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Comparison between Fingerprint and Behavioral Biometric Authentication Using 2D and 3D Gestures

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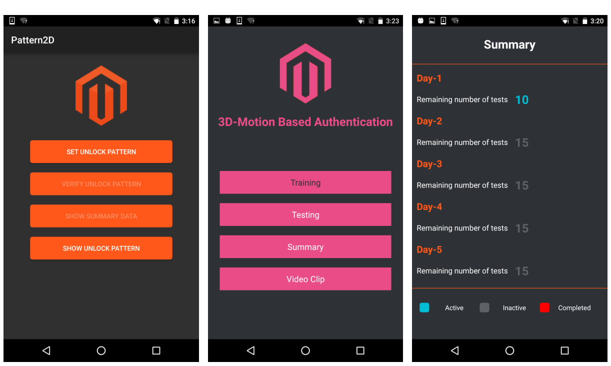
***Abstract*—With the popularity of biometric authentication, a natural question is how to compare different biometric authentication mechanisms. By answering this question, we can better understand the strength and weakness of each biometric in authentication. In this paper we report our recent study on comparing most popular physiological biometric authentication method–fingerprint–with behavioral biometric authentication methods using 2D and 3D free-form gestures, which serves as the first step towards that goal. In our study, We have developed a different Android application for each form of authentication. We recruited 6 volunteers in the preliminary evaluation. Each participant tests the three apps for 5 consecutive days. Our preliminary results reveal some interesting findings and suggest more data collection and further data analysis.**

***Index Terms*—Behavioral Biometric Authentication; Gestures; Smartphones**

I. Introduction

Smartphones can hold a great deal of personal data and access virtually unlimited data from the Internet. Safeguarding personal or sensitive data with an effective and efficient authentication mechanism is crucial. Since traditional passwords become inadequate in protecting data privacy, the interest in applying biometrics to mobile authentication keeps growing. Fingerprint scanners have been a built-in component in the latest high-end smartphones. At the same time, many gesture based behavioral biometric authentication schemes have been proposed (e.g., [1], [3]. The flourish of different biometric authentication systems poses an interesting question: Can we compare different biometric authentication schemes including fingerprint and gesture based behavioral biometrics?



(a) (b) (c)

Fig. 1: Screenshots of the 2D and 3D gesture apps

In this paper we report our recent study on comparing fingerprint to 2D and 3D gesture based authentication, which serves as the first step for answering the question. Our purpose is to compare different biometric authentication methods and to gain a deep understanding of their strength (and weakness), especially for behavioral biometrics. Towards this goal, we have developed three Android applications to test online fingerprint authentication and behavioral biometric authentication using 2D and 3D gestures and to also collect data for further offline analysis. We recruited 6 volunteers and asked each of them to use the three apps for 5 consecutive days. Our preliminary results suggest that fingerprint has higher accuracy while the accuracy of gesture based authentication can vary dramatically. More data collection and further data analysis are needed to better understand gesture based behavioral biometrics in user authentication.

II. Study Design

To collect data for comparison, we developed three Android applications (or simply apps), each app for testing a different authentication method: fingerprint, 2D gestures and 3D gestures. All three apps run on LG's Nexus 5X running Android 6.0 (Marshmallow). The fingerprint authentication app is the simplest, directly invoking Android built-in fingerprint verification API. The API only returns a binary answer (true or false). Some screenshots of the 2D and 3D gesture apps are depicted in Fig. 1. The main UI for 2D and 3D apps are displayed in Fig. 1 (a) and (b) respectively. Fig. 1 (c) shows the summary page. Each application has two phases: training and testing. A user's profile is set up in the training phase. In the testing phase, the user was provided with the same smartphone for use for 5 days, during which they would have to test each of the three authentication methods 15 times a day. The apps were designed in such a way that a user can only complete the tests of the present day. A user will also be prompted to complete required tests via notification if the app detects that the user has unfinished tests by certain time points (e.g., 12PM and 6PM). Fig. 2 shows the screenshots of 2D gesture app including a training attempt being completed (a), the profile being generated (b), and a testing attempting being completed (c). The apps will give instant authentication result once a test is performed.

