Investigating Mobile Device Picking-up Motion as a Novel Biometric Modality

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Abstract

Employing mobile sensor data to recognize user behavioral activities has been well studied in recent years. However, exploiting mobile motion data as a novel biometric modality remains a new area. In this paper, we propose two novel methods, a Statistic Method to intuitively apply classifier on the statistic features of the data; and a Trajectory Reconstruction Method to reconstruct the Mobile Device Picking-up(MDP) motion trajectories and extract specific identity features from the traces. We evaluated our methods on a multi-session motion dataset. A Equal Error Rate of 6.13% and 7.09% has been respectively achieved by the Statistic Method and the Trajectory Reconstruction Method, which demonstrated the feasibility of the proposed methods. Furthermore, experimental results showed several interesting evidences: 1) the accuracy of the methods declined in the inter-session tests; and 2) user movements(e.g., walking) have a high impact on the verification performance.

1. Introduction

Reported by the market database and forecast [2], the Smartphone sales to end user are expected to reach 1,048 million units by 2015. The growth in popularity of smartphone devices have opened doors for newer and enhanced capabilities in high power mobile computing. However, one flaw in this trend is with regard to the fact that smartphones are more prone to unauthorized access(due to theft for example) than desktop computers. Meanwhile, with the wide implementation of motion sensors (*e.g.,* accelerometer, gyroscope and magnetometer on the mobile devices) the gesture or movement detected by the aforementioned motion sensors have been employed for motion recognition [10], [16], and furthermore, can be used as a modality for user identification or verification.

The useful gestures are performed when users interact with the phone via holding the mobile devices in hand, moving the arm or/and changing hand pose. Though users can create numerous gestures, the number of frequent gestures is limited due to the limited usage of the mobile devices. These common gestures generated during the human-device interaction are shared by most of the users, which provides us an opportunity to compare their motion patterns and conduct non-intrusive biometric authentication. For example, one of the major usage of the mobile phone is answering the call, for this purpose users perform a gesture of picking up their phone, which is referred as Mobile Device Picking-up(MDP) motion. Meanwhile, although Bluetooth headsets may avoid the MDP motion when answering a phone call, estimated by [1], in 2015, there is still only a 45 million market for the Bluetooth headsets for all purpose of usage. Comparing it to the market of smartphone, it is easy to understand most people(at least 95.8%) performs MDP motion when answers phone call.

In this paper, we investigate the MDP motion based implicit mobile authentication via two methods, a Statistic Method (SM), and a Trajectory Reconstruction Method (TRM). For the SM, it first smooth the sensor data by a low pass filter, then extract temporal and numerical features and apply verification algorithms on the features after normalization and segmentation. While for the TRM, it adopts Kalman filter and rotation matrix to reconstructs the MDP motion trajectories by utilizing the data from multiple sensors, and verifies the users' identity by score metrics calculated by Discrete Frèchet Distance. We tested the proposed methods on two sets of MDP motions, one stationary MDP motion(the user performs MDP motion sitting or standing stationary), and one moving MDP motion(the user performs MDP motion when walking).

Our main contributions are: (1) proposed two verification methods, Statistic Method and Trajectory Reconstruction Method, to extract specific features and verify user's identity; (2) collected a multi-session MDP motion database; and (3) provided evidence that verification performance can be affected by the user body movements, such as walking.

The rest of paper is organized as follows. First, we discuss the related work in section 2. In section 3, we demonstrated the evidence of unique biometric qualities of MDP Motion. The two verification methods, Statistic Method and Trajectory Reconstruction Method, are depicted in section 4. Section 5 presents the experimental results. In section 6, we conclude our study.

2. Related Work

Although physiological biometrics (*i.e.,* retinal patterns [9], fingerprint [13], facial features [17]) could provide stable and accurate verification rate for the their trait of static, behavioral biometrics [15] have advantage over traditional biometric technologies due to their non-obtrusive.

