Continuous Authentication based on Hand Micro-movement during Smartphone Form Filling by Seated Human Subjects

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Abstract: Mobile devices typically rely on entry-point and other one-time authentication mechanisms such as a password, PIN, fingerprint, iris, or face. But these authentication types are prone to a wide attack vector and worse still, once compromised, fail to protect the user's account and data. In contrast, continuous authentication, based on traits of human behavior, can offer additional security measures in the device to authenticate against unauthorized users, even after the entry-point and one-time authentication has been compromised. To this end, we have collected a new data-set of multiple behavioral biometric modalities (49 users) when a user fills out an account recovery form in sitting using an Android app. These include motion events (acceleration and angular velocity), touch and swipe events, keystrokes, and pattern tracing. In this paper, we focus on authentication based on motion events by evaluating a set of score level fusion techniques to authenticate users based on the acceleration and angular velocity data. The best EERs of 2.4% and 6.9% for intra- and inter-session respectively, are achieved by fusing acceleration and angular velocity using Nandakumar et al.'s likelihood ratio (LR) based score fusion.

1 INTRODUCTION

Currently smartphones are predominantly protected through one-time authentication mechanisms such as password, PIN, patterned password, and fingerprint scanning. These one-time mechanisms are prone to a wide vector of security attacks. For example, PINs and passwords can be guessed and social engineered, a patterned password is prone to smudge attacks, and fingerprint scanning is prone to spoof attacks. Other forms of attacks include video capture and shoulder surfing. Given the increasingly important roles smartphones play in e-commerce and other operations where security is crucial, there lies a strong need of continuous authentication mechanisms to complement and enhance one-time authentication such that even if the authentication at the point of login gets compromised, the device is still unobtrusively protected by additional security measures in a continuous fashion.

The research community has investigated several continuous authentication mechanisms based on unique human behavioral traits, including typing, swiping, and gait. To this end, we focus on investigating the performance of acceleration and angular velocity of a smartphone for continuous authentication. Our data is collected from 49 users in two visits when they sit in a laboratory to fill out an account recovery form on Android phones. The present study is motivated by observations over two broad groups of factors that we believe can uniquely identify individuals, namely, *postural preferences* and *physiological traits*. While interacting with hand-held devices, individuals strive to achieve *stability* and *precision*. This is because a certain degree of *stability* is required in order to manipulate and interact successfully with smartphones, while *precision* is needed for tasks such as touching or tapping a small target on the touch screen (Sitová et al., 2015). As a result, to achieve stability and precision, individuals tend to develop their own postural preferences, such as holding a phone with one or both hands, supporting hands on the sides of upper torso and interacting, keeping the phone on the table and typing with the preferred finger, setting the phone on knees while sitting cross-legged and typing, supporting both elbows on chair handles and typing. On the other hand, *physiological traits*, such as hand-size, grip strength, muscles, age,

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gender and others (Kim et al., 2006), can also affect a user's behavior when interacting with a smartphone. In general both postural preferences and physiological traits can contribute towards unique behavioral characteristics of individuals.

In our study, 49 users sit and fill out an Android account recovery form with their personal information to simulate the familiar password resetting scenario. We hypothesize that such human-phone interactions can be unique to individuals and be measured for authentication purpose by phone sensors like accelerometer and gyroscope. Therefore in this work we have made the following contributions:

(1) A Novel User-behavior Data-set Involving Filling Out an Account Recovery Form While Sitting.

The state of the art has studied user behavior of answering questions on phones while sitting (Kumar et al., 2016) and walking (Sitová et al., 2015), movement patterns in different contexts (e.g., swipe, type, talk while sitting, standing, walking, in an elevator, in a moving bus, train, or in a car), picking up a phone (Feng et al., 2013), and hand-waving (Hong et al., 2015). Behavior authentication during form filling is also a common and important activity that warrants further study.

(2) Fusion of Multiple Readings Both within and across the Acceleration and Angular Velocity Modalities.

Since our initial SVM-based binary classification using individual readings for each modality does not produce good performance, we focus on fusing multiple readings both within (in case of *independent* acceleration and angular velocity) and across modalities (*both* acceleration and angular velocity). However, fusing the two motion events (across the modalities) significantly enhances the performance, in both intra- and inter-session experiments. Overall, our score level fusion using Nandakumar et al.'s likelihood ratio produces the best EERs of 2.4% and 6.9%, respectively, among all the intra-session and inter-session experiments.

