SenseHandle: Investigating Human-Door Interaction Behaviour for Authentication in the Physical World

Sarah Delgado Rodriguez[1†], Lukas Mecke[1,2†], Florian Alt[1]
[1] *University of the Bundeswehr Munich, Munich, Germany, {firstname.lastname}@unibw.de,*
[2] *LMU Munich, Munich, Germany, {firstname.lastname}@ifi.lmu.de*
[†] *both authors contributed equally*

Abstract

This work explores the integration of behavioural biometrics in the physical world. We developed *SenseHandle*, a system to unobtrusively measure users' interactions with door handles, thus, enabling authentication on demand. Our system is based on consumer sensing technologies from related work for easy replicability and can be non-invasively integrated into existing environments with lever-style door handles. From an initial pilot test with four participants we compare the performance of the technologies we used and discuss possible improvements and applications beyond authentication.

1 Introduction

Every year numerous new authentication approaches for digital devices like smartphones or computers are published. At the same time, one of the oldest applications for authentication, namely getting physical access to a room or building through a door, is still done using tokens like keys or access cards. While they provide benefits like following an established metaphor and being shareable they also come with disadvantages like being easily lost or stolen and requiring extra interaction (i.e. a door has to be *actively* unlocked in addition to having to open it).

We propose to leverage the interaction behaviour when using a door for authentication, be it as a sole or second factor. Our vision is, that no additional (un)locking action is necessary and users still retain control: authentication is triggered if and only if the user is physically interacting with a door (in contrast to, e.g., face recognition which is triggered on sight).

USENIX Symposium on Usable Privacy and Security (SOUPS) 2022.
August 7–9, 2022, Boston, MA, United States.

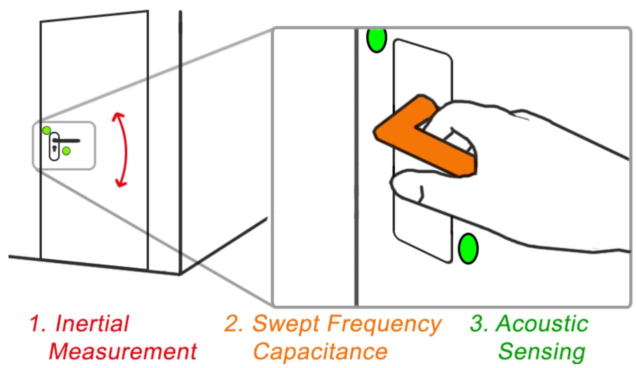

Figure 1: We propose *SenseHandle*, a prototype that leverages user's interactions with door handles for authentication. We use inertial, swept frequency capacitive and acoustic sensing to capture interactions.

In this work we investigate, if and to what extent users behaviour can be utilized to realize this vision. Previous work has shown the potential of motion data for this purpose [3,5]. We extend this approach by considering additional sensors and providing a discussion on how different sensors and phases in the interaction contribute to authentication success. To this end we developed *SenseHandle*, a system to capture user's behaviour while interacting with a door handle (see Figure 1). Our prototype can be unobtrusively integrated into existing environments and uses simple, commercially available electronic components to support future replication. We explored *SenseHandle*'s capabilities in a first pilot test ($N = 4$). Based on the results, we discuss and compare the performance of the integrated sensing technologies and potential improvements to inform future iterations and usage of our approach.

2 Related Work

Common door locks make use of object-based authentication, e.g. through a physical key, smart cards (ownership) or other Bluetooth or NFC-enhanced objects. Access control mechanisms using other metaphors are pin-pads (knowledge) and fingerprint- or face-recognition (inherence) [5, 6, 12, 14, 24]. The use of biometrics (i.e. mechanisms that leverage unique characteristics in human physiology and/or behaviour for the purpose of authentication [17]) is a promising direction to improve on this state-of-the-art. In this work we focus on behavioural biometrics, as they can be integrated seamlessly with the user's interaction, for example, using keystroke-dynamics [2, 11, 23], mouse [8, 20], touch [1, 7], gait [15, 16] or eye-movement patterns [10, 22, 25]. Even though such approaches have been generally investigated in the context of digital security, related works suggest applying behavioural biometrics to door access controls [3, 5, 9, 13]. In a Wizard-of-oz study, Mecke et al. [13] compared different mechanisms to unlock doors. Although participants liked a biometric mechanism integrated into the handle most, they still valued the control gained from using a key. However, to the best of our knowledge, few have developed functional prototypes that measure users' interaction patterns in this context.

