When CSI Meets Public WiFi: Inferring Your Mobile Phone Password via WiFi Signals

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ABSTRACT

In this study, we present WindTalker, a novel and practical keystroke inference framework that allows an attacker to infer the sensitive keystrokes on a mobile device through WiFi-based side-channel information. WindTalker is motivated from the observation that keystrokes on mobile devices will lead to different hand coverage and the finger motions, which will introduce a unique interference to the multi-path signals and can be reflected by the channel state information (CSI). The adversary can exploit the strong correlation between the CSI fluctuation and the keystrokes to infer the user's number input. WindTalker presents a novel approach to collect the target's CSI data by deploying a public WiFi hotspot. Compared with the previous keystroke inference approach, WindTalker neither deploys external devices close to the target device nor compromises the target device. Instead, it utilizes the public WiFi to collect user's CSI data, which is easy-to-deploy and difficult-to-detect. In addition, it jointly analyzes the traffic and the CSI to launch the keystroke inference only for the sensitive period where password entering occurs. WindTalker can be launched without the requirement of visually seeing the smart phone user's input process, backside motion, or installing any malware on the tablet. We implemented Windtalker on several mobile phones and performed a detailed case study to evaluate the practicality of the password inference towards Alipay, the largest mobile payment platform in the world. The evaluation results show that the attacker can recover the key with a high successful rate.

Keywords

Password Inference; Channel State Information; Online Payment; Wireless Security; Traffic Analysis

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1. INTRODUCTION

Smartphones and tablets are commonly used for performing privacy sensitive transactions of banking, payment, and social applications. Unlike stationary devices connecting to a secure network and sitting in a physically-secure space, these mobile devices are often carried by a mobile user and connected to a dynamic network environment where attackers can physically approach the target user's device and launch various direct and indirect eavesdropping attacks. While direct eavesdropping attacks aim at directly observing the input of the target device from screen and keyboard, indirect eavesdropping attacks, a.k.a. side-channel attacks make use of side channels to infer the inputs on the target devices. Prior works [2, 3, 12, 13, 15, 16, 18, 23, 25] have shown that both types of attacks can be effective in certain situations. Particularly for the side-channel attacks, it is shown that the PIN and the words entered at keyboard can be inferred from the acoustic signal at microphone [3, 12, 25], electromagnetic signal at radio antenna [2], visible light at camera [18, 23], and motion status at motion sensors [13, 15, 16]. To access the side channels, these works often assume either external signal collector devices are close to the target device (for example, 30 cm) or the sensors of the target devices are compromised to provide side channel information. However, in a mobile scenario, either assumption is hardly true and the impact of attacks is thus limited. In addition, the prior works [2, 3, 12, 13, 15, 16, 18, 23, 25] have studied the keystroke inference aiming at achieving a high inference accuracy on a series of keystrokes during a relatively-long period of time. However, the keystrokes on a mobile device are not always highly sensitive. Obviously, the eavesdropping attacker has a greater interest in obtaining the payment PIN number in a short moment than a regular typing. Therefore, the application context information also needs to be considered in the keystroke inference framework. We will show how to use application context to increase the inference effectiveness.

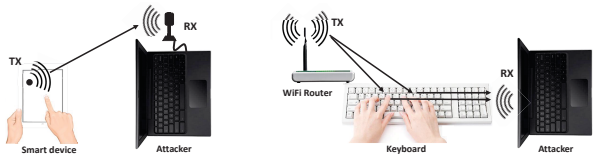
We present WindTalker, a novel and practical keystroke inference framework that allows an attacker to infer the sensitive keystrokes on a mobile device through WiFi signals. WindTalker is motivated from the observation that the typing activity on mobile devices involves hand and the finger motions, which produce a recognizable interference to the multi-path WiFi signals from the target device to the WiFi router that connects to the device. Unlike prior side-channel attacks or traditional CSI based gesture recognition, WindTalker neither deploys external devices close to the tar-

get device nor compromises any part of the target device; instead, WindTalker setups a 'rogue' hotspot to lure the target user with free WiFi service, which is easy-to-deploy and difficult-to-detect. As long as the target device is connected to the hotspot, WindTalker at the hotspot intercepts the traffic and time-adaptively collect the channel state information (CSI) between the target device and the hotspot.

The design of WindTalker faces three major technical challenges. i) The impact of the hand and finger movement of keystrokes on CSI waveforms is very subtle. An effective signal analysis method is needed to analyze keystrokes from the limited CSI. ii) The prior CSI collection method requires two WiFi devices, one as a signal sender and the other as a signal receiver, which are deployed close to the victim. A more flexible and practical CSI collection method is highly desirable for the mobile device scenario. iii) The key inference must be done at some selective moments for obtaining a sensitive keystroke, such as payment PIN number. Such context-oriented CSI collection has not been addressed by prior works. In this paper, We introduce a novel CSI based keystroke inference framework, which consists of four specifical contributions.

- We present a practical CSI collection method using public WiFi architecture without compromising the victim's device or deploying an external device very close to the victim's device. The victim's device is connected to a WiFi hotspot that stealthily collects the CSI from the victim's device by enforcing the ICMP protocol. We further adopt the directional antenna to eliminate CSI noises introduced by other factors in public places, such as other people's movement.
- We propose a keystroke recognition algorithm based on the collected CSI. Specifically, we adopt low pass filter to remove the high frequency noises and we use Principal Component Analysis (PCA) to reduce the dimensionality of the feature vectors.
- We propose a context-oriented CSI collection method, which employs both of the traffic analysis towards meta data in WiFi traffic and CSI data analysis to recognize the PIN input moment based on certain CSI tags. The proposed method can be used to successfully figure out the time of the PIN entry on Alipay (a popular mobile payment platform in China) and launch the keystroke recognition accordingly.
- We perform an extensive evaluation on keystroke inference towards PIN input at the mobile payment process, which is secured by the HTTPS protocol and thus traditionally believed to be secure. Through our evaluation, we demonstrate that the attacker can infer the PIN number at a high successful rate.

To the best of our knowledge, this is the first work to launch the keystroke inference towards PIN entry at the mobile payment (e.g., Alipay). The remainder of this paper is organized as follows. In Section 2, we introduce the background of this work. In Section 3, we introduce the research motivation by showing the correlation of keystroke and CSI changing. We present the detailed design in Section 4, which is followed by Evaluation, Real-world experiment, Discussion and Related work in Section 5, 6, 7 and 8, respectively. Finally, we give the conclusion and future work in Section 9.



(a) IKI Model (b) OKI Model

Figure 1: WiFi-based Keystroke Inference Models

2. BACKGROUND

In this section, we introduce the scenario, the overview of the keystroke inference methods, and preliminaries of channel state information.

2.1 Scenario

We consider a scenario where a user has a mobile device, such as a smartphone, or a tablet and he or she is using the public free WiFi through the device. It is a very common situation that people could have in the shopping mall, the airport, and restaurants. A WiFi hotspot is set up at a corner or on the ceiling, an unnoticeable location from the user's view. The user searches all the available WiFi signals at her device, and may choose to use the WiFi network if the name of the network "looks" good and the network is authentication-free. With the application layer security (HTTPs), the user may believe that the Internet traffic is protected from end-to-end such that the content shown at the device and the user's inputs at the device will be only available to herself and the service provider. However, as we will show, our WindTalker framework suggests effective keystroke inference methods targeting at the mobile device.

2.2 In-band keystroke inference model

WindTalker chooses *In-band keystroke inference (IKI)* model. As shown in Fig.1(a), WindTalker deploys one Commercial Off-The-Shelf (COTS) WiFi device close to the target device, which could be a WiFi hotspot. The WiFi hotspot provides free WiFi networks for nearby users. When a user connects her device to the hotspot, the WiFi hotspot is able to monitor the application context by checking the pattern of the transmitted packets. In addition, the WiFi hotspot periodically sends ICMP packets to obtain the CSI information from the target device. With the meta data of the WiFi traffic, the hotspot knows when the sensitive operations happen. And then, the hotspot adaptively launches CSI-based keystroke inference method to recognize sensitive key inputs. To the best of our knowledge, the IKI method we propose is the first one using existing network protocols of IEEE 802.11n/ac standard to obtain the application context and the CSI information at mobile devices.

