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Pick Me Up and I Will Tell You Who You Are: Analyzing Pick-Up Motions to Authenticate Users

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***Abstract*—Authentication is a cumbersome task for users, as it needs to be repeated multiple times a day. While the introduction of fingerprint authentication on mobile devices reduces users' memorization and typing efforts, users still need to perform a specific action to unlock, e.g., their smartphone. In order to further reduce the associated overheads, we analyze in this paper the feasibility of identifying users based on the way they pick up their device located on, e.g., a table. By doing so, no dedicated actions would be required from the users, as the authentication motion is already done when they want to access different services available on their devices. We have therefore designed and conducted a lab study involving 24 participants to collect the sensor data associated to these pick-up motions. The obtained classification results are promising and suggest that motion sensors could be integrated in a future implicit authentication scheme.**

I. Introduction

According to the study conducted in [1], users spend one hour per month in authenticating to their mobile devices. Most of the currently available authentication schemes are based on alphanumeric, graphical passwords, and/or biometrics. As compared to alphanumeric and graphical passwords, biometrics are advantageous, as most of them cannot be forgotten [2], thus reducing the cognitive load for the users. Nevertheless, physical biometrics like fingerprints or faces are sensitive information and the associated authentication mechanisms still require users to actively authenticate by, e.g., putting their thumbs on a dedicated button or looking at a camera. To further reduce the users' authentication efforts, behavioural biometrics aims at implicitly authenticating users in the background based on non-static biometric traits [3]. Examples of behavioural biometrics include keystrokes, gait, or motions [4].

Following this research line, we therefore examine within the scope of this paper whether the motions performed by users picking up their devices from a surface located in front of them can be leveraged to authenticate them. We have especially selected this motion, as it is a natural motion done by users leaving their devices on, e.g., tables or desks, and picking them up to write an instant message, use an app, or take a phone call. Our contributions are as follows:

1) We have conducted a lab study involving 24 participants whose demographics are detailed in Sec. III-A. In this study, our participants have picked up a smartphone located on a desk according to two scenarios: (a) sitting and (b) standing. As a result, we have collected a dataset including accelerometer, gyroscope, and rotation data during pick-up motions according to the settings presented in Sec. III-B.
2) After preprocessing the collected dataset as described in Sec. IV, we extract the associated feature vectors (see Sec. V) and focus on the *Multi-Layer Perceptron* (MLP) classification algorithm (see Sec. VI).
3) We show in Sec.VII that 85% of our participants can be correctly identified when picking up a phone based on accelerometer, gyroscope, and rotation data. We discuss our results in Sec. VIII. Our results are encouraging and suggest that building on this sensor combination may open new possibilities for the development of implicit authentication mechanisms as detailed in Sec. IX.

II. Related Work

Different authentication schemes based on behavioural biometrics have been proposed as illustrated in [5], [6]. However, not all of them are applicable in our scenario. For example, gait recognition [7] would require users to walk to authenticate to their devices. We therefore focus on behavioural biometrics resulting from natural user interactions with their devices. A first proposed solution is to authenticate users based on their keystrokes through touch sensors [8], [9]. This approach, however, requires users to first input content on their mobile phone, resulting in either additional efforts for the users or usage of the phone's functions without an initial authentication. Consequently, the authentication should ideally happen before users are able to access the phone's services. This is the case with the approaches proposed in [10], [11], [12], which rely on the phone's motion when users lift it to their ear to, e.g., take a call. In their solutions, the authors build solely on accelerometer data in [10], while gyroscope values are further considered in [11]. In contrast, accelerometer, gyroscope, and magnetometer values are taken into consideration in [12]. In our work, we therefore rely on similar sensors, but consider a different motion, namely picking up the phone from a surface in front of the user and holding it in front of her. As a result, our approach is not only limited to authenticate users receiving phone calls, but also covers multiple application scenarios when users want to write/read emails/messages, use apps, or browse the Internet. Our work shares more similarities with [13].