The rest of this paper is organized as follows. Section 2 presents related work. Section 3 describes the data collection procedure. Section 4 reports all the experiments, results, and analyses. Lastly, Section 5 concludes our study and discusses future works.

2 RELATED WORK

Lee and Lee (Lee and Lee, 2015) investigates combination of accelerometer, gyroscope and magnetometer data for authentication. Using two data-sets of four subjects and feature fusion using SVM,they conclude that both higher sampling rates and fusion increase performance, with accuracy ranging between 58.3% and 97.4%.

In a preliminary work with 20 users in sitting (Lin et al., 2012), Lin et al. demonstrate that different subset of orientation features can be selected per user and per vertical and horizontal flicks, accomplishing an EER as good as 6.85% based on a majority vote of seven readings using kNN.

Feng, Zhao, and Shi (Feng et al., 2013) authenticates users based on phone picking up as a novel biometric modality. Using data from accelerometer, gyroscope, and magnetometer sensors of 31 users, a best EER of 6.13% is achieved for the inter session and stationary condition.

Hong et al. (Hong et al., 2015) investigates hand-waving patterns as a biometric modality for phone screen unlocking. Based on a dataset from 200 users and SVM, they obtain an average false positive rate of 15% and an average false negative rate of 8%.

Fusion can be done at different levels/stages of the authentication process, including sensor level, feature level, score level, and rank and decision level are broadly discussed in (Ross et al., 2008). Giuffrida et al. (Giuffrida et al., 2014) investigates the fusion of password keystroke dynamics with motion events. Jain and Kanhangad (Jain and Kanhangad, 2015) performs score level fusion of swipe and touch related gestures with the motion data from phone's accelerometer and gyroscope sensors.

Sitova et al. (Sitová et al., 2015) studied the phone movement patterns as hand-movements, orientation and grasp (HMOG) under two specific conditions: walking and sitting. They showed that the phone movement patterns while typing achieved EERs of 19.67% and 13.62% respectively under the sitting and walking conditions. The fusion of typing patterns with HMOG achieved EERs of 7.16% and 10.05% respectively for walking and sitting conditions.

Kumar, Phoha, and Serwadda (Kumar et al., 2016) investigates the fusion of phone movement patterns (acceleration) with typing and swiping when a user uses a web browser in sitting, achieving an accuracy of 93.33% for a feature fusion of movement and swipes, and 89.31% for a score fusion of movement and typing. We focus instead on fusion of acceleration and angular velocity.

Gait-based authentication uses acceleration from smartphones during walking or similar movements. Derawi et al. (Derawi et al., 2010) seems to be the first work in this area. By applying Dynamic Time Warping (DTW) over data from 51 users during normal walk on flat ground, they obtain an EER of 20.1%.

Kwapisz, Weiss, and Moore (Kwapisz et al.,

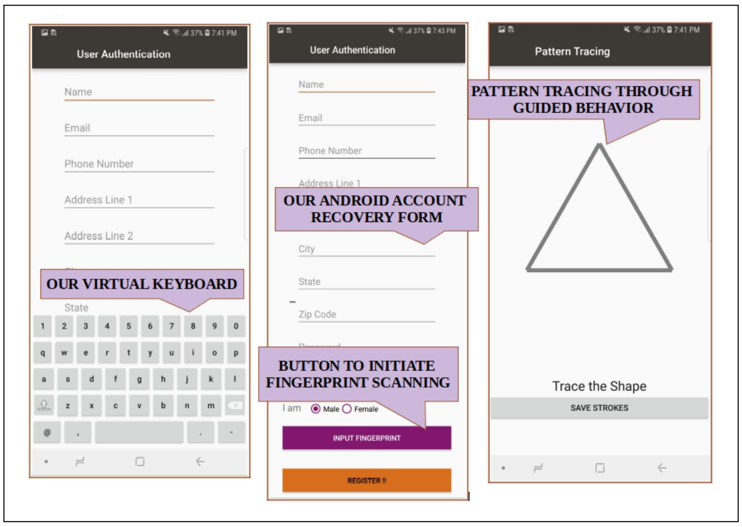


Figure 1: User interface of our Android logging app where our user simulates the account recovery process by filling out a form with personal information such as name/phone/address to reclaim an account, performing fingerprint scanning, and tracing geometrical patterns. Keystrokes, acceleration and angular velocity, and swipe and touch data were logged throughout the process.