Note that the existing works about CSI based gesture recognition choose another strategy: *Out-of-band keystroke inference (OKI)* model[2]. In this model, the adversary deploys two COTS WiFi devices close to the target device and makes sure the target device is placed right between two COTS WiFi devices. One is the sender device continuously emitting signals and the other one is the receiver device continuously receiving the signals. The keystrokes are inferred from the multi-path distortions in signals.

Compared with OKI model, the proposed IKI model has the below advantages. Firstly, compared with OKI model,

IKI model does not require the placement of both sender and receicer device and can be deployed in a more flexible and stealthy way. Secondly, OKI model fails to differentiate the non-sensitive operations on mobile devices (e.g., clicking the screen to open an APP or just for web-browsing) from sensitive operation (e.g., inputting the password). Instead, IKI model allows the attacker to obtain both of un-encrypted meta data traffic as well as the CSI data to launch a more fine-grained attack.

2.3 Channel State Information

The basic goal of WindTalker is measuring the impact of hand and fingers's movement on WiFi signals and leveraging correlation of CSI and the unique hand motion to recognize PIN. In the below, we briefly introduce the CSI related backgrounds.

WiFi Standards like IEEE 802.11n/ac all support Multiple-Input Multiple-Output (MIMO) and Orthogonal Frequency Division Multiplexing (OFDM), which are expected to significantly improve the channel capacity of the wireless system. In a system with transmitter antenna number N_{TX}, receiver antenna number N_{RX} and OFDM subcarriers number N_s, system will use $N_{TX} \times N_{RX} \times N_s$ subcarriers to transmit signal at the same time.

CSI measures Channel Frequency Response (CFR) in different subcarriers f. CFR $H(f,t)$ represents the state of wireless channel in a signal transmission process. Let $X(f,t)$ and $Y(f,t)$ represent the transmitted and received signal with different subcarrier frequency. $H(f,t)$ can be calculated in receiver using a known transmitted signal via

$$H(f,t) = \frac{Y(f,t)}{X(f,t)}$$

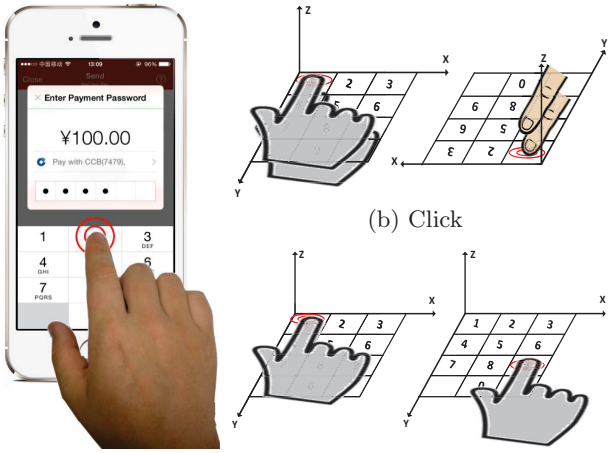
Since the received signal reflects the constructive and destructive interference of several multi-path signals scattered from the wall and surrounding objects, the movements of the fingers while password input can generate a unique pattern in the time-series of CSI values, which can be used for keystrokes recognition.

Many commercial devices such as Atheros 9390 [17], Atheros 9580 [22] and Intel 5300 [8] network interface cards (NICs) with special drivers provide open access to CSI value. In this study, we adopt Intel 5300 NICs, which follows IEEE 802.11n standard [1] and can work in 2.4GHz or 5GHz. By selecting $N_s = 30$ OFDM subcarriers, Intel 5300 NICs collect CSI value for each TX-RX antenna pair.

3. MOTIVATION

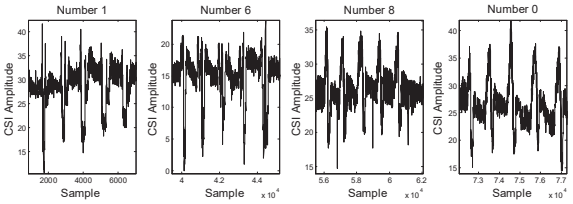
In this section, we illustrate the rationale behind CSI based keystroke inference on smart phones using real-world experiments. Fig.2(a) shows the sketch of typical touching screen during the PIN entry for mobile payment (e.g., Alipay or Wechat pay). We particularly focus on the vertical touch and the oblique touch, which are two most common touching gestures [4, 7, 20]. As shown in the left of Fig.2(b), oblique touch is the most common typing gesture, which happens when people press different keys. Vertical touch usually happens when the human continuously presses the same key, (e.g., continuously pressing 1) in the right of Fig.2(b).

We further investigate how these two common typing gestures influence CSI. Generally speaking, since CSI reflects the constructive and destructive interference of several multi-path signals, the change of multi-path propagation during

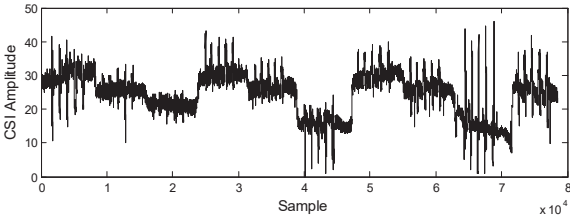


(a) Finger typing (b) Click (c) Coverage

Figure 2: Finger's influence on CSI



(a) Continuously Click in Different Keys



(b) Continuously Click in the Same Key

Figure 3: CSI Change When Typing

the PIN entry can generate a unique pattern in the time-series of CSI values, which can be used for keystrokes inference. From our experiments, we found that two main factors contributing to CSI changes are hand coverage and the finger click.

Hand coverage and finger position on a smart phone touchscreen are one of the major factors that cause the fluctuation of CSI waveform. It is widely acceptable that finger position and coverage have a direct impact on the calling quality. Similarly, since time series of CSI waveform reflects the interference of several multi-path signals, different finger position and coverage will inevitably introduce the interference to the WiFi signals and thus lead to the changes of the CSI. We further demonstrate the it via a series of experiments. Fig.3(b) shows a CSI stream when continuously pressing different number from 1 to 9, followed by 0, each for 5 times. It can be seen that the different coverages lead to the different fluctuation range of the CSI value, which can be exploited for key inference.

Finger click is another important factor that contributes to the fluctuation of CSI. Compared with CSI change caused

by the hand coverage, the experiment shows that finger click has a more direct influence on CSI by introducing a sharp convex in Fig.3(a), which corresponds to the quick click's influence on multi-path propagation. This feature can be used to distinguish the oblique touches in the case that the human continuously presses the same key or the adjacent keys, which produce similar CSI values.

4. THE DESIGN OF WINDTALKER

4.1 System Overview

The basic strategy of WindTalker is hitting two birds with one stone. On one hand, it analyzes the WiFi traffic to identify the sensitive attack windows (e.g., PIN number) on smartphones. On the other hand, as long as an attack window is identified, WindTalker starts to launch the CSI based keystroke recognition. As shown in Fig.4, WindTalker is consisted of the following modules: *Sensitive Input Window Recognition Module*, which is responsible for distinguishing the sensitive input time windows, *ICMP Based CSI Acquirement Module*, which collects the user's CSI data during his access to WiFi hotspot, *Data Preprocessing Module*, which preprocesses the CSI data to remove the noises and reduce the dimension, *Keystroke Extraction Module*, which enables WindTalker to automatically determine the start and the end point of keystroke waveform, and *Keystroke Inference Module*, which compares the different keystroke waveforms and determines the corresponding keystroke.

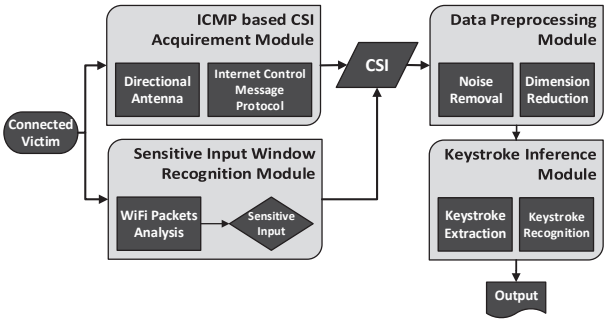


Figure 4: WindTalker Framework

4.2 Sensitive Input Window Recognition Module

To distinguish the time window of the sensitive input from that of insensitive input, WindTalker captures all the packets of the victim with Wireshark and records timestamp of each CSI data. Currently, most of the important applications are secured via HTTPS, which provides end-to-end encryption and prevents the eavesdropper from obtaining the sensitive data such as the password. Our insight is that though HTTPS provides end-to-end encryption, it cannot protect the meta data of the traffic such as the IP address of the destination sever, which can be used to recognize sensitive input window.