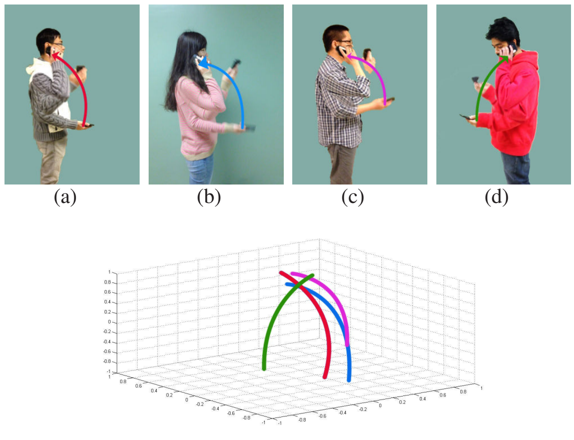
Prior research on mobile motion is focusing on two aspects, activity recognition and mobile motion based user authentication. Some existing works have explored user activity inference methods with accelerometer sensors [5], [11], [4]. In [12], Lu *et. al.,* proposed a continuous sensing engine for activity recognition on mobile platform, which can robustly detect five common physical activities, stationary, walking, cycling, running, and in a vehicle (i.e., car, bus). Yang *et. al.,* [16] also researched on activity recognition by exploiting the accelerometer data. For mobile motion based user authentication, [7] demonstrated an identity verification method using gait data. In [18], authors modeled gesture patterns through a continuous n-gram language model using a set of features constructed from mobile sensors, where picking-up a mobile device from table is considered as a task in the context sequence. Different from the aforementioned existing works, to our best understanding, we first consider the process of MDP motion as a biometric modality for user authentication.

3. Evidence of Unique Biometric Qualities

When users picking up a mobile device, they typically grab the phone from a surface or a pocket, raise the arm and hold the phone near the ear. This process is user specific since the curvature of the movement trajectory curve in 3D space is affected by the arm length and upper body morphology, the rotation of the phone is affected by the muscles near the wrist and the speed is affected by the arm muscle behavior. In such a way, the device motion during a specific task corresponds to the physiological and behavioral biometric gleaned from users' upper body morphology and muscle movement of the arm. Fig. 1 shows the difference of four people's MDP motion.

In Fig. 2, we demonstrate the smoothed accelerometer, gyroscope, and magnetometer data from three different users. The sensor data varies not only in duration time, but also in the numerical range along the curves. Consequently, after normalization and segmentation, we can extract features including duration time, mean, variance and standard deviation. And based on these features, we can perform user identity management.

Furthermore, in Fig. 3, we show reconstructed trajectories from two users, and explicit distinguishes can been found from two users' trajectories. The two trajectories share the same starting points because when we transfer the trajectories from local coordinate system to world coordinate system, we initialize the first position as coordinate origin.



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

(e)

Figure 1. Illustration of the feasibility of distinguishing user's identity employing MDP motion, (a), (b), and (c) are MDP traces from 3 right-handed user, (d) is a trace from a left-handed user, (e) is a comparison among the 4 users' traces.

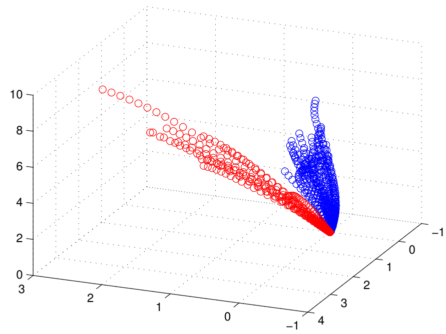


Figure 3. Illustration of the feasibility of distinguishing 2 user's identity using trajectory reconstruction method.