2010) performs a binary classification based study over acceleration data from 36 users in three gait activities (walking, jogging, and climbing stairs) and shows that user authentication is impacted significantly by the gait activities.

Our user behavior during the data collection process involves static scenario where a user sits and fills out an Android account recovery form. Our authentication is based on analysis of motion-event data (both acceleration and angular velocity) to capture the user's hand micro-movements during the process.

3 DATA COLLECTION

3.1 Collection Procedure

After approval from the University Institutional Review Board (IRB), official announcements were made through university email for advertising our data collection process. In total we could recruit 49 subjects, which included both students and staff. There were 17 participants in the 18-20 age group, 9 participants of age 21-25, 12 participants of age 26-30, 5 participants from age group 30-35, and 6 participants of 35 years of age or older. 23 out of the 49 subjects were female and 26 male participants, which is an approximately equal ratio across the two genders.

Each user was scheduled to visit us twice. During the visits, our subjects simulate the typical account recovery process using an Android app on smartphones provided by us (Figure 1). In the first visit, a subject is asked to use our Android app to fill out an account recovery form 10 times with their own personal information. In the second visit, the subject is required to use our app for 15 times; the subject first enters their own information 5 times, and for the other 10 times, the subject attacks five other users by entering their information each twice. We provided our subjects with Android smartphones (one of each Samsung Galaxy S8, Samsung Galaxy Note 9, and Motorola X4). In the end, all 49 subjects completed visit 1 as required, but only 15 fully completed visit 2.

We observed that in general users hold the mobile phone with both hands and type. They either support their hands on a table kept in front of them or they support their hands on their upper torso. In general, every individual has manifested a conscious psychological trait.

3.2 Account Recovery Android App

Our data collection was designed to maximize the kinds of research problems we can study in future with the data. As shown in Figure 1, users interact and fill out the account recovery form with their credentials. They also use the fingerprint scanner when the logger prompts the user and in the end users are asked to trace several geometrical shapes. Through the above user interactions, the Android logger captures keystrokes, on-touch events (taps, double taps, long-presses, and swipes), motion events (acceleration and angular velocity), motion events during fingerprint scanning, and strokes from pattern tracing

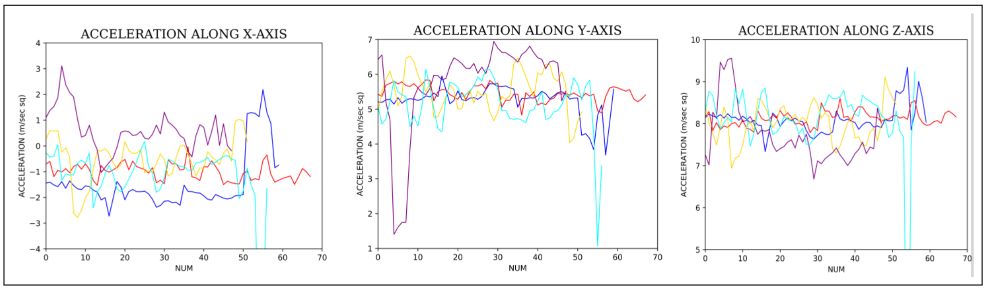


Figure 2: Acceleration data of 5 random users: left- acceleration along x-axis, center- acceleration along y-axis, right- acceleration along z-axis.

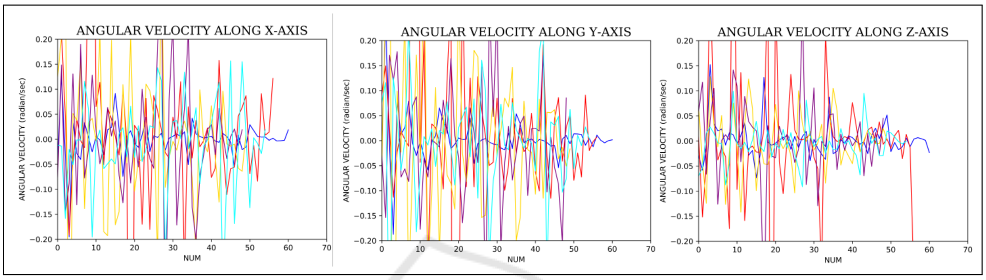


Figure 3: Angular velocity data of 5 random users: left- angular velocity along x-axis, center- angular velocity along y-axis, right- angular velocity along z-axis.

through guided behavior. These events are logged using event listeners provided by the Android API. We have used a sampling interval of 0.5 second, which is consistent with other research (Deb et al., 2019). Therefore, two data points per second get logged from each sensor. The motion events collected during normal form filling and during fingerprint scanning are separated. Our data is stored in the phone's internal SQLite3 database during the visit and copied to a secured server after each visit. We have plotted the acceleration and angular velocity data of 5 random users to visualize the data, in Figure 2 and Figure 3, respectively. As shown, both kinds of data can be used to separate users.