In particular, WindTalker builds a Sensitive IP Pool for the interested applications or services. Take the AliPay as an example. During the payment process, it will be directed to a limited number of IP addresses, which can be obtained via a series of trials. In the experimental evaluation, it is shown that, for Alipay users, the traffics of the users under the same network will be directed to the same server IP, which will last for a period (e.g., several days for one round of experiment). This allows WindTalker to figure out the sensitive input time window.

During the attack process, as long as the traffic to the Sensitive IP Pool is observed, WindTalker will record the corresponding start time and the end time, which serve as the start and the end of the Sensitive Input Window. Then, it starts to analyze the CSI data in this period to launch the password inference attack via WiFi signals.

4.3 ICMP based CSI Acquirement Module

4.3.1 Collecting CSI Data by Enforcing ICMP Reply

Different from the previous works which rely on two devices including both of the sender and the receiver to collect CSI data, we apply an approach that leverages Internet Control Message Protocol (ICMP) in hotspot to collect CSI data during the user accesses to the pre-installed access point. In particular, WindTalker periodically sends a ICMP Echo Request to the victim smartphone, which will reply an Echo Reply for each request. To acquire enough CSI information of the victim, WindTalker needs to send ICMP Echo Request at a high frequency, which enforces the victim to replay at the same frequency. In practice, WindTalker can work well for several smartphones such as XiaoMi, Samsung and Nexus at the rate of 800 packets per second. It is important to point out that this approach does not require any permission of the target smartphone and is difficult to be detected by the victim.

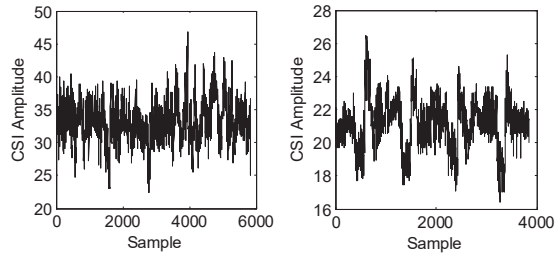
ICMP based CSI collection approach introduces a limited number of extra traffic. For a 98 bytes ICMP packet, when we are sending 800 ICMP packets per second to the victim, it needs only 78.4 kB/s for the attack where 802.11n can theoretically support the transmission speed up to 140 Mbits per second. It is clear that the proposed attack makes little interference to the WiFi experience of the victim.

4.3.2 Reducing Noise via Directional Antenna

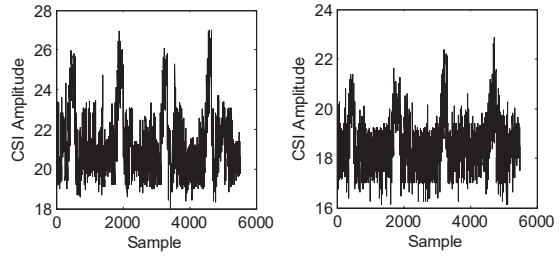
CSI will be influenced by both finger movement and people's body movement. One of the major challenges of obtaining the exact CSI data in public space is how to minimize the interference caused by the nearby human beings. We present a noise reduction approach by adopting the directional antenna. Different from omni-directional antennas that have a uniform gain in each direction, directional antennas have a different antenna gain in each direction. As a result the signal level at a receiver can be increased or decreased simply by rotating the orientation of the directional antenna. WindTalker employs directional antenna to focus the energy toward the target of interest, which is expected to minimize the effects of the nearby human body movement.

WindTalker employs a TDJ-2400BKC antenna working in 2.4GHz to collect CSI data of the targeted victim, whose Horizontal Plane -3dB Power Beamwidth and Vertical Plane -3dB Power Beamwidth are 30° and 25° respectively. Considering the case that the distance between the victim and access point is 1.5 meter, we illustrate the effective acceptance area of 0.67 meter high and 0.80 meter long.

Fig.5 shows the comparison of CSI collection with directional antenna and without directional antenna in public place. Fig.5(b), Fig.5(c), Fig.5(d) show CSI amplitude in



(a) Omni-directional Antenna in 75cm (b) Directional Antenna in 75cm



(c) Directional Antenna in 125cm (d) Directional Antenna in 150cm

Figure 5: Antenna Performance in Public Place

the case that a victim is located at 75, 125, 150 cm accordingly away from directional antenna while one people moving nearby. Unique pattern caused by finger click in number 1 can be easily caught from the original CSI stream without any preprocessing. However, these patterns are submerged in human body's influence on CSI stream obtained by omni-directional antenna even when the victim and attacker is close as 75 cm, which is shown in Fig.5(a).

4.4 Data Preprocessing Module

Before launching keystroke inference module, WindTalker needs to preprocess the CSI data to remove the noises introduced by commodity WiFi NICs due to the frequent changes in internal CSI reference levels, transmit power levels, and transmission rates. To achieve this, WindTalker first turns to low pass filter to remove the high frequency noise. Then, WindTalker leverages the Principal Component Analysis to reduce the dimensionality of the feature vectors to enable better analysis of the data.

4.4.1 Low Pass Filtering

The observation behind low pass filtering is that the variations of CSI waveforms caused by finger motion lie at the low end of the spectrum while the frequency of the noise lies at the high end of the spectrum. To remove noise, we adopt Butterworth low-pass filter, which is designed to have a flat frequency response in the passband and thus does not distort the finger motion signal much. It is observed that the frequencies of the variations in CSI time series due to hand and finger movements lie between 2 Hz and 30 Hz. As we sample CSI values at a rate of $S = 800$ packets/s, WindTalker sets some parameters to choose a proper filter in which the transition band ranges from 30Hz to 80Hz. We set the passband corner frequency $W_p = \frac{2*f_p}{S} = \frac{2*30}{800} \approx 0.075\ \pi rads/sample$ with 1 corresponding to the normalized Nyquist frequency and stopband corner frequency $W_s = \frac{2*f_s}{S} = \frac{2*80}{800} \approx 0.2\ \pi rads/sample$. Passband ripple in decibels is 1 and Stopband attenuation in decibels is 40. After low-pass filter, most of the burst noises can be removed.

4.4.2 Dimension Reduction

Dimension reduction is essential for keystroke inference via CSI information. For a CSI recording system using Intel 5300 NICs with N_{TX} transmitter antennas and N_{RX} receiver antennas, it can collect $N_{TX} \times N_{RX} \times 30$ CSI streams. It is important to reduce the dimensionality of the CSI information obtained from 30 subcarriers in each TX-RX stream and recognize those subcarriers which show the strongest correlation with the hand and finger movements. WindTalker adopts PCA, which is expected to choose the most representative or principal components from all CSI time series. PCA is also expected to remove the uncorrelated noisy components. The procedure of dimension reduction of CSI time series based on PCA includes the following steps.

Sample Centralization: Performing sample centralization in every subcarries. We use a matrix H to present original CSI stream data. For example, in a system with one pair of TX-RX antenna, we will get 30 CSI streams from 30 subcarriers. Thus, with sample rate S and time T, H has dimension of $M \times 30$, where $M = S \times T$. Every column of H represents a CSI time series data stream in one subcarrier. Then we calculate the mean value of each column in H and subtract the corresponding mean values in every column. After the centralization step, we get a processed matrix H_p.

Calculating Covariance Matrix: Calculating the correlation matrix of H_p as ${H_p}^T \times H_p$.

Calculating Eigenvalues and Eigenvectors of Covariance: Calculating the Eigenvalues and Eigenvectors of Covariance. The Eigenvectors are normalized to unit vectors.

Choosing Main Eigenvalues: Sorting the Eigenvalues from large to small and choosing the maximum k number of Eigenvalues. Then the corresponding k Eigenvectors are used as the column vectors to form a Eigenvector matrix. We will get a Eigenvector matrix whose dimension is $30 \times k$.