3 SenseHandle

Here we provide details on the integration and implementation of the technologies used in *SenseHandle* (see Figure 3).

3.1 Inertial Measurements

Gupta et al. [5] achieved promising results using a inertial measurement unit (IMU) for behavioural biometric based identification of 11 study participants (true acceptance rate of 87.27% and false acceptance rate of 1.39%). Similarly, we integrated a high-end 9 DOF IMU, to accurately measure the angular velocity, acceleration and magnetic field in all 3 axis[1](see Figure 2 a). The IMU is fixed to the door handle using a 3D printed mount, double-sided tape and cable ties.

3.2 Swept Frequency Capacitance

Self-capacitive touch sensing uses one electrode, which is repeatedly charged and discharged and allows for simple touch detection, since a nearby human body would affect the (dis-)charging of the electrode [4]. Sato et al. [21] extended this approach by looping through different charging cycle frequencies (aka. frequency sweeps), instead of using a fixed one and could thereby recognize touch gestures. We adapted their technique to sample additional touch features but chose a simplified circuit[2] that uses an Arduino Uno to generate frequency sweeps that are not sinusoidal but square-waves. Those signals were then filtered with an LC circuit (aka. resonant circuit) to generate nearly sinusoidal waves and passed through an envelope detector. We approximated Sato et al.s' [21] frequency range by generating sweeping signals from roughly 0.6kHz to 4MHz (189 irregular steps in 130ms, at least 1.5 KHz between frequencies).

3.3 Acoustic Sensing

Ono et al. [18, 19] used acoustic sensing to classify multi-touch gestures and applied force on common objects. This is done using two piezoelectric components, one serving as a vibration actuator and the other one as a sensor. The measured resonant responses are influenced by different touch and grasp gestures, as well as force. We adapted this approach using a Raspberry Pi 4[3] instead of a notebook for the signal generation and data processing to reduce the size of *SenseHandle*. We implemented the acoustic sensing using a compatible Hi-FiBerry DAC + ADC pro shield[4] with a sampling rate of 192kHz and used two unimorph piezoelectric elements as actuator and sensor (200 Ohm, 4.4 kHZ, 27mm diameter). In our setup we found the strongest effect on frequencies of up to 5kHz and thus implemented sweeps from 100Hz to 5kHz (in 91 uniform steps) in 310ms (see Figure 2 c).

3.4 Limitations of the Prototype

We used a conductive lever-style door handle, though *SenseHandle* could also be used on door knobs or non-conductive door handles with minor modifications (e.g. covering the handle with conductive paint, foil or tape). We also designed the setup to not obstruct the usage of the door handle from one side only (we attached the IMU to the handle on the other side). An adapted design could allow operation from both sides (e.g. by connecting the IMU to the tip of the handle).

4 Pilot Test

We conducted a pilot test to gain first insights into the feasibility of user identification using the different sensing technologies. Our test was, therefore, not restricted to user's interaction with a locked door only, but included a complete interaction cycle with the door handle to also explore uses cases differing from physical access control (see section 6.2). Hence, we evaluated a setting, where participants had to open a door, enter and subsequently leave the room and close the door.

Our goal with this evaluation was not to achieve a competitive identification accuracy but rather to get insights into the performance of the sensors and to inform a larger follow-up study. This is also reflected in our sample size that would be too small for an authentication study.

[1] https://learn.adafruit.com/nxp-precision-9dof-breakout, last accessed January, 7, 2022

[2] https://www.instructables.com/Touche-for-Arduino-Advanced-touch-sensing/, last accessed January, 7, 2022

[3] https://www.raspberrypi.com/products/raspberry-pi-4-model-b/, last accessed January, 7, 2022

[4] https://www.hifiberry.com/shop/boards/hifiberry-dac-adc-pro/, last accessed January, 7, 2022