4. Methods

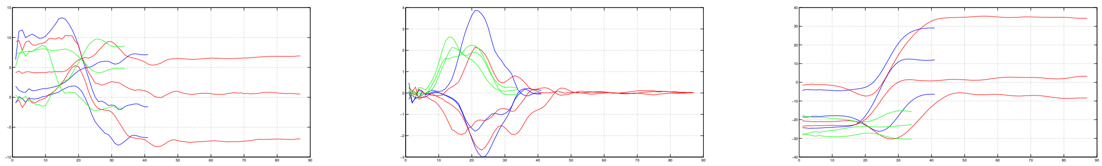
To record a mobile picking up motion movement, we employ motion sensors such as 3-degree accelerometer, 3-degree gyroscope and 3-degree magnetometer that are integrated with mobile devices. By employing the 9-degree sensor data, from each mobile picking up motion, we can capture the 3-axes acceleration, 3-axes ambient geomagnetic field, the 3-axes angular velocity for the device coordinates and corresponding time stamp information. In this section, we show the explicit differences of mobile picking up motion among different users caused by arm geometry, mobile use habit and muscle behaviour. Further, based on the data collected, we introduce two methods, a statistic method and a trajectory reconstruction method, to exploit the specific motion as a novel biometric modality.

4.1. Statistic Method

Different sensor data can reflect different motion features. Accelerometer data can be used to depict the motion speed and direction change, gyroscope data and magnetometer data show the rotation movement of wrist and the lift movement of elbow and arm. Because the characteristics of each person's motion varies, by extracting and employing the statistic features from the sensor data, we can perform user identity management.

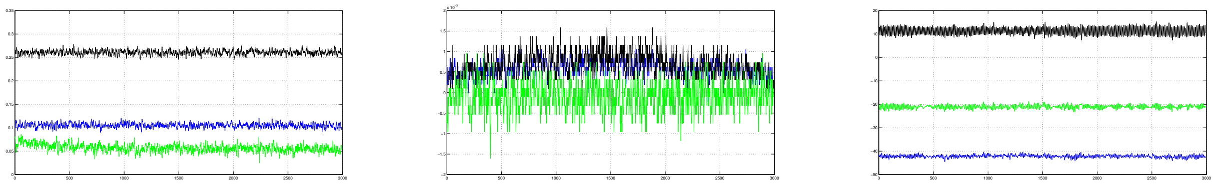
4.1.1 Statistic Features

Fig. 4 shows some raw data collected from the 9-degree sensors. Even the mobile is fully stationary on the table, obvious jittering noises still exist in the sensor data. We



(a) Accelerometer data (b) Gyroscope data (c) Magetometer data

Figure 2. Illustration of the feasibility of distinguishing 3 user's identity using statistic features. Three smoothed 3 users' data are represented respectively by red, blue and green curves.



(a) Accelerometer raw data (b) Gyroscope raw data (c) Magetometer raw data

Figure 4. Collected 9-degree raw data from 3 types of mobile sensors when a mobile device is stationary on a table. The acceleration data of z-axis has already minus a 9.8(the gravity impact)

can reduce the effect of jittering noise by scaling down (x, y, z) readings by a factor M and rounding, followed by a smoothing technique using a moving-average filter of span L, i.e.,

$$(x', y', z') = mvfilter(round[(x, y, z)/M], L) \tag{1}$$

After smoothing the raw data, we segment each motion trajectory into n segments. For each segment, we extract its duration time, mean value, variance, and standard derivation as features for evaluation, and totally $28 * n$ features(1 time duration feature, and respectively 9 features for the mean, standard deviation, and variance of the 9-degree sensors data in a segment).