Data Reconstruction: Projecting H_p onto the selected k Eigenvector matrix. The reconstruction CSI data stream H_r has the dimension of $M \times k$.

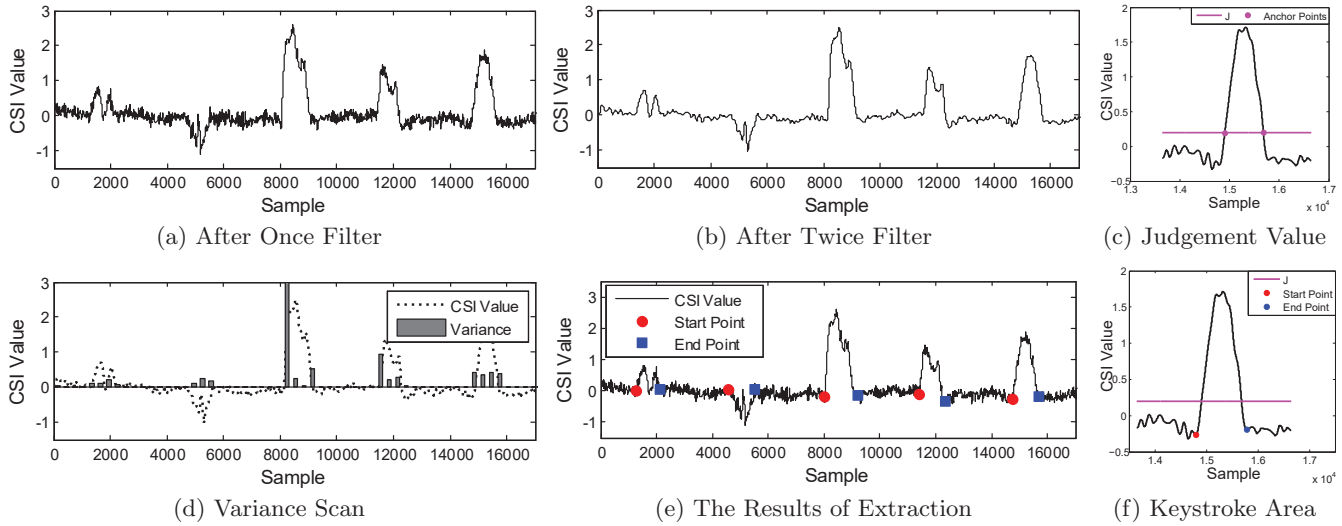
$$H_r(M \times k) = H_p(M \times 30) \times EigenVectors(30 \times k)$$

With PCA, we can identify the most representative components influenced by the victim's hand and finger's movement and remove the noisy components at the same time. In our experiment, it is observed the first $k = 4$ components almost show the most significant changes in CSI streams and the rest components are noises. We only take one PCA component from the first 4 components in the password inference module. We observed that the first PCA component reserves most changes in CSI while the ambient noise is weakly. Otherwise, the first component has a large noise and the succeeding $k - 1$ components reserve most changes in CSI.

4.5 Keystroke Inference Module

4.5.1 Keystroke Extraction

By processing the low pass filtering and dimension reduction, it is observed that the CSI data shows a strong correlation with the keystrokes. In the experiment, the sharp rise



(a) After Once Filter (b) After Twice Filter (c) Judgement Value

(d) Variance Scan (e) The Results of Extraction (f) Keystroke Area

Figure 6: Keystroke Extraction

and fall of the CSI waveform signals are observed in coincidence with the start and end of finger touch. How to determine the start and the end point of CSI time series during a keystroke is essential for keystroke recognition. However, the existing burst detection schemes such as Mann-Kendall test [9], moving average method [10] and cumulative anomalies [14] do not work well in our situation since the CSI waveform has many change-points during the password input period. Therefore, we propose a novel detection algorithm to automatically detect the start and end point. The proposed algorithm includes the following three steps.

Waveform Profile Building: As shown in Fig.6(a), it is observed that there is a sharp rise and fall which correspond to the finger motions. However, there is a strong noise which prevents us from extracting interested CSI waveform related to the keystrokes. This motives us to perform another round of noise filtering. In the experiment, we adopt Butterworth filter and choose 10Hz as the cutoff frequency to make the waveform smooth. After being filtered, the CSI data during the keystroke period are highlighted while the waveform during non-keystroke period becomes smooth, which are shown in Fig.6(b).

CSI Time Series Segmentation and Feature Segment Selection: To extract the CSI waveforms for individual keystrokes, we slice the CSI time series into multiple segments, which be grouped together according to the temporal proximity, and then choose the center of segment as the feature waveform for a specific keystroke. Without loss of the generality, it is assumed that each segment contains W samples. Given the sampling frequency S, and the time duration τ, W can be represented by $S \times \tau$. For the waveform with time duration of T, the number of segments N can be calculated as below:

$$N = \left[\frac{T \times S}{W}\right]$$

It is observed that the CSI segments during the keystroke period show a much larger variance than those happening out of the period, which is shown in Fig.6(d). Motivated by this, we are only interested in the segments with the variance which is larger than a predetermined threshold while removing the segments with the variance under this threshold. The selected segments are grouped into various groups according to the temporal proximity (e.g., five adjacent segments grouped into one group in the practice). Each group represents the CSI waveform of an individual keystroke and the center point of this group is selected as the feature segment of this keystroke. The process of time series segmentation and feature segment selection is shown in Fig.6(d).

Keystroke Waveforms Extraction: To extract keystroke waveforms, the key issues is how to determine the start and the end point of CSI time series, which could cover as much keystroke waveform as possible while minimizing the coverage of the non-keystroke portion. We choose the average value of the segment samples J as the key metric and the intersection of J and the CSI waveform serves as the anchor points. In particular, starting from the leftmost anchor point, it performs a local search and chooses the nearest local extremum which is below J as the start point. Similarly, beyond the rightmost anchor point, it can choose the nearest local extremum which is below J as the end point. As shown in Fig.6(c), Fig.6(f), Fig.6(e), with the start and the end point, keystroke waveform can be extracted.

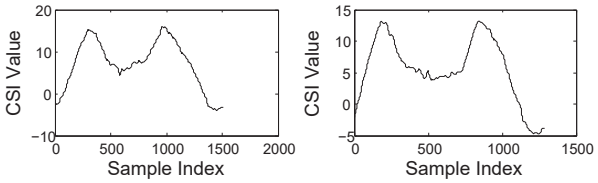
Thus, we can divide a CSI stream into several keystroke waveform. The i^{th} keystroke waveform K_i from the k^{th} principal component $H_r(:,k)$ of CSI waveforms as follows.

$$K_i = H_r(s_i : e_i, k)$$

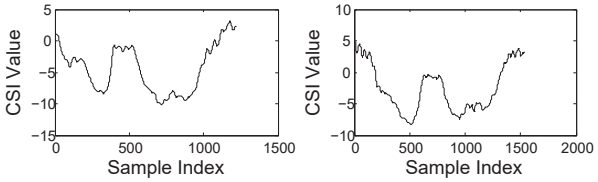
where s_i and e_i be the start and the end time of i^{th} keystroke. After keystroke extraction, we use these keystroke waveform to conduct recognition process.

4.5.2 Keystroke recognition

One of the major challenges for differentiating keystrokes is how to choose the appropriate features that can uniquely represent the keystrokes. As shown in Fig.7, it is observed that different keystrokes will lead to different waveforms, which motivates us to choose waveform shape as the feature for keystroke classification. To compare the waveforms of different keystrokes, we adopt the Dynamic Time Warping (DTW) to measure the similarity between the CSI time series of two keystrokes. However, directly using the keystroke



(a) Two samples of keystroke waveforms number 2



(b) Two samples of keystroke waveforms number 4

Figure 7: CSI Difference Between Two Number

waveforms as the classification features leads to high computational costs in the classification process since waveforms contain many data points for each keystroke. Therefore, we leverage Discrete Wavelet Transform (DWT) to compress the length of CSI waveform by extracting the approximate sequence. In the below, we will introduce the details.