We recruited 6 volunteers (4 males and 2 females) with ages ranging from 20 to 29 for the evaluation. All the participants

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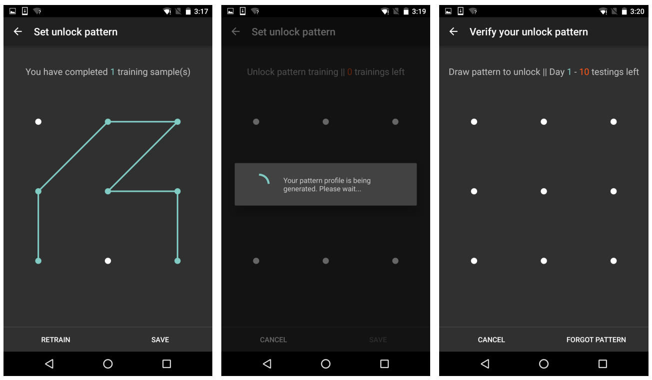

(a) (b) (c)

Fig. 2: Screenshots of training and testing using 2D app

were students (5 undergraduates and 1 graduate). Data was kept anonymous by assigning each participant a unique ID number.

The fingerprint authentication app accesses the system fingerprint scanner and Android API to verify the user. The training phase requires a user to input his or her fingerprint 6 times to set up the profile. During the testing phase, we were able to collect the number of successes and failures to derive an error rate. The 2D and 3D gesture authentication apps require a user to input 30 training samples during the training phase where a threshold and 5 templates will be derived from the data generated by motion sensors using the dynamic time warping (DTW) method to set up the user profile. During the testing phase, the sensory data will collected from each test attempt and compared to each of the templates to derive DTW distances. If at least 3 out of the 5 distances fall below the threshold then the user is verified and accepted.

One of the major issues concerning online authentication accuracy is feature extraction [2]. According to Hong *et al.*, calculating the composite acceleration of the raw data captures the user behavior as a whole by estimating the strength when a gesture is performed [2]. The composite acceleration is derived using $a_c(i) = \sqrt{a_x(i)^2 + a_y(i)^2 + a_z(i)^2}$. From the 2D gesture data, the minimum, maximum, mean and standard deviation of x and y coordinates, pressure and area were used as features. We chose to exclude the accelerometer and gyroscope data as during the training phase there was no variation in the participants' postures (in sitting). From the 3D gesture data, we calculated the the min, max, mean, and standard deviation of the accelerometer data on the 3 axes as well as the composite acceleration.

III. Preliminary Results

Both online and offline results can be obtained from this study. Online results are reported by the app in real time right after a user performs a test (either fingerprint, 2D gesture, or 3D gesture) using the corresponding app. Offline results will be derived by various data analysis methods such as one-class SVM. All the participants' motion data have been recorded by the 2D and 3D apps for in-depth offline analysis, which currently is being undertaken. Table I presents the online results directly reported by the three developed apps. The results are the percentage of successful verifications among all verification attempts. Note that there is no result for participant U5's fingerprint tests (marked as 'NA') since no data was recorded by the fingerprint authentication app for U5's testing period. It is not clear whether the missing data was caused by the app (app's bug) or by the participant (did not use the app). We have a few interesting observations from the online results. First, although fingerprint authentication achieves the overall highest accuracy, false rejection does exist for fingerprint authentication. Second, the accuracy of gesture based behavioral biometric authentication vary significantly from person to person, no matter for 2D gestures or 3D gestures. In addition, a person can have a high false rejection rate for 3D gesture but a low one for 2D gesture or vice versa. Since participants were performing those gestures in an uncontrolled environment, significant variation in accuracy for gestures may be attributed in part to that the participants did not perform their gestures in the same manner they did during training. Posture may be another reason. All participants conducted their gesture training in sitting but they might conducted their tests in sitting, standing, lying, or walking, which certainly can cause a mismatch between the testing data and profile data from training. More extensive offline data analysis will help us to gain a deeper understanding of the collected gesture data and to improve our study design.

TABLE I: Online testing results of three authentication methods

ID	Fingerprint	2D Gestures	3D Gestures
U1	100%	59%	100%
U2	87%	89%	63.55%
U3	100%	100%	96%
U4	96%	38.7%	54%
U5	NA	90.9%	33%
U6	95.6%	51.7%	69%

IV. Conclusion

In this research we compared the accuracy of fingerprint authentication and behavioral biometric authentication using 2D and 3D gestures. Each method is evaluated through a separate Android application. Preliminary results collected from 6 participants each of whom used the apps for 5 days suggest more and comprehensive data collection and in-depth data analysis are necessary to better understand the capability of gesture based behavioral biometrics in user authentication.

Acknowledgment

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