4 EXPERIMENTAL DESIGN AND RESULTS

4.1 Design Overview

We first evaluate the authentication performance of acceleration and angular velocity as an independent modality by training one SVM binary classifier per user. Because these classifiers are based on individual data samples, not surprisingly they have not produced strong performance. We therefore focus on improving the performance by performing score fusion both within and across the two modalities of acceleration and angular velocity. In particular, we have performed two types of score fusion experiments, namely, the weighted sum and Nandakumar et al.'s likelihood ratio based score fusion (Nandakumar et al., 2007). Moreover, we have performed both intra-session (where training, validation, and testing are done with data from the first visit) and inter-session (where training and validation are done with the first visit data and the second visit data is tested) experiments.

In all fusion experiments, we have utilized a sliding window strategy to specify the range of readings needed to make each authentication decision. The sliding window is defined by two parameters, k and n, where k is the the number of consecutive rows of readings included in the window, and n is the number of rows by which the sliding window moves forward to formulate the input for the next decision. Each authentication decision is made by fusing k consecutive score outputs from the basic binary classifiers.

Each user's data is partitioned into three portions for training, validation, and testing, respectively, where validation is used to determine the optimal sliding window size, k, and the step size, n, that produces the best EER. During testing, we use the same k and n obtained from the validation step to calculate the EER for the user. We repeat the same fusion process for all the users and calculate the average EER as an estimation of the overall performance of the system. In our experiments, we let k range from 5 to 150 (with a step size of 5) and a set of values of n = 5, 10 to 140 (with a step size of 10). A k value of 150 amounts to 75 seconds of data, which is an average time for a user to fill out the account recovery form completely for once. The value of n is always less than or equal to k. For the intra-session experiments, we use 40% of a user's visit 1 data for training, 40% for validation, and 20% for testing. We have performed cross validation, where each user's data is partitioned into five equal portions and then in each combination the five portions are distributed as training, validation, and testing data. This results in 10 combinations. The overall performance is measured by taking the average across all the 10 combinations.

For the inter-session experiments, we use 40% and 60% of a user's visit 1 data for training and validation, and the entire visit 2 data for testing. Therefore, we performed cross-validation by shuffling the training and the validation portions of the visit 1 data, which results in 10 combinations. The overall performance is measured by taking the average across all the 10 combinations.

The results of all of our experiments are compiled in Table 1, where we have reported the descriptive statistics (average, median, minimum, maximum, and standard deviation) for EERs, sliding window (k,n), numbers of Gaussian components for GMM (K), and weights (W_a, W_g), across all the users.

4.2 Features and SVM Configuration

We have used the following features for acceleration: acceleration along x, y, z- axes and the resultant acceleration, and for angular velocity: rate of rotation along x, y, z- axes and the resultant of angular velocity. The unit of acceleration data is *meter/second*^{2}. The unit of angular velocity data is *radian/second*. The resultant or magnitude of the motion-event (acceleration or angular velocity) is defined as the square root of the sum of the squares of the motion-events along x, y, and z axes:

$$resultant = \sqrt{x^2 + y^2 + z^2}$$

In general, we train one binary classifier per user. The min/max/median numbers of data points for all 49 users are 903/4756/2477 and 837/2551/1270 for acceleration and angular velocity, respectively. The intra-session experiments make use of the motion data from visit 1 only, where the data from the user are used as genuine samples and data from all the other 48 users are used as imposters. In all experiments, training data are properly balanced by up-sampling the genuine samples.