4.5.3 Discrete Wavelet Transform

Different from the traditional frequency analysis such as Fourier Transform, DWT is the time-frequency analysis which has a good resolution at both of the time and frequency domains. A discrete signal $x[n]$ can be expressed in terms of the wavelet function by the following equation:

$$x[n] = \frac{1}{\sqrt{L}} \sum_{k} W_{\phi}[j_0, k]\phi_{j_0,k}[n] + \frac{1}{\sqrt{L}} \sum_{j=j_0}^{\infty} \sum_{k} W_{\psi}[j, k]\psi_{j,k}[n],$$

where $x[n]$ represents the original discrete signal and L represents the length of $x[n]$. $\phi_{j_0,k}[n]$ and $\psi_{j,k}[n]$ refer to wavelet basis. $W_{\phi}[j_0, k]$ and $W_{\psi}[j, k]$ refer to the wavelet coefficients. The functions $\phi_{j_0,k}[n]$ refer to scaling functions and the corresponding coefficients $W_{\phi}[j_0, k]$ refer to the approximation coefficients. Similarly, functions $\psi_{j,k}[n]$ refer to wavelet functions and coefficients $W_{\psi}[j, k]$ refer to detail coefficients. To obtain the wavelet coefficients, the wavelet basis $\phi_{j_0,k}[n]$ and $\psi_{j,k}[n]$ are chosen to be orthogonal to each other.

During the decomposition process, the origin signal is first divided into the approximation coefficients and detail coefficients. Then the approximation coefficients are iteratively divided into the approximation and detail coefficients of next level. The approximation and the detail coefficients in j^{th} level can be calculated as follows:

$$W_{\phi}[j_0, k] = \langle x[n], \phi_{j_0+1,k}[n] \rangle = \frac{1}{\sqrt{L}} \sum_{n} x[n]\phi_{j_0+1,k}[n]$$

$$W_{\psi}[j, k] = \langle x[n], \psi_{j+1,k}[n] \rangle = \frac{1}{\sqrt{L}} \sum_{n} x[n]\psi_{j+1,k}[n]$$

In the first DWT decomposition step, the length of approximation coefficients is half of L. For the j^{th} decomposition step, the length is half of the previous decomposition. We use the approximation coefficients to compress the original keystroke waveforms to reduce computational cost. In order to achieve the tradeoff between the sequence length reducing and preserving the waveform information, we need to choose an appropriate wavelet basis and decomposition level. In practice, we choose Daubechies D4 wavelet and perform 3-level DWT decomposition in the classification model. Therefore, for i^{th} keystroke, the third level approximation coefficients of K_i is chosen as the feature of the keystroke.

4.5.4 Dynamic Time Warping

To compare features of different keystrokes, WindTalker adopts DTW to achieve keystroke recognition. DTW utilizes dynamic programming to calculate the distance between two time series of keystroke waveforms with different lengths. With DTW, the sequences (e.g., time series) are warped nonlinearly in the time dimension to measure their similarity. The input of DTW algorithm is two time series and the output is the distance between two series. A low distance indicates that these two sequences are highly similar.

4.5.5 Classifier Training

We build a classifier to recognize the keystrokes based on their keystroke waveform shapes. Our classifier gives each keystroke waveform a set of scores, which allows the keystrokes to be differentiated based on the user's training dataset (keystrokes on different numbers). For a certain key number, classifier first calculates the DTW distances between the input waveform and all the key number's waveforms in dataset. Then classifier chooses the average value of the previous distances as the score between the input waveform and the certain key number. The smaller the score, the higher possibility the certain number is actual input number. The classifier choose the key number which has the minimum score as the predicted key number. Note that the classifier saves all scores in order to generate password candidates in Section 5.3.

5. EVALUATION

5.1 System Setup

WindTalker is built with the off-the-shelf hardware, which is actually a commercial laptop computer equipped with Intel 5300 NIC with one external directional antenna and two omni-directional antennas. WindTalker also serves as the WiFi hotspot to attract the users to access to the WiFi. The laptop runs Ubuntu 14.04 LTS with a modified Intel driver to collect CSI data. To collect the CSI data related to the user's touch screen clicks, WindTalker uses ICMP echo and reply to achieve the sampling rate of 800 packets/s. In this evaluation, the distance between the mobile user and the AP is 75 cm and the AP is placed on the left side of mobile phone.

In the online phase, we recruit 10 volunteers to join our evaluation, including 7 males and 3 females. All of the volunteers are right-handed and they perform the touch-screen operations by following their own fashions. During the experiment, the volunteers should participate in the data training phase and keystroke recognition phase by inputting the numbers according to the system hints. In the data training phase, WindTalker records each input and its corresponding CSI data. In the test phase, WindTalker infers the input data based on the observed CSI time series. The training data and testing data collection should be finished within 30

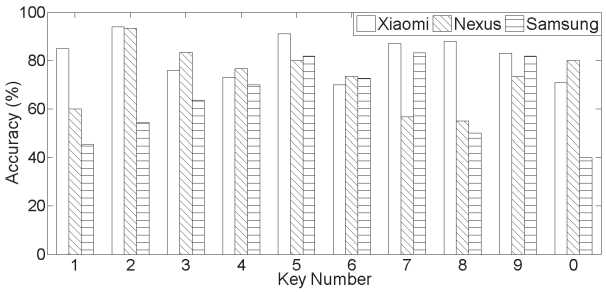


Figure 8: Classification Accuracy per key

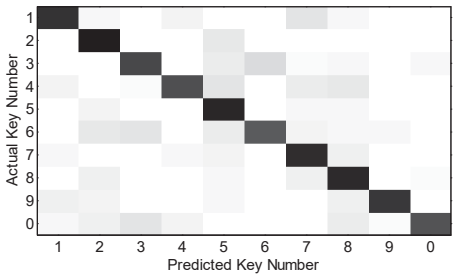


Figure 9: Color Map

minutes since CSI may change with the change of environment.

We start the evaluation by testing the classification accuracy and the 6-digit password inference accuracy. Then we investigate various metrics that may influence the inference accuracy of WindTalker including the distance and the direction. Afterwards we perform a more specific case study by inferring the password of mobile payment for Alipay in Section 6. In the current stage evaluation, we only perform user specific training and will discuss it's limitation in Section 7.

5.2 Classification Accuracy

In Section 3, we have shown that different keystrokes may be correlated with different CSI waveforms. In this section, we aim to explore whether the differences of keystroke waveforms are large enough to be used for recognizing different keys inputs in the real-world setting. We collected training and testing data from 10 volunteers. Each volunteer first generates 10 loop samples, where a loop is defined as the CSI waveform for key number from 0 to 9 by pressing the corresponding digit. After that, we evaluate the classification accuracy of WindTalker through the collected CSI data. The classification accuracy is evaluated in terms of cross validation accuracy. In our problem setting, for every 10 loops dataset, we pick up one loop in turn for the testing data and choose the other 9 loops as the training dataset. WindTalker adopts the classifier introduced in Section 4.5 to recognize the keystroke. We perform the evaluation on Samsung Note 5 , Xiaomi Redmi Note 3 and Nexus 5. These mobile are run with Android 6.0.1, 5.0.2 and 6.0.1, respectively. When we use all ten loops data, WindTalker achieves average accuracy classification of 81.8% in Xiaomi, 73.2% in Nexus and 64% in Samsung. Fig.8 shows average classification accuracy of all 10 volunteers in 10 PIN number.

Fig.9 describes the color map of confusion matrix of Xiaomi. For a specific typed number, it gives the corresponding inference results. The darker the area is, the higher the possibility of keystroke inference result is. Intuitively, it is easier for an input number that is confused with the neighboring numbers during the keystroke inference process.

5.3 Password Inference

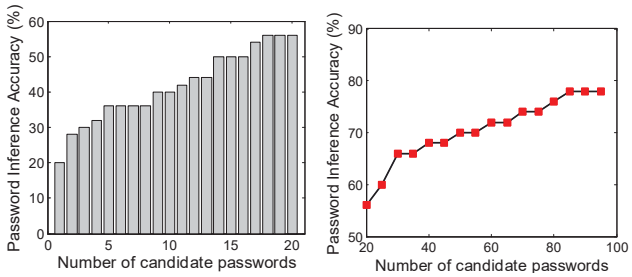
In a practical scenario setting, it may not be easy for WindTalker to get 10 training samples for each PIN number. So in the remaining section, we only use 3 samples per number for training. To illustrate the performance of WindTalker for password Inference, in this part, we ask volunteers to press 10 randomly generated 6-digit passwords and use their corresponding 3 loops as training dataset. This experiment is repeated in both Samsung and XiaoMi.