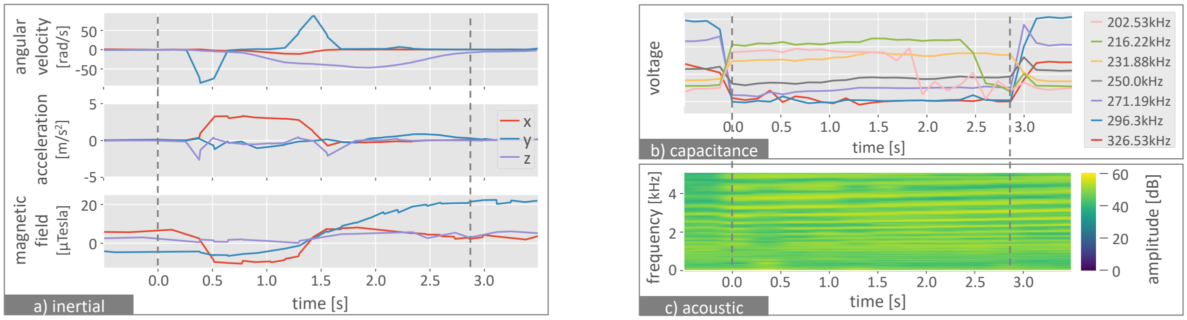

Figure 2: Door opening in our pilot test: a) IMU values (angular velocity, acceleration, magnetic field), b) capacitance (selection), and c) fft-transformed acoustic signals. Bounds of the interaction (see Section 4.3) are marked with dashed lines.

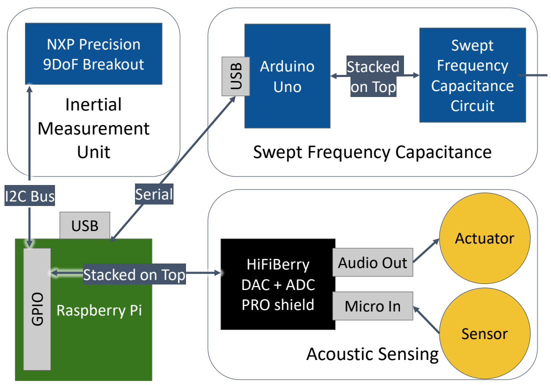

Figure 3: *SenseHandle* consists of an Arduino Uno, a circuit for swept frequency capacitive sensing, a Raspberry Pi 4, a HiFiBerry DAC+ ADC pro shield and an adafruit precision NXP 9-DoF breakout board.

4.1 Method

We applied a within-subjects study design with two conditions and two levels each: participants would start at a DISTANCE of 5m (*far*) or 25cm to the door (*near*). We also asked participants to interact *fast* (imagining a ringing phone behind the door) or at *normal* SPEED.

Conditions were chosen to reflect potential alterations when interacting with doors and repeated 10 times; resulting in 40 repetitions per participant. The order of the conditions was counter-balanced. Participants had to consent to the data collection beforehand. Furthermore, participants filled in a survey on their demographics and the perceived usability of the system at the end of the session. Sessions took between 20 and 30 minutes and participants were compensated with 5€. Following our institutions guidelines and local laws, our low-risk pilot test required no formal approval by an IRB.

4.2 Participants

We recruited 4 participants from our personal environment as the pandemic situation did not allow for external participants. Participants were aged 26 to 64, two identified as female and two as male. They reported to not feel influenced in their behaviour by *SenseHandle* or the environment.

4.3 Measures

We split each repetition in the opening and closing phase and excluded samples outside the duration of the interactions based on one specific capacitive touch feature (320kHz frequency) that proved to be a stable measure for touch detection.

Values were repeated until a new measurement was available to compensate for different sampling rates between the technologies (e.g., acoustic sensing: 3.2Hz vs IMU: 25.9Hz). Our final dataset consisted of 18600 samples from 320 interactions (80 per participant) with an average sampling rate of 25.9Hz (718s summed interaction duration). It included 288 features: 9 IMU features, 189 features for swept frequency capacitance and 90 features for acoustic sensing.

4.4 Random Forest Classification

We used random forest classification with default parameters trained on 75% of all full repetitions. We made a prediction for each sample and the final decision was based on the prevailing class (*winner-takes-it-all*). Since identification accuracy might vary, we report the mean over 10 executions.

5 Results

Overall, we found a mean identification accuracy for the combination of all three sensing technologies of 84.25% (opening the door) and 83.5% (closing). With regards to the different sensing technologies our results (see Table 1, top) showed the best accuracy for the IMU (90.0% and 94.75%), followed by swept frequency capacitive sensing (77.75% and 78.75%). Acoustic sensing performed worst (55.50% and 76.0%).