We use the SVM implementation from Python sklearn, with gamma set as *auto*, a value of 100 for the parameter C, and RBF (Radial Basis Function) as kernel. There are two SVMs per user, one for each of acceleration and angular velocity. We have also fused both within and across the modalities. We measure the performance of the fused classifiers using Receiver Operating Characteristic (ROC) curves and report Equal Error Rates (EER). We compute the pair-wise correlation between acceleration and angular velocity features. The correlation coefficients do not show any substantial correlation between any two features, which is an ideal precondition for fusion.

4.3 Within-modality Score Level Fusion

4.3.1 Score Fusion of Acceleration

This experiment is about authentication using only acceleration data. Recall that the features extracted for this modality are acceleration along x, y, and z axes, and the resultant acceleration. Based on the acceleration data, we train one binary classifier per user and measure the performance of the classifier using the ROC curve. To improve performance, we apply a score level fusion to each user by averaging the distance scores of k consecutive acceleration readings (scores) from the binary classifier. During the validation step, we decide the values of k and n that yield the best EER. At testing, we use the same k and n obtained from validation to calculate the EER for the user. We repeat the same fusion process for all the 49 users and calculate the average across all the 49 EERs as an estimation of the overall performance of the system. As shown in Table 1, the average EERs obtained in this experiment are 20.5% in intra-session and 8.4% in inter-session.

4.3.2 Score Fusion of Angular Velocity

This experiment uses only the angular velocity data from gyroscope for authentication. Features extracted include angular velocity along x, y, z axes, and the resultant angular velocity. Again, similar to the acceleration modality, we train one binary classifier per user, based on the angular velocity data and measure the performance of the classifier using the ROC curve.

Given that in our case a user sits and fills out an account recovery form on Android phones, they stay mostly static and there is not much somatic movements involved during data collection. Therefore, we hypothesize that the angular velocity data is skewed toward the 0 value, which might bias the classifiers. Visualizations of angular velocity data over multiple small time intervals confirm this. Therefore we decide

Table 1: Summary of Experiments and Performance Results (k,n: width and step size of sliding window; K: number of Gaussian components for GMM; and W_a,W_g: weights for weighted sum score fusion).

Experiment	Intra-session avg/med/min/max/std	Inter-session avg/med/min/max/std
Within-modality		
Score fusion	EER-20.5/20.2/3/35/7	**EER-8.4/4.1/0/31/10.8**
of acceleration	k-122/123/94/143/11	k-89/92/17/124/32
(Section 4.3.1)	n-105/105/85/132/11	n-83/88/11/121/31
of angular velocity	EER-18.3/19.9/0/34.6/9.6	**EER-8.5/5.7/0/34.9/10.9**
(Section 4.3.2)	k-120/122/41/146/18	k-99/112/17/127/31
	n-104/105/41/131/16	n-91/102/11/123/30
Cross-modality		
Weighted score fusion	EER-8.3/8/0/28/5.6	EER-7.9/0.8/0/34.5/11.5
	k-90/94/27/127/22	k-73/77/16/117/30
(Section 4.4.1)	n-82/86/25/121/20	n-67/75/11/103/28
	W_a-0.6/0.5/0.2/0.9/0.2	W_a-0.5/0.5/0.1/0.8/0.1
	W_g-0.4/0.5/0.1/0.8/0.2	W_g-0.4/0.4/0.1/0.8/0.1
Likelihood ratio based	**EER-2.4/0.9/0/15.3/3.3**	**EER-6.9/2/0/33.4/10.1**
score fusion	k-80/82/12/120/25	k-80/73/16/134/31
(Section 4.4.2)	n-73/77/9/112/24	n-71/64/11/110/28
	K-3/2/2/10/2	K-3/3/2/7/2

to experiment with thresholding the data to improve authentication performance. Specifically, we take the 10th percentile value of all the magnitudes of angular velocity data as a threshold, which turns out to be 0.05 radian/sec, and eliminate all data points of which the magnitude is less than the chosen threshold. As a result, the remaining angular velocity data for all users shows a magnitude between 0.05 and 5 radian/second.

The same score level fusion as for acceleration is applied to angular velocity. As shown in Table 1, with the threshold of 0.05 rad/sec, the average EER for all 49 users for the score level fusion is 18.3%. The inter-session experiment taking 15 users produced an EER of 8.5% in this experiment.