Table 1: Recovery Rate and Candidates Number

Phone	One	Two	Three
SamSung	0.63	0.83	0.89
XiaoMi	0.79	0.88	0.95

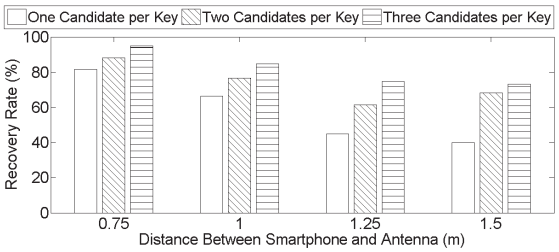
We test totally 200 set of passwords, which include 1200 keys. The inference results show that totally 852 keys were recovered. As shown in Table.1, WindTalker can achieve an average 1-digit recovery rate of 79.0% in XiaoMi and 63.0% in SamSung. For a 6-digit password in AliPay, the attacker can try several times to recover the password at an increased successful rate. Thus, we introduce a new metric, recovery rate with Top N candidates, which indicates the rate of successfully recovering the password for trying N times and represents a more reasonable metric to describe the capability of the attacker in the practical setting. As shown in Table.1, if we evaluate the 1-digit recovery rate under top 2 and top 3 candidates, it is found that the recovery rate can be significantly improved.

We further study how many candidates can help us to succeed in predicting the right 6-digit payment password in WindTalker. In particular, we will investigate the inference accuracy under top N candidates. In the experiment, each 6-digit password will be correlated with six CSI waveforms. For each waveform, WindTalker calculates the probability of matching the waveform with the predict key number. The probability of a predicted password is defined by the product of the six probabilities. For a 6-digit password, we can obtain 100000 predicted password, then sort these password by their probabilities in descending order. A successful password inference is defined as that the real password

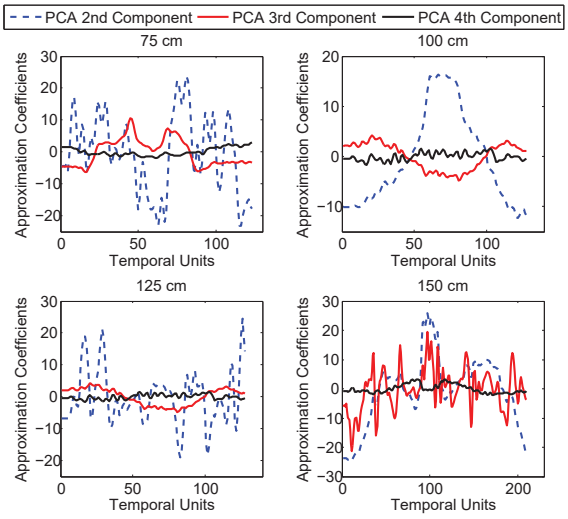


(a) Top 20 Candidates (b) Top 100 Candidates

Figure 10: 6-digit Password Inference Accuracy



(a) Distance



(b) CSI Shape Change by Distance

Figure 11: Distance's influence in WindTalker

is included in top N candidates. In Fig.10(a) ,we give the password inference accuracy under top N candidates, where N ranges from 1 to 20. The result is encouraging. It is shown that, given top 1 candidate, the inference accuracy is only 20%. The inference rate can be significantly improved if given top 5 candidates or top 10 candidates, which correspond to 38% and 42%, respectively. It is also shown in Fig. 10(b) that, if given enough top N candidates (e.g., set N as 85), the inference accuracy can reach almost 80%.

5.4 Impact of Distance and Direction

There are many factors potentially impacting the CSI. Even clicking at the same key, the different distance and direction between AP and the mobile device may also lead to a quite different CSI. We will investigate the impact of the distance and the direction on CSI in our experiments.

5.4.1 Distance

In a real scenario, the distance between victim's mobile device and AP is not fixed. As shown in Fig.11(a), the recovery rate of WindTalker will decrease along with the increase of the distance. However, it is observed that, even if the distance is enlarged to 1.6m, WindTalker can still achieve 1-digit recovery rate 70% under top 3 candidates. It demonstrates that WindTalker can work well even if the distance reaches 1.6m. This is because with WindTalker, the attacker can enforce the smart phones to send WiFi signals and AP to receive the WiFi signals. In this setting, though the distance between the victim and receiver (AP) is enlarged, the distance between the WiFi sender (smart phone) and the victim (fingers) is relatively stable, which guarantees key recognizing. Fig.12 shows that both CSI shape and degree will change under different distance. This indicates that WindTalker needs to retrain dataset even for the same victim with different distances. To partially solve this limitation, in practice, the attacker can fix the location of table and chairs, which will make the user's position relatively stable.

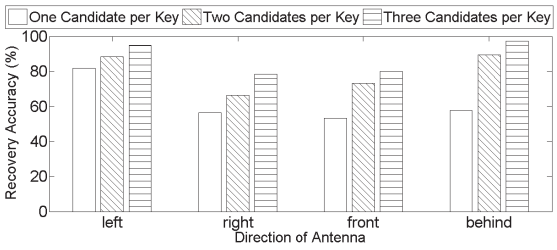


Figure 12: Accuracy in Different Direction

5.4.2 Direction

The relative direction between the victim and attacker may seriously affect the CSI since different directions mean different multi-path propagation between the transmitter and the receiver. Thus, we show the performance of WindTalker under different directions. Note that the mobile device is in front of victim in experiments. It is important to point out that, for a right-handed user, WindTalker shows a better performance when the AP is on the left side of the victim. This is because it is easier for WindTalker to sense victim's finger clicks and the hand motion. Fig.12 shows the recovery accuracy of WindTalker in different direction. It is interesting that WindTalker can achieve a high performance even the AP is deployed behind victims, which means that the proposed CSI based keystroke inference can work well even if the attacker is behind the user without visually seeing the clicking actions. This represents one of significant merits which cannot be achieved by any previous work.

6. REAL-WORLD EXPERIMENT: MOBILE PAYMENT PASSWORD INFERENCE TOWARDS ALIPAY

6.1 System Setup

To demonstrate the practicality of the WindTalker, we perform an experimental evaluation of password inference on Alipay, a popular mobile payment platform on Both of Android and iOS system. Alipay is the largest mobile payments company in the world and has 450 million monthly active user including 270 million mobile payment users. As shown in Fig.13, we deploy a WindTalker system at a cafeteria-like environment and release an authentication-free WiFi. The AP (including Intel 5300 NIC and the antennas) is set up behind the counter, which makes it less likely to be detected visually. The victim is 1 meter away from our deployed WiFi devices. When we collect the data, one user walks pass by the victim but none of users walks between the victim and the AP.

To simulate the real-world attack scenarios, the recruited volunteers are required to access to this free WiFi access

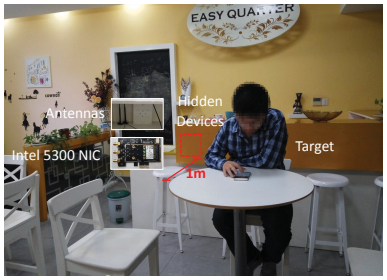


Figure 13: Real Case Scenario

points and perform the following three phases: 1) Online Training Phase: the volunteers are required to input some randomly generated numbers by following a similar way as Text Captchas. This phase is designed to collect the user's input number and the corresponding CSI data to finish the data training. 2) Normal Use Phase: the volunteers perform the online browsing or use the applications as a normal user. 3) Mobile Payment Phase: when the users use the online shopping applications, it will be ended with the mobile payment. All of the online shopping and mobile payments are secured with HTTPS protocol. According to Alipay mobile payment policy, the mobile users must input the password to finish an mobile payment transactions. The goal of the attacker is to recover the mobile payment password of the volunteers.