4.1.2 Statistic Based Verification Algorithms

We evaluate the performance of our system using Support Vector Machine (SVM) [6] algorithm. SVM classifiers are characterized by a decision surface that can be written as a hyper-plane in a high dimensional space $\mathfrak{H}$. The mapping between the input space and $\mathfrak{H}$ is handled implicitly by means of a kernel function $\mathfrak{K}$, which is a (generally nonlinear) symmetric scalar function of two input vectors. The decision function can then be written as,

$$\mathfrak{f}(\vec{v}) = \sum_j \alpha_j y_j \mathfrak{K}(\vec{s_j}, \vec{v}) + b \lesseqgtr 0 \tag{2}$$

where $\vec{v}$ is the input to be classified. The support vectors $\vec{s_j}$ constitute a subset of the training data which is determined through an optimization process. The optimization also defines the weight α_i; the y_j are constant and have a value $+1$ for the support vectors of the 'accept' class, -1 for those of the 'reject' class. Finally, b is fixed so that the hyper-plane in $\mathfrak{H}$ cuts exactly halfway between the closest training examples of the two antagonistic classes. This choice is optimal provided that the training set is equally descriptive of both populations. In the case that one class is poorly represented in the training set, we might want to compensate for that by shifting the hyper-plane further away from its support vectors.

4.2. Trajectory Reconstruction Method

As explained by the Section 3, the motion trajectory varies from person to person for congenital physical and acquired habits, which could provides effective biometric features for user verification. To verify a user's identity by trajectory based method, two following steps are required: (i) reconstruct the motion trajectory; and (ii) compute the distance of different trajectory using different distance functions and perform verification.

4.2.1 Trajectory Reconstruction

Due to Einstein's principle of equivalence [8], the collected acceleration data includes both the impact of motion acceleration and gravity acceleration. Thus, we have to first use a low pass filter to isolate the contribution of the force of gravity in 3 axes as in Eq.3. The α is calculated as $t/(t + dT)$, where with t, the low-pass filter's time-constant, and the dT is the sampling rate. The force of gravity is substracted from the acceleration as shown in Eq.4 to calculate the linear acceleration.

$$gravity_i = \alpha * gravity_i + (1 - \alpha) * acc_i \tag{3}$$

$$linacc_i = acc_i - gravity_i \tag{4}$$

where acc_i stands for acceleration raw data on i axis, and $linacc_i$ stands for linear acceleration on i axis.

Because all the 9-degree sensor data we collected are in the device's local coordinates, it should be transferred into a canonical world coordinate system for comparison. The rotation matrix RM is employed and formulated as

$$RM = \begin{bmatrix} H_x & H_y & H_z \\ M_x & M_y & M_z \\ A_x & A_y & A_z \end{bmatrix}$$

,

H_i, M_i, and A_i are calculated in Eq.5, where A_i is stand for the gravity acceleration of i axis, E_i is stand for the geomagnetic field of i axis, and i+1 and i+2 are stand for the next and next next axis(for example, i+1 of y is z, i+2 of y is x).

$$\begin{aligned} H_i &= E_{i+1} * A_{i+2} - E_{i+2} * A_{i+1} \\ invH &= 1.0/\sqrt{H_x^2 + H_y^2 + H_z^2} \\ H_i &= H_i * invH \\ invA &= 1.0/\sqrt{A_x^2 + A_y^2 + A_z^2} \\ A_i &= A_i * invA \\ M_i &= A_{i+1} * H_{i+2} - A_{i+2} * H_{i+1} \end{aligned} \quad (5)$$

As long as we have the rotation matrix, we can calculate the acceleration along the world axis(WA) by multiply the acceleration along mobile axis(MA) with rotation matrix RM:

$$WA = RM * MA \quad (6)$$

However, as mentioned before, the noise of the hardware sensors is not trivial and could severely affect the correctness of the trajectory reconstruction. In order to reconstruct the motion trajectory correctly, the noise of the raw data should be eliminated. Here we adopt Kalman Filter [14] to solve the problem. We formulate our system model and correction equation as Eq.7 and Eq.8.

$$x_{t+1} = A * x_t + W_t \quad (7)$$

where $x_i = [x_p, x_v, x_a, y_p, y_v, y_a, z_p, z_v, z_a]^T$, $p(W) \sim N(0, Q)$ and

$$A = \begin{bmatrix} m & 0 & 0 \\ 0 & m & 0 \\ 0 & 0 & m \end{bmatrix}, m = \begin{bmatrix} 1 & T & 0.5T^2 \\ 0 & 1 & T \\ 0 & 0 & 1 \end{bmatrix}$$

$$\hat{x}_{t+1} = A * x_{t+1} + K_t * (M_{k+1} - H * x_{t+1}) \quad (8)$$

where

$$H = \begin{bmatrix} n & 0 & 0 \\ 0 & n & 0 \\ 0 & 0 & n \end{bmatrix}, n = \begin{bmatrix} 0 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 1 \end{bmatrix}$$

(x_p, y_p, z_p) is the location of the mobile device in world coordinate system, (x_v, y_v, z_v), (x_a, y_a, z_a) are the velocity and acceleration of the mobile movement. A and H are the process model and measurement model for Kalman filter. T is the time interval between two continuous samplings, i is the index of samplings. W is the process noise, white Gaussian noise with diagonal variance Q. $\hat{x}_{t+1}$ is the corrected system state, M_{k+1} is the measurement of the mobile location. K_t is the Kalman gain calculated.

4.2.2 Trajectory Distance Function and Decision Rule

After the trajectories are reconstructed, we can employ the Discrete Frèchet Distance [3] to calculate the distance between a pair of polygonal trajectories representing mobile picking up motion sequences. Let $S_1 =< p_1, p_2, ..., p_m >$ and $S_2 =< q_1, q_2, ..., q_n >$ be two polygonal trajectories, $M = (p_i, q_i)$ be an order-preserving complete correspondence between S_1 and S_2, and $d(p, q)$ is a matching cost between p and q, the following distances are defined as the following,

$$\delta_D(S_1, S_2) = \min_M (\max_{(p_i, q_i) \in M} d(p, q)) \quad (9)$$

For a training set $T_t = S_1, S_2, ..., S_n$, which comprises n trajectories of one user, we rate each trajectory with a training score $SCORE_S$ as following,

$$SCORE_S(S_i) = \sum_{j \neq i, t_j \in M} \delta_D(S_i, S_j) \quad (10)$$

We select the trajectory S_i with the lowest $SCORE_S$ as the model of this specific user. When a new trajectory S_t inputs, we calculate the similarity score $SCORE_T$ by comparing the input trajectory S_t with the model trajectory S_i,

$$SCORE_T(S_t) = \delta_D(S_i, S_t) \quad (11)$$

5. Experimental Results and Discussion

5.1. Data Acquisition

To collect user motion data, we developed an Android program which simultaneously sampled acceleromter, gyroscope and magetometer at 25Hz using a standard API of Android system. When a data collection procedure begins, a subject is asked to pressing the "Record" button when she/he is ready to perform the MDP motion. The application will keep recording the raw multi-sensor data from the API until the button is released when the MDP motion is terminate. For each MDP motion sample, 3-axes acceleration, 3-axes ambient geomagnetic field, 3-axes angular velocity, and corresponding timestamps are captured.

We recruited 31 subjects for our study, of which 24 were inclined to perform MDP motion with right hand. Their ages ranged from 20 to 45 years. Out of these, 20 were male. The data acquisition contains 3 sessions collected over several weeks. The entire dataset is 930 samples (31 subjects * 3 sessions * 10 data samples per session). Sessions differ with each other in terms of collecting date or body movement status. In the first session for each subject, we explained the purpose of the study and the usage of our data acquisition program. Then the subject is asked to practice the experiment procedure for 5 to 10 times to ensure data is correct collected and the MDP motion is her/his natural usage habit. After the subject finished the practice procedure, she/he performed 10 times MDP motion when she/he is stationary. To investigate the stability of the biometric modality, after one week, the subjects were asked

Table 1. EER for different MDP motion dataset under different methods and segmentation settings. 5 segments to 20 segments respectively stands for the result of Statistic Method, while Trajectory stands for the result of Trajectory Reconstruction Method.

%	5 segments	10 segments	15 segments	20 segments	Trajectory
MDPdt1	6.38	5.87	6.13	3.67	5.56
MDPdt2	8.67	5.06	5.32	3.93	8.72
MDPdt3	18.67	17.88	18.73	17.93	29.31
MDPdt1& MDPdt2	10.67	10.86	7.13	6.13	7.09
MDPdt1& MDPdt3	20.31	19.67	19.13	22.31	24.69
MDPdt1& MDPdt2& MDPdt3	20.67	17.32	19.32	18.96	24.34
Mean	14.23	12.78	12.62	12.08	16.62

to perform the same MDP motion for 10 times as the second session. The third session is similar to the previous sessions, however, it differs from previous sessions by requesting subjects to perform MDP motion when she/he was walking. There is no limitation on which side of hand the subjects hold the mobile or the holding pattern the subjects use, so that the subjects can perform MDP motions in their natural way. We name the dataset collected in session 1 to session 3 respectively as MDPdt1 to MDPdt3. In our study, the MDPdt1 is mainly utilized for the feature evaluation and authentication system design. The MDPdt2 and MDPdt3 are mainly utilized in the research on investigating if the performance of our proposed methods is time constant and stable to different user body movement status. We employ the Equal Error Rate (EER), which can balance False Acceptance Rate(FAR) and False Rejection Rate(FRR), to evaluate the MDP motion based verification.

5.2. Experimental Result

Table 1 depicts the EER of authentication when different methods and segmentation settings are applied on different MDP motion dataset. For intra-session result using SM, verification performance of MDPdt1 and MDPdt2 demonstrated competitive results with EER respectively of 3.67% and 3.93%, while the performance of MDPdt3, with a EER of 16.88%. The result of MDPdt1 and MDPdt2 are acceptable, however the result of MDPdt3 is not encouraging. Such situation could be caused by the extra body movement in MDPdt3. To test the real world performance of our methods, in MDPdt3, we did not limit the walking pattern of the subjects, which means uniform motion, variable motion, and changing directions are all acceptable. Due to Einstein's principle of equivalence, the accelerometer cannot separate the MDP motion acceleration with the body movement. The accelerometer data is not only useless for verification but also would cause negative impact on the authentication for its noisy and incorrect features. This may also explains why the performance of MDPdt3, unlike the result of MDPdt1 and MDPdt2, would not increase as the number of segmentation grows: detailed segmentation features do no provide extra useful features but noise.

Because the TRM is based on the Discrete Frèchet Distance of reconstructed traces, the noise of acceleration caused even severe impact on this method (the EER of MDPdt3 increased to almost 30%). Meanwhile, the performance of TRM is equally good but a slightly declined comparing to SM in the intra-session result of MDPdt1 and MDPdt2. The declination may be caused by the Integrated Error and Calculation Error when reconstructing the trajectory. Integrated Error mainly comes from two sources, (1) integration time, and the (2) hardware drift. For the integration time, the longer it is, the higher the error is. In our case, the integration time is fixed and it is determined by the sampling rate($1s/25Hz = 40ms$). For the hardware drift, even we employed Kalman filter to remove the drift and noise, there might still remains minor noises. And the minor noises of acceleration and velocity are amplified by the integration process. Calculation Error comes from the complex matrix and trigonometric calculations explained by the Section 4.2.1. All the aforementioned errors might lead to trajectory distortion and hence reduce the accuracy the proposed method.

From the inter-session result employing SM, we can see a slightly decline on EER in the combination of mixed MDPdt1& MDPdt2 comparing to the intra-session result of separate MDPdt1 and MDPdt2. Behavioral inertia may contribute to this phenomenon. In an intra-