smart pens, smart bands). As a result, users are often forced to introduce and use secondary device, most commonly the user's smart phones, to configure devices or to establish secure connection with authorized devices. This makes traditional password- or pin-based authentication significantly more tedious, difficult, and time-consuming [15].

ii) Because device manufacturers do not consider overloading number of devices from the user's perspective, there currently exist no efficient and usable form of collective device management, and the burden of managing collection of devices falls on the user. For instance, in a typical home IoT scenario, communication network comprises of multiple edge devices connected to a single, centralized access point (WiFi router). To newly introduce or to re-authenticate devices into this network setting, users need to individually interact with different apps for different devices, which results the overall device configuration and management process to be labor-intensive and mentally overloading.

Usability is a key aspect of the authentication mechanism for IoT systems that are deployed and maintained by non-professional users. The lack of usable authentication scheme has forced many personal and mobile devices to choose usability over security and resulted in failures in properly securing critical data. For instance, without a user interface to enter a password, Bluetooth 5 devices use a common default password to encrypt the communication messages used to establish an authentication token [47, 22]. If a malicious adversary manages to gain physical access to a Bluetooth 5 headset and unpair it, they can intercept the pairing messages and extract the authentication token, ultimately gaining perpetual access to the plaintext of all subsequent communications at a distance [60]. In the case of home IoT systems, some IoT device manufacturers have inadvertently chosen usability over security and miserably failed in providing even a minimum level of security. For instance, it was reported a few years ago that 73,000 private unsecured smart cameras, including 11,000 in the U.S. alone, were being streamed on the Internet because it was not mandated to change the default password [20]. Despite the federal government's consumer advisory [29], more than 15,000 private smart cameras are still unknowingly being streamed. In the industrial sector, according to report by Palo Alto Networks' threat intelligence team, out of 1.2 million IoT

devices in thousands of physical locations across information technology and healthcare organizations in the United States, 98% of all IoT device's traffic remains unencrypted, leaving data communications vulnerable to eavesdropping by any adversary within the wireless range [13]. This vulnerability can lead to catastrophic leakage of sensitive personal data such as medical imaging, video monitoring footage, etc. Unfortunately, authenticating devices with the password does not adequately address this concern. Difficulties of authentication results in inexperienced users opting not to change default or old WiFi passwords that leads to imminent threat as disclosed in the 2016 Data Breach Investigations Report — 63% of the confirmed data breaches are attributed to using weak, default, or stolen passwords [69]. Also, in current IoT systems, once a common password is leaked, all devices using the same password must undergo tedious and error-prone password update procedures which is burdensome and sluggish. As the number of IoT devices that each user has to manage increases, combined with their heterogeneous and distributed nature, employing traditional security solutions fails to address the current problems in terms of both security and usability.

## 1.2 OBJECTIVES AND CONTRIBUTIONS

In this dissertation, I propose series of novel device authentication techniques towards the goal of improving usability of current IoT device authentication, so that people who have limited or no skills to operate computers can easily keep a secure connected environment. The proposed techniques successfully give users an enhanced user experience by eliminating inconveniences of conventional methods without compromising the overall security. Furthermore, the proposed techniques require minimal or no extra hardware overheads, which implies that they can easily be adopted to wide range of resource-limited devices within today's dynamic

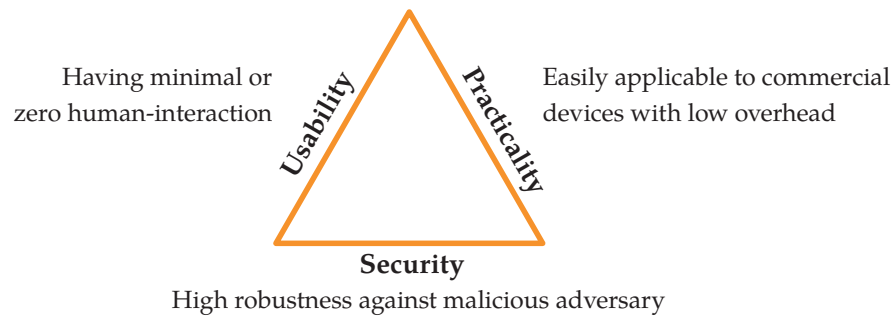


Figure 1.2: The three design aspects of the proposed device authentication techniques.

IoT deployment and usage scenarios.

Overall, the proposed authentication methods successfully improves upon conventional techniques in terms of the following three design aspects as illustrated in Figure 1.2.

1. Usability: The device authentication process can take place more quickly and efficiently with minimal or no human involvement.
2. Practicality: The authentication technique requires minimal or no hardware modifications to seamlessly be implemented into deployed devices with various form factors.
3. Security: The authentication technique provides robust protection against malicious adversaries attempting to gain unauthorized authentication.

With the three design aspects in mind, the proposed techniques are systematically evaluated in various real-world settings to demonstrate their effectiveness. Moreover, while building these series of techniques, I find that there currently exist no efficient way for the end users to balance the trade-off between usability and security of existing authentication techniques. As such, this dissertation additionally presents the generic

framework to automatically determine proper authentication parameter that balances the security and usability of device authentication schemes.

This dissertation presents different techniques designed for IoT devices that are classified into two deployment categories: *mobile* and *indoor*. Devices that are in the mobile category refers to the battery operated devices that are freely carried around by users such as smart phones, smart watches, and wearable devices. On the other hand, devices within the indoor category include all types of devices (including mobile) that are used indoors, including constantly powered devices such as smart thermostats or speakers that are designed to be mounted or not moving.

The rest of this dissertation is outlined as the following. Chapter 2 presents the background information and previous efforts of the research, as well as defining the commonly used terminologies. Next, Chapter 3 details the two device authentication techniques named SYNCVIBE [40] and ivPAIR [39] designed towards authentication between mobile and wearable devices using physical vibration that can be sensed with ubiquitously available accelerometers. In Chapter 4, I describe the techniques named VOLTKEY [38] and AEROKEY [41] to address indoor IoT device authentication using power line noise and ambient electromagnetic radiation that are omnipresent in the indoor environment. Followed by presenting solutions to balance between security and usability of usable device authentication [37] in Chapter 5, I discuss the future works and conclude the dissertation in Chapter 6 and Chapter 7, respectively.

## 2 BACKGROUND

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This Chapter provides the underlying background information and define the terminologies used to describe the presented works. In addition, I comprehensively provide and discuss previous efforts to improve the usability and security of device authentication through an emerging notion called zero-interaction device authentication.

### 2.1 DEVICE AUTHENTICATION

Device authentication is a fundamental security process where two or more devices that share no prior knowledge of each other build trust to establish a secure wireless channel to communicate with each other [76]. Traditionally, the most basic form of device authentication leverages shared secret (e.g., pre-shared key (PSK) or password), a something that only the owner "knows", to verify each others identity [21]. For IoT devices, device authentication is most commonly used to establish communication protocol such as WiFi or Bluetooth, which is the standard backbone of the wireless communication in IoT systems. For instance, in a typical smart home setting, WiFi access points and IoT end-point devices mutually authenticate each other through WiFi PSK (i.e., WiFi access point password) to agree on cryptographic keys used to encrypt and decrypt packets within the secure wireless channel [79]. Another example of device authentication which takes place between mobile devices (e.g., smart phone, smart watches) is during the Bluetooth pairing procedure. Similar to WiFi PSK, devices leverage a manually typed secret called pairing pin, typically much shorter in length, to mutually agree on the cryptographic keys for secure communication between devices.

However, secrets like PSK and passwords are usually recycled or easily gets passed around, which makes the entire network susceptible to