6.2 Operations of WindTalker

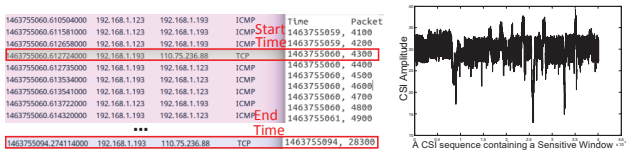
After the volunteers connect to the authentication-free WiFi hotspot, WindTalker triggers ICMP based CSI Acquirement Module to collect the CSI data at the sampling rate of 800 packets/s. WindTalker records the timestamp per one hundred CSI data. Simultaneously, WindTalker utilizes Wireshark to capture and record WiFi traffic packets and their corresponding timestamp. During the real-world experiment, WindTalker collects WiFi traffic data and CSI data in the online phase. After collecting the data, WindTalker infers the user's mobile payment password in the offline phase.

6.3 Recognizing The Sensitive Input Windows:

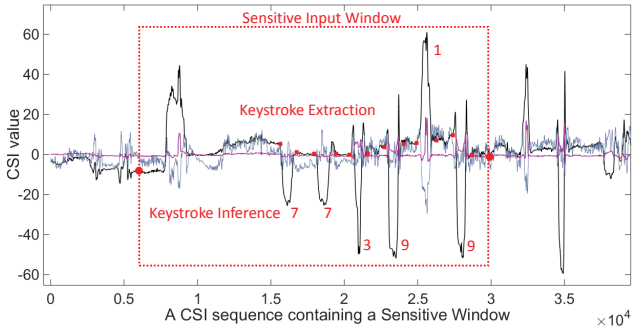
To determine the sensitive input windows, WindTalker runs in a real-time fashion to collect the meta data (e.g., IP address) of the targeted sensitive mobile payment applications (e.g., Alipay). For example, in the experiment, Alipay applications will always route their data to the server of some specific IP address such as "110.75.xx.xx". This IP address will be kept to be relatively stable for one or two weeks. With the traffic meta data, as shown in Fig.14(a), WindTalker obtains the rough start time and end point of Sensitive Input Window via searching packets whose destination is "110.75.xx.xx". Then WindTalker begins to analyze the corresponding CSI data in that period of time.

6.4 CSI based Password Inference

Fig.14(b) shows the original 12th subcarrier CSI data in Sensitive Input Window. After data preprocessing, Fig.14(c) shows the first three principal components of CSI data after PCA. It is found that in the real-world experiment that besides input payment password, victim may have other operations such as selecting credit card for payment in period



(a) Sensitive Input Windows Recognition Module (b) Original CSI



(c) Keystroke Inference Module

Figure 14: WindTalker in Case Study

of time of Sensitive Input. In order to handle this situation, WindTalker only needs to find a continuous keystroke of certain length. In our case, we are interested in continuous 6-bit password input since Alipay chooses 6-digit mobile payment password. Thus after keystroke extraction and recognition process, WindTalker is able to list possible password candidates according to probability. The top three password candidates in this case is 773919, 773619, 773916 while the actual password is 773919. We carry out the real-world experiment ten times, each time the password is different. Our experiment results show that the attacker can successfully recover 2, 4, 7 and 9 passwords if allowing to try the password input for 5, 10, 50 and 100 times (or Top 5, 10, 50, and 100 candidates). This further demonstrates the practicality of the proposed attack in the practical environment.

7. DISCUSSIONS

7.1 Limitations

In this section, we discuss the main limitations of WindTalker. WindTalker's high performance is achieved in an experiment environment. However, if we try to apply WindTalker in anytime and anyplace, we need to overcome the limitations as follows.

Hardware Limitations. In WindTalker, we use Intel 5300 NIC and Linux 802.11n CSI Tool[8]. In our experiments, it is observed that the system will crash when we perform ICMP based CSI data collection for iPhone or some version of android smart phones. This is because, according to the statement of the author of CSI Tool, it is very easy to crash when one Intel 5300 NIC works with other NICs (e.g., an iPhone). However, our implementation and evaluation on a wide range of smart phones (including XiaoMi phones, Nexus and Samsung phones) demonstrate the practicality of the proposed CSI based keystroke inference method. We will leave the issues of improving the compatibility of Intel 5300 NIC with a wider range of mobile devices to our future work.

Table 2: Recovery Rate and Loop Times

Loop Times	One	Three	Five	Ten
Recovery Rate	68.3%	73.3%	78.3%	81.7%

Fixed Typing Gesture. Currently, WindTalker can only work for the situation that the victim can only touch the screen with a relatively fixed gesture and the phone needs to be placed in a relative stable environment (e.g., a table). In reality, the user may type in an ad-hoc way (e.g., the victim may hold and shake the phone, or even perform some other actions while typing). We argue that is a common problem for most of the side channel based keystroke inference schemes such as [2, 13, 16]. This problem can be partially circumvented by profiling the victim ahead or performing a targeted attack by applying the relevant movement model as pointed out by [13].

User Specific Training. Using WindTalker, the victim's input can be recognized via the classifiers trained from the same user. In the real-world experiments, it is hard to adopt the classifiers trained by other people to infer the victim's input. This is because different people have different finger coverage and clicking model. A large number of training data based on a wide range of training samples may overcome this limitation. In practice, the attackers have more choices to achieve the user specific training. For example, it can simply offer the user free WiFi access and, as the return, the victim should finish the online training by clicking the designated numbers. It can also mimic a Text Captchas to require the victim to input the chosen numbers. We further analyze the impact of the number of training data on recovery rate in WindTalker. Table.2 shows the recovery rate increases with the training loop increases. Even if there is only one training sample for one keystroke, WindTalker can still achieve whole recovery rate of 68.3%.

7.2 Defending Strategies

One of the most straightforward defense strategies is to randomize the layouts of the PIN keypad, such that the attacker cannot recover the typed PIN number even if he can infer the keystroke positions on the touchscreen. As pointed out by [23], randomizing the keyboards is the effective at the cost of the user experience since the user needs to find every key on a random keyboard layout for every key typing.

A more practical defense strategy is preventing the collection of CSI data. For example, the user refuses to connect to free public WiFi or pays attention to the deployed WiFi devices nearby. Note that, to have the successful CSI based keystroke inference, the sender WiFi device should be deployed close enough to the victim (e.g., 30 cm as shown in [2]). To prevent the accurate CSI data collection, another strategy is obfuscating the CSI data by adding some randomized noises to CSI data. In particular, the user can intentionally change his typing gestures or clicking patterns, since finger coverage and click pattern are considered as two major factors that affect CSI value for the keystroke. Further, since CSI reflects the change of multi-path propagation of WiFi signals, the users can take some actions to introduce the unexpected interferences to the CSI data. For example, the randomized human behaviors (e.g., human mobility) or wireless signals will reduce the successful chance of the adversary. Lastly, for the proposed ICMP based CSI collection approach, CSI based typing inference requires collecting CSI data with a high frequency. Therefore, detecting and preventing a high-frequency ICMP ping represent a practical and ease of use countermeasure.

8. RELATED WORK

In this section, we review two domains of prior works that are tightly related to WindTalker.

8.1 Public free Wi-Fi with malicious behaviors

Free Wi-Fi services provided by public hotspots are attractive to users in a mobile environment when their mobile devices have limited Cellular connection. Existing works [5, 6, 11, 21] have demonstrated it is feasible to deploy a malicious Wi-Fi hotspot in a public area. For example, an iPhone can turn itself into a Wi-Fi hotspot. If the iPhone user changes the session ID to "Starbucks Free Wi-Fi", other people may connect their phones to the iPhone while wrongly believe they are using free WiFi services from a nearby Starbucks.

In our considered scenarios, attackers may make use of user's trusts on pubic WiFi and lure the the users to connect their devices to a fake access point. Then, the attacker eavesdrops the WiFi traffic to identify the sensitive windows and selectively analyzes the CSI information to infer the keystroke information.

8.2 Keystroke Inference methods

Prior keystroke inference methods have been developed based on the information from various sensors and communication channels, such as motion, camera, acoustic signals, and WiFi signals.

Motion: Owusu et al. [16] presented an accelerometer-based keystroke inference method, which aims to recover six-character passwords on smartphones. Later, Liu et al. [13] applied a similar idea to the smartwatch scenario. Their objective is to track user's hand movement over the keyboard using the accelerometer readings from the smartwatch, and the keystroke inference achieves 65% recognition accuracy.