III. Data Collection

To examine the feasibility of our approach, we have hence conducted the following lab study to investigate whether the pick-up motions differ between users, and hence would allow to classify a user in our participants' sample.

A. Demographics

We have recruited our sample via mailing lists and advertising boards at the university and via our social contacts. The study has been conducted between the 12th and 14th of July, 2017. 24 participants (14 men and 8 women) contributed to the study. Their age ranges between 19 and 62 (median: 27). All participants are at least right-handed with one being ambidextrous. Their height varies between 153 and 198 cm.

B. Settings

Before starting the experiments, we have distributed an consent form to the participants in order to inform them about both data collection and processing modalities. Note that none of our institutions has an ethical board for reviewing user studies in our field. We have, however, limited the data collection to the minimum and conducted it anonymously. The participants have been informed that they could opt out at any time and that their data would be removed. After agreeing to participate, each participant has been assigned a pseudonym and asked to answer a questionnaire to gather his/her demographics. The completion of the study took approximately 15 min per participant. The participants have been offered a compensation of 5€ for their contributions.

The following experiments have been conducted in the same room including a desk and a chair as depicted in Fig. 1. For the study purpose, a Nexus 6 smartphone (Android 7.1.1) and a dice are located on the desk as well as common office equipment. The smartphone is configured to continuously record the accelerometer, gyroscope, and rotation data using the *Sensor Kinetics Pro* app [14] and its *Multi-Sensor Recorder* function. Two positions referred to as A and B are marked on the desk and serve as references for the original phone location. Position A is used when participants are sitting, while position B is used when they are standing. Note that the position of the chair is the same for all participants, while they can freely choose their standing position. In each experiment, we ask the participants to pick up the phone from the marked position as if they would, e.g., read a message, before putting it back. The number of seconds they hold the phone is previously determined by rolling the dice. By doing so, we do not only aim at simulating, e.g., a reading action, but also at preventing participants from mechanically repeating the same motion by rolling the dice in between in order to increase the realism of the experiments. Consequently, the participants repeated the same sequence of actions, i.e., *rolling the dice→picking up→holding→putting back the phone*, ten times from position A (i.e., sitting), ten times from position B (i.e., standing), ten times from A, and ten times from B. The participants were free to choose the way they picked up, held, and put back the phone.

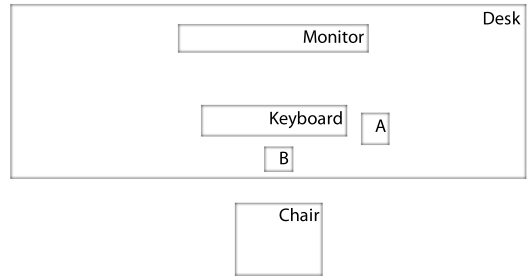


Fig. 1. Experiment setting

IV. Data Preprocessing

In our experiment, we have therefore recorded accelerometer, gyroscope, and rotation data for 40 sequences of actions performed by 24 participants. Due to different sampling frequencies between these sensors, we virtually synchronize them. If no value is available at a given timestamp, we adopt the next available measurement as replacing value. Next, we isolate the different steps recorded by the phone, i.e., *→pick up→hold→put back* based on the gyroscope values. To this end, we automatically annotate the beginning and end of a motion when the absolute sum of the gyroscope readings is greater than 0.2 and then falls below this value after 1s as shown in Fig. III-B. We manually verify and discard the sequences of actions that cannot be clearly isolated. In the following, we especially focus on the isolated pick-up motions, as we aim at investigating whether this motion can be leveraged in an implicit authentication scheme. To have a common baseline, we further discard participants having fewer than 18 valid sitting and standing sequences, respectively. We further only consider the first 18 sitting and standing sequences of participants having more than 36 valid sequences in total. This results in $19 \times (18 \times 2) = 684$ valid sequences used in our evaluation.