Even though *fast* conditions generated much less data samples (34.89% of all samples) than *normal* ones, we observed only slight corresponding effects on the accuracy. Overall, the

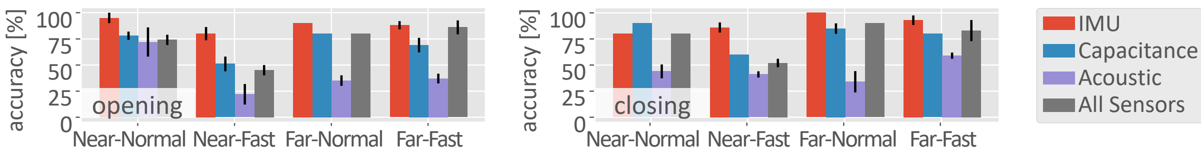

Figure 4: Identification accuracy for the different conditions of our pilot test when opening (left) and closing (right) the door.

Table 1: Mean identification accuracy of the sensing technologies for opening/closing and before opening the door.

	technology	unique samples overall	unique samples for testing	accuracy mean	accuracy std
opening	IMU	6938	1780	90.00	2.24
	capacitance	2460	630	77.75	2.08
	acoustic	1075	277	55.50	2.70
	all sensors	7248	1862	84.25	3.17
closing	IMU	9918	2625	94.75	0.75
	capacitance	3433	908	78.75	3.40
	acoustic	1471	387	76.00	1.66
	all sensors	10356	2746	83.50	2.29
before	IMU	239	7.47	70.94	2.81
	capacitance	105	3.00	66.57	3.63
	acoustic	31	1.41	57.27	6.80
	all sensors	254	7.26	69.43	5.12

IMU again performed best and achieved prediction accuracies of up to 95% (*near-normal*) for opening the door and up to 100% (*far-normal*) for closing the door. For the combination of all features, the highest accuracies were related to the *far-fast, opening* (86%) and *far-normal, closing* (90%) conditions. Figure 4 provides an overview over all combinations.

Table 1 (bottom) shows identification accuracy before the door is opened, i.e. the handle is pressed but the door did not yet move. We observed fewer samples per interaction ($mean = 7.26$) and worse accuracy of the combination (69.43%) and all single sensors except acoustic sensing (57.27%).

6 Discussion & Future Work

In our pilot study we gathered insights on the performance of different sensing technologies integrated into *SenseHandle*. We found that the IMU performs best, followed by swept-frequency capactive sensing. Acoustic sensing consistently performed worst. Our results also show that overall accuracy drops when only using samples before the door opens. This is not surprising as fewer samples are available and performance was mainly driven by the IMU and thus the (opening) motion.

6.1 Authentication with *SenseHandle*

Based on our results we identified two directions to turn *SenseHandle* into a functional authentication system:

Technical Improvements: We found both tested touch-based approaches to perform comparably weak. One possible improvement could be the addition of curved force sensitive resistors on the handle to collect higher resolution data on the grip. This would also be valuable when limited movement data is available.

Robust Authentication Performance: Our test was not aimed at training a competitive classifier. Future steps to enable robust authentication would be to collect data at a larger scale as well as to optimize and test different models. Moreover, contextual factors like carrying an item or getting distracted in the opening process could also affect the performance of *SenseHandle*. Hence, we further propose to study the impact of such changes in a less constrained setting (e.g. as study in the wild).

6.2 Beyond Access Control

Reliable user identification before the door starts to swing open is challenging. Technical changes (see Sec. 6.1) may overcome this challenges, but we also see opportunities to leverage *SenseHandle* in different ways. Those include setting off an alarm when unauthorized persons enter an area or personalization of devices or smart home environments. User interactions with door handles could also indicate their physiological state (e.g., level of stress) or be used for explicit interaction. Overall, we see many opportunities to use *SenseHandle* both for security research and beyond.

7 Conclusion

In this paper, we presented and tested *SenseHandle*, a prototype for leveraging user's behaviour when interacting with door for authentication. Our promising results can serve as a base for future improvements and more extensive evaluations. By presenting *SenseHandle* as a poster to SOUPS, we hope to gather feedback on further application areas and inspiring open question regarding user's interaction with door handles.

Acknowledgments

This project is funded by the Deutsche Forschungsgemeinschaft (DFG) under project no. 425869382 and is part of Priority Program SPP2199 Scalable Interaction Paradigms for Pervasive Computing Environments.

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