Acoustic signals: Zhu et al. [25] presented a context-free and geometry-based keystroke inference. They use the microphones at a smartphone to record keystrokes' acoustic emanations. Liu et al. [12] further proposed a keystroke snooping system by exploiting the audio hardware to distinguish mm-level position difference. Their experiments showed the system can recover 94% of keystrokes.

Camera based: Yue et al. [23] introduces a camera-based keystroke inference using Google Glass or off-the-shelf webcam. This method can achieve a per-input success rate of over 90%. Shukla et al. [18] also presented a video-based attack relies on the spatio-temporal dynamics of the hands during typing. The paper can breaks an average of over 50% of the PINs. Sun et al. [19] use camera to record tablet backside motion and infer the victim's typing content.

WiFi signal based: Using Wi-Fi signals to infer the keystroke recently draws a large research attention because it offers device-free and non-invasion advantages. The channel state information (CSI) are obtained from the commercial Wi-Fi network interface cards. Many research works have demonstrated such fine-grained information can be very effective in detecting the ambient physical movement because it well captures the reflected multi-path WiFi signals.

Liu et al. [2] proposed a keystroke inference systems called WiKey, which uses the CSI waveform pattern generated by finger's unique motion to distinguish keystrokes on a external keyboard. Compared with our work, WiKey works on the OKI keystroke inference model and it can not recognize the sensitive input windows. Zhang et al. [24] also presented WiPass, which can work in mobile device to detect the graphical unlock passwords.

9. CONCLUSION AND FUTURE WORK

In this paper, we have designed and evaluated a novel side-channel attack based on CSI which can infer victim's input on smartphone via WiFi signals. Our evaluation shows that our attack can work well in recognizing the victim's password on smart phones. Compared with the previous side channel based keystroke inference work, WindTalker neither deploys external devices close to the target device nor compromises the target device. It can even be launched behind the victim without the requirement of visually seeing the smart phone user's input process, backside motion, or installing any malware on the tablet. Due to the limitation of Intel 5300 NIC, the current WindTalker cannot work for iOS smartphones, which will be a part of our future work. We will investigate how to further improve the inference accuracy of WindTalker under different environments.

Acknowledgments

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10. REFERENCES

[1] IEEE Std. 802.11n-2009: Enhancements for higher throughput. http://www.ieee802.org, 2009.

[2] Ali, K., Liu, A. X., Wang, W., and Shahzad, M. Keystroke recognition using wifi signals. In *Proceedings of the 21st Annual International Conference on Mobile Computing and Networking* (2015), ACM, pp. 90–102.

[3] Balzarotti, D., Cova, M., and Vigna, G. Clearshot: Eavesdropping on keyboard input from video. In *Security and Privacy, 2008. SP 2008. IEEE Symposium on* (2008), IEEE, pp. 170–183.

[4] Benko, H., Wilson, A. D., and Baudisch, P. Precise selection techniques for multi-touch screens. In *Proceedings of the SIGCHI conference on Human Factors in computing systems* (2006), ACM, pp. 1263–1272.

[5] Cheng, N., Wang, X., Cheng, W., Mohapatra, P., and Seneviratne, A. Characterizing privacy leakage of public wifi networks for users on travel. In *INFOCOM, 2013 Proceedings IEEE* (2013), IEEE, pp. 2769–2777.

[6] Fan, Y., Jiang, Y., Zhu, H., and Shen, X. S. An efficient privacy-preserving scheme against traffic analysis attacks in network coding. In *INFOCOM 2009, IEEE* (2009), IEEE, pp. 2213–2221.

[7] Forlines, C., Wigdor, D., Shen, C., and Balakrishnan, R. Direct-touch vs. mouse input for tabletop displays. In *Proceedings of the SIGCHI conference on Human factors in computing systems* (2007), ACM, pp. 647–656.

[8] Halperin, D., Hu, W., Sheth, A., and Wetherall, D. Tool release: gathering 802.11 n traces with channel state information. *ACM SIGCOMM Computer Communication Review 41*, 1 (2011), 53–53.

[9] Hamed, K. H., and Rao, A. R. A modified mann-kendall trend test for autocorrelated data. *Journal of Hydrology 204*, 1 (1998), 182–196.

[10] Holt, C. C. Forecasting seasonals and trends by exponentially weighted moving averages. *International journal of forecasting 20*, 1 (2004), 5–10.

[11] Konings, B., Bachmaier, C., Schaub, F., and Weber, M. Device names in the wild: Investigating privacy risks of zero configuration networking. In *Mobile Data Management (MDM), 2013 IEEE 14th International Conference on* (2013), vol. 2, IEEE, pp. 51–56.

[12] Liu, J., Wang, Y., Kar, G., Chen, Y., Yang, J., and Gruteser, M. Snooping keystrokes with mm-level audio ranging on a single phone. In *Proceedings of the 21st Annual International Conference on Mobile Computing and Networking* (2015), ACM, pp. 142–154.

[13] Liu, X., Zhou, Z., Diao, W., Li, Z., and Zhang, K. When good becomes evil: Keystroke inference with smartwatch. In *Proceedings of the 22nd ACM SIGSAC Conference on Computer and Communications Security* (2015), ACM, pp. 1273–1285.

[14] Lozowski, E., Charlton, R., Nguyen, C., and Wilson, J. The use of cumulative monthly mean temperature anomalies in the analysis of local interannual climate variability. *Journal of Climate 2*, 9 (1989), 1059–1068.

[15] Marquardt, P., Verma, A., Carter, H., and Traynor, P. (sp) iphone: decoding vibrations from nearby keyboards using mobile phone accelerometers. In *Proceedings of the 18th ACM conference on Computer and communications security* (2011), ACM, pp. 551–562.

[16] Owusu, E., Han, J., Das, S., Perrig, A., and Zhang, J. Accessory: password inference using accelerometers on smartphones. In *Proceedings of the Twelfth Workshop on Mobile Computing Systems & Applications* (2012), pp. 1–6.

[17] Sen, S., Lee, J., Kim, K.-H., and Congdon, P. Avoiding multipath to revive inbuilding wifi localization. In *Proceeding of the 11th annual international conference on Mobile systems, applications, and services* (2013), ACM, pp. 249–262.

[18] Shukla, D., Kumar, R., Serwadda, A., and Phoha, V. V. Beware, your hands reveal your secrets! In *Proceedings of the 2014 ACM SIGSAC Conference on Computer and Communications Security* (2014), ACM, pp. 904–917.

[19] Sun, J., Jin, X., Chen, Y., Zhang, J., Zhang, R., and Zhang, Y. Visible: Video-assisted keystroke inference from tablet backside motion.

[20] Wang, F., Cao, X., Ren, X., and Irani, P. Detecting and leveraging finger orientation for interaction with direct-touch surfaces. In *Proceedings of the 22nd annual ACM symposium on User interface software and technology* (2009), ACM, pp. 23–32.

[21] Xia, N., Song, H. H., Liao, Y., Iliofotou, M., Nucci, A., Zhang, Z.-L., and Kuzmanovic, A. Mosaic: Quantifying privacy leakage in mobile networks. In *ACM SIGCOMM Computer Communication Review* (2013), vol. 43, ACM, pp. 279–290.

[22] Xie, Y., Li, Z., and Li, M. Precise power delay profiling with commodity wifi. In *Proceedings of the 21st Annual International Conference on Mobile Computing and Networking* (New York, NY, USA, 2015), MobiCom '15, ACM, pp. 53–64.

[23] Yue, Q., Ling, Z., Fu, X., Liu, B., Ren, K., and Zhao, W. Blind recognition of touched keys on mobile devices. In *Proceedings of the 2014 ACM SIGSAC Conference on Computer and Communications Security* (2014), ACM, pp. 1403–1414.

[24] Zhang, J., Zheng, X., Tang, Z., Xing, T., Chen, X., Fang, D., Li, R., Gong, X., and Chen, F. Privacy leakage in mobile sensing: your unlock passwords can be leaked through wireless hotspot functionality.

[25] Zhu, T., Ma, Q., Zhang, S., and Liu, Y. Context-free attacks using keyboard acoustic emanations. In *Proceedings of the 2014 ACM SIGSAC Conference on Computer and Communications Security* (2014), ACM, pp. 453–464.