V. Feature Extraction

For each isolated pick-up motion, we extract a feature vector consisting of the average and variance for each axis of all considered sensors, i.e., accelerometer, gyroscope, and rotation sensor. The obtained feature vectors are divided into two sets: *SIT* and *STA*. The former contains the 18 feature vectors of the 19 sitting participants, while the later contains the feature vectors of the same participants while standing. Hence, each set contains 342 feature vectors.

VI. Classifier Design

For our evaluation, we then select the *Multi-Layer Perceptron* (MLP) as classifier. Note that we have tested the random forest, bayesian network, and support vector machine algorithms, which however do not improve the results and have therefore not been included in this manuscript. We finally run a leave-one-out cross-validation [15] using WEKA [16].

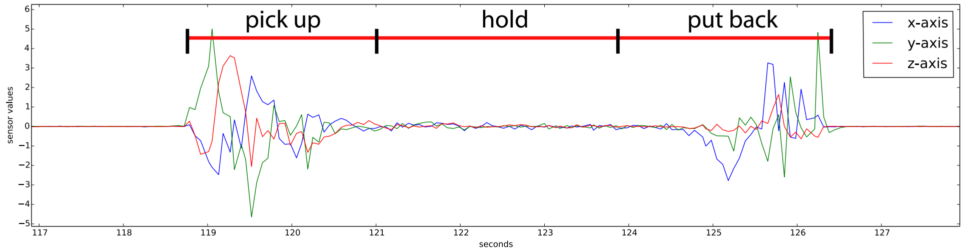
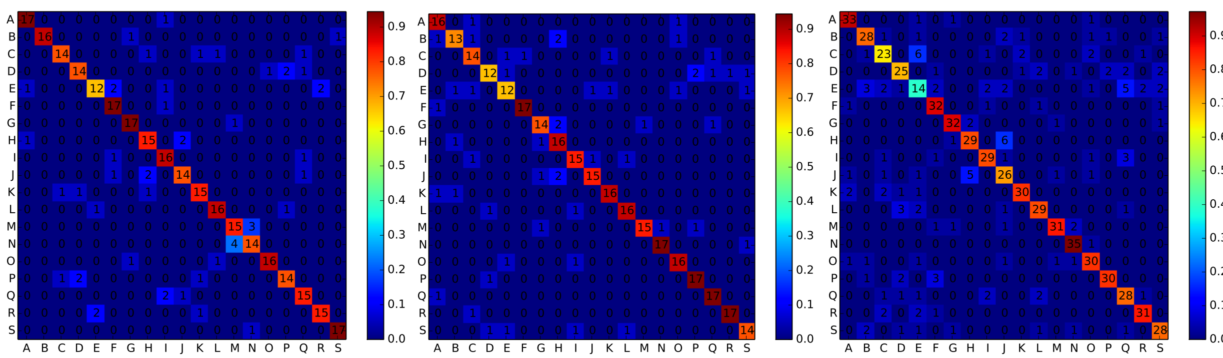


Fig. 2. Collected gyroscope data over time

TABLE I
DIFFERENCES IN THE CLASSIFICATION PERFORMANCE WHEN CONSIDERING (1) DIFFERENT SENSORS AND (2) DIFFERENT POSITIONS

Set	Accelerometer	Gyroscope	Rotation	Precision	Recall	F-measure	Kappa
SIT	x	x	x	0.848	0.845	0.845	0.8364
	x			0.539	0.567	0.547	0.5432
		x		0.586	0.591	0.585	0.5679
			x	0.754	0.749	0.746	0.7346
STA	x	x	x	0.846	0.845	0.844	0.8364
	x			0.664	0.670	0.661	0.6512
		x		0.579	0.594	0.583	0.571
			x	0.656	0.655	0.649	0.6358
SIT&STA	x	x	x	0.793	0.794	0.792	0.7824
	x			0.552	0.550	0.543	0.5247
		x		0.518	0.518	0.512	0.4907
			x	0.560	0.567	0.555	0.5432



(a) SIT (b) STA (c) SIT&STA

Fig. 3. Confusion matrices for the SIT, STA, SIT&STA datasets

VII. RESULTS

Tab. I summarizes the performance of the MLP classifier obtained for the different sensors in either isolation or combination as well as different participants' positions, i.e., *sitting participants* (SIT) and *standing participants* (STA). Additionally, we consider both positions in the SIT&STA dataset.

