Motion-based Authentication for Wrist Worn Smart Devices

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1. INTRODUCTION

Wrist worn smart devices such as smart watches become increasingly popular. As those devices collect sensitive personal information and often work as a companion component of smartphones and therefore treated trustworthy, appropriate user authentication mechanisms are necessary to prevent illegitimate accesses to those devices. However, the small form and function-based usage of those wearable devices also pose a big challenge to authentication, which should be user friendly, unobtrusive and does not alter user's normal experience with the devices.

In this work, we study the efficacy of motion based authentication for smart wearable devices. We propose MotionAuth, a behavioral biometric based authentication method, to collect a user's behavioral biometrics through a wrist worn device and verify the identity of the person wearing the device. MotionAuth builds a user's profile based on motion data collected from motion sensors such as accelerometer and gyroscope during the training phase and applies the profile in validating the alleged user during the verification phase.

MotionAuth imposes no constraint on the form of gesture, that is, simple gestures can be applied as well as complex ones although more complex, uncommon gestures generally can render higher discernibility. The design of MotionAuth is strongly motivated by a simple idea: verifying a user with simple, natural gestures that are often performed; therefore normal people do not need to remember their verification gesture and can always perform it effortlessly. To examine this idea, we selected 3 natural gestures plus a special one and asked volunteers to perform them in evaluating the prototype of MotionAuth.

We applied two typical verification techniques for MotionAuth. They are Dynamic Time Warping (DTW) method and the histogram method [3]. DTW has been used in various studies on behavioral biometric authentication [1, 2]. Both methods use the same data acquisition process in which readings from accelerometer and gyroscope are collected when a user is performing a gesture.

We implemented a prototype of MotionAuth on Android platform. We conducted a user study to evaluate the viability of MotionAuth. We recruited 30 volunteers (24 males and 6 females) to participate in the study that spanned from June to Sept. in 2014. The study was approved by the IRB of the authors' institution. In the study each participant was asked to wear a Samsung Galaxy Gear smart watch and use the arm wearing the watch to perform the same set of 4 designated gestures each 10 times in one trial of experiment. Intervals between two consecutive experiments span 3 to 7 days. As 4 out of 30 participants did not complete all the required experiments, their gesture data are not included in the evaluation. We collected 40 samples from each participant for each gesture and in total 4,160 gesture samples are used in our evaluation.

Table 1 shows the EER value (in %) for each user and each gesture obtained by using the histogram and DTW methods. Figure 1 shows the EER distribution of each gesture for both the histogram and DTW methods. Among the four gestures, Arm-Circle (gesture I) gives the lowest EER with the Histogram method. Surprisingly, the three simple, natural gestures (Arm-Down, Arm-Up, Forearm-Rotation) also achieve quite good accuracy. Some users such as U_{15} have higher EER values across all four gestures, which suggests that some users may have difficulty in performing gestures consistently assuming no bias or error introduced in data collection. Overall, small EERs achieved by two different methods make it promising to apply MotionAuth in practice.

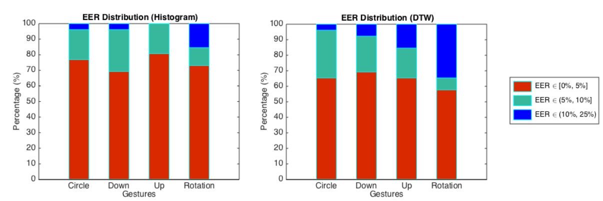

Figure 1: User Distribution of EER

2. REFERENCES

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Table 1: EER (%) of the Histogram (H) and DTW (D) methods (leave-one-out cross validation)

Gesture	U_1	U_2	U_3	U_4	U_5	U_6	U_7	U_8	U_9	U_{10}	U_{11}	U_{12}	U_{13}	U_{14}	U_{15}	U_{16}	U_{17}	U_{18}	U_{19}	U_{20}	U_{21}	U_{22}	U_{23}	U_{24}	U_{25}	U_{26}	$\mu \pm \sigma$
I (H)	2.6	0.6	5.3	11.3	2.4	2.5	7.0	2.4	5.7	5.9	2.8	2.3	0.6	0.1	6.7	0.0	2.5	0.4	0.1	0.2	0.0	1.9	2.4	2.4	0.0	0.0	2.6 ± 2.8
I (D)	2.5	2.8	2.5	5.7	2.4	7.4	7.3	0.1	10.8	9.8	2.6	7.2	8.6	0.5	7.7	0.0	5.8	0.0	2.3	3.8	1.3	2.1	2.0	3.6	1.7	0.0	3.8 ± 3.2
II (H)	0.0	7.1	1.9	5.0	2.7	1.6	5.1	2.3	8.3	10.5	0.3	5.3	2.0	2.2	8.7	0.1	7.1	0.0	2.4	0.3	7.1	1.0	0.0	0.4	0.4	0.0	3.1 ± 3.2
II (D)	0.0	4.8	1.5	0.0	2.1	3.0	6.8	0.8	7.9	9.9	0.0	5.1	6.9	4.8	10.4	2.1	10.3	0.8	2.1	4.7	4.3	9.2	0.1	1.8	4.9	0.0	4.0 ± 3.5
III (H)	2.2	2.8	2.7	5.9	0.0	0.1	7.9	3.1	1.9	2.2	1.4	4.5	2.1	3.4	9.2	0.1	9.3	0.1	7.2	2.6	2.4	4.9	0.0	0.1	0.0	0.0	2.9 ± 2.9
III (D)	2.2	4.1	2.4	0.7	0.0	9.9	14.2	0.1	2.3	4.2	5.2	9.7	23.0	0.8	7.0	2.8	13.0	2.5	2.2	0.0	10.0	10.6	0.4	4.7	0.0	0.0	5.1 ± 5.7
IV (H)	0.0	2.7	0.0	14.4	5.5	2.5	5.0	2.9	11.1	0.2	5.0	18.2	2.8	1.8	22.7	2.6	5.8	0.6	0.2	0.1	7.4	4.9	0.6	4.3	0.2	0.0	4.7 ± 5.8
IV (D)	0.1	3.7	0.0	2.6	2.9	15.0	17.6	2.5	14.2	20.4	12.6	3.3	19.1	3.9	20.5	2.5	9.1	9.2	3.3	0.0	10.3	24.1	1.8	4.5	0.5	0.0	7.8 ± 7.6