4.4 Cross-modality Score Level Fusion

4.4.1 Weighted Score Fusion

This score level fusion experiment makes use of acceleration and angular velocity events occurring at a common time instant. Once they are classified using their respective SVMs, we compute the weighted sum of the average of the k distance scores generated from the two SVMs as a new score (Nandakumar et al., 2007). So, in addition to k and n, the validation step also selects the pair of weights (for acceleration and angular velocity) that yields the best EER for the user. Therefore, the pair of weights is user-specific. The weights range from 0 to 1.0 with a step size of 0.1, and always add up to 1. The validated k, n, and pair of weights are then used in testing.

As shown in Table 1, the average EERs for the intra-session and inter-session experiments are 8.3% and 7.9% respectively. Recall that the best EERs of acceleration and angular velocity as uni-modality are 20.5% and 18.3%, respectively, in the intra-session experiments. So the 8.3% EER from this intra-session score fusion of two modalities represents a noticeable improvement.

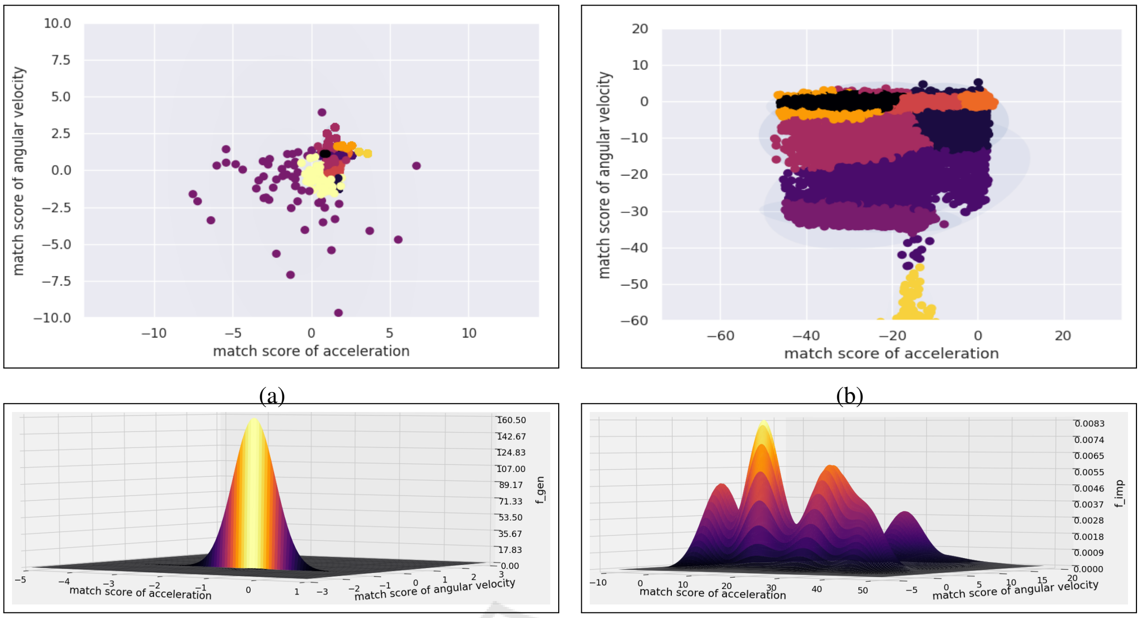
4.4.2 Likelihood-ratio based Score Fusion

This experiment applies Nandakumar et al.'s likelihood ratio based score level fusion (Nandakumar et al., 2007). We then take the 2-dimensional vectors of match scores of acceleration and angular velocity from their respective classifiers and create genuine and impostor distributions. The genuine and impostor distributions are estimated as Gaussian Mixture Models (GMMs). The likelihood ratio (LR), which is defined as the ratio of the genuine distribution to the impostor distribution, is then used as a new match score for a test sample:

$$LR = \hat{f}_{gen}(x)/\hat{f}_{imp}(x)$$

where $\hat{f}_{gen}(x)$ and $\hat{f}_{imp}(x)$ are the estimated genuine and impostor density functions, respectively, and x is a 2 dimensional vector of match scores of acceleration and angular velocity. The calculated LR is used as a match score for identifying a genuine user.

During validation, for each user we validate the optimal combination of k, n, and the number of Gaussian components (K) that produce the best EER for the user. Hence, the number of Gaussian components



(a) (b) (c) (d)

Figure 4: Density estimation based on Gaussian Mixture Models for the motion event data from our mobile logger. (a) Scatter plot of genuine scores along with 10 fitted mixture components shown in different colors, (b) scatter plot of impostor scores along with 10 fitted mixture components in different colors, (c) density estimate of genuine scores, (d) density estimate of impostor scores. Number of mixture components for both genuine and impostor densities in this example is 10.

is user-specific, which ranges from 2 to 18 (with a step size of 2). We then use the validated k, n, and component number (K) in testing. By taking the mean of k likelihood ratios as a final match score, we calculate an EER for each user.