For all participants' positions, the best results are obtained when combining all sensors. When individually compared, the collected rotation data allow a better classification with sitting participants than the other data types. In contrast, with standing participants, the accelerometer data lead to better results than both gyroscope and rotation sensor. These differences may be due to the differences between both positions. For example, the distance from the desk to the hand of the participant in hold position may be longer when participants are standing. Participants can also hold the phone at different angles when respectively sitting and standing, especially when their wrists or forearms rest on the desk in the sitting setting.

For both SIT and STA, precision and recall are the same, namely 85%, while both values are close to 79% for SIT&STA. Recall however that the number of instances are different between SIT/STA and SIT&STA. More precisely, the number of instances in SIT&STA is the twice the number of instances in either SIT or STA by definition.

Fig. 3 shows the confusion matrices for the different positions for all participants. Only one instance is incorrectly classified for four out of 19 participants in SIT. In comparison, the same result is obtained for five participants in STA. Participant F is the only common participant in both SIT and STA datasets showing the best results. In SIT&STA, the best classification results are obtained by participant N with 35 correct instances out of 36. For all positions, the classification performance are the worst for participant E, especially in SIT&STA.

VIII. Discussion and Limitations

In this first set of experiments, we have aimed at investigating the feasibility of authenticating users based on the way they are picking up a phone. To this end, we have chosen to conduct a lab study in a controlled environment with its inherent limitations. To improve the realism of the experiments, we have however introduced the idea of the dice, so that users will not mechanically repeat the same motion, but may be distracted by the dice rolling action, thus not focusing on the motion itself. We have additionally varied the duration during which the participants held the phone and alternated the positions taken by the participants to avoid habituation effects. The order of the positions adopted by the participants remained the same, though. We finally let them freely choose their standing position to relax the controlled conditions. Nevertheless, the starting and final positions of the phone were given in both sitting and standing cases. It would therefore be interesting to conduct further experiments to determine wether similar results could be reached when increasing these degrees of freedom. We however consider these experiments as future work as detailed in Sec. IX.

Furthermore, our sample may not be representative of the whole population and does not contain users sharing the exact same physical characteristics and demographics, thus preventing us to compare them.

IX. Conclusions and Future Work

Within the scope of this paper, we have shown in a lab study that it is possible to classify participants based on the way they pick up a phone with both a precision and a recall of 85% in two scenarios: standing and sitting. Our results are therefore comparable to previously obtained as detailed in Sec. II. Additionally, they are encouraging and can be further considered in the development of new implicit user authentication schemes based on motion sensors.

To reach this objective, additional efforts are however required. Future directions include the deployment of a long-term user study under realistic conditions and in an uncontrolled environment to address the limitations introduced by the lab study. Before starting this long-term study, additional lab studies will be conducted to examine whether additional motions naturally performed by users to get their phone before using it (e.g., getting it from their pockets or bags) could and should be considered to improve the classification performance. In this context, further sensing modalities will be considered. Leveraging the collected data, additional feature vectors as well as classifiers will be considered to refine the obtained results. The consistency of the same participants' gestures will also be investigated. Future studies will involve participants showing the same physical characteristics and demographics to examine the consistency of the results between these users. Additionally, we aim at recruiting participants being more representative of the population. The obtained results will be taken into consideration to further improve the reliability of the future implicit authentication schemes. Their realization may be supported by the integration of chips dedicated to machine learning processes integrated in upcoming phones, thus allowing an on-board processing.

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