As shown in Table 1, the average EER of all 49 users is 2.4%, which is the best among all intra-session, cross-modality fusion experiments. Lastly, the inter-session EER for this experiment is increased to 6.9%, which is also the best performance among all the inter-session experiments.

The genuine and impostor distributions are modeled as a mixture of Gaussian components using Gaussian Mixture Model (GMM).

The genuine distribution is defined as:

$$\hat{f}_{gen}(x) = \sum_{j=1}^{M_{gen}} P_{gen,j}\phi^K(x;\mu_{gen,j},\Sigma_{gen,j})$$

and the impostor distribution is defined as:

$$\hat{f}_{imp}(x) = \sum_{j=1}^{M_{imp}} P_{imp,j}\phi^K(x;\mu_{imp,j},\Sigma_{imp,j})$$

Note that ϕ^K is a K-variate Gaussian density function with mean μ, and covariance matrix Σ:

$$\phi^K(x;\mu,\Sigma) = (2\pi)^{-K/2}|\Sigma|^{-1/2}exp(-1/2(x-\mu)^T\Sigma^{-1}(x-\mu))$$

M_{gen} (M_{imp}) is the number of mixture components used to model the density of the genuine (impostor) scores. $P_{gen,j}(P_{imp,j})$ is the weight assigned to the j^{th} mixture component in $\hat{f}_{gen}(x)$ ($\hat{f}_{imp}(x)$). The weights assigned to the j-components must sum up to one:

$$\sum_{j=1}^{M_{gen}} P_{gen,j} = 1 \text{ and } \sum_{j=1}^{M_{imp}} P_{imp,j} = 1$$

$\mu_{gen,j}$ ($\mu_{imp,j}$) and $\Sigma_{gen,j}$ ($\Sigma_{imp,j}$) are the mean and covariance matrix of the jth Gaussian, respectively.

Our experiment chooses from 2 to 18 components to identify GMMs that produce the best performance. Figure 4 depicts the scatter plots of genuine and impostor scores as well as the estimated density functions for both genuine and impostor scores for a particular user that achieves the best performance with GMMs of 10 Gaussian components for both modalities. Note that the genuine scores and imposter scores lie in different regions in the scatter plots. Figure 4c shows the 10-component GMM estimated from the genuine scores. Note that this distribution peaks at a value around 160 but there are also several smaller peaks that are not visible in this graph. On the other hand, there are more visible components in the impostor score distribution shown in Figure 4d.

5 CONCLUSION AND FUTURE WORK

We evaluate the potential of using motion events (acceleration and angular velocity) generated during a common activity when a smartphone user is filling out a form in sitting, to continuously authenticate the user. Using a new data-set collected from 49 users when they fill out an account recovery form on Android phones while sitting in a laboratory, we have performed score-level fusion experiments, of two types, namely, weighted score fusion and the likelihood ratio based score fusion. In addition, we have also performed both intra- and inter-session experiments.

By fusing both modalities, the likelihood ratio based score fusion performs the best in both intra- and inter-sessions, between the two score fusion strategies, with EERs of 2.4% and 6.9%, respectively. An average sliding window width of 80 for the best-performing likelihood ratio approach is equivalent to 40 seconds of data per decision.

As shown in Table 1, in the score fusion of acceleration experiment and score fusion of angular velocity experiment, the average and the median EERs are very close, which shows that the data is evenly distributed. The standard deviation implies that the EERs do not vary much among the users. Overall, the cross-modality fusion outperforms the within-modality and the likelihood ratio based score fusion performs the best in all experiments. Lastly, it is noticed that in the score fusion experiments, the k and n parameters of the sliding window are typically high. Based on our sampling rate of 2 Hz, these would amount to less than 2 minutes of data per authentication decision.

Our future work will include replicating this study on other public data-sets to increase the reliability of the reported performance. It will also be worthwhile to investigate the fusion of motion events with other modalities such as typing and swiping to identify the optimal combination of multi-modalities while considering user experiences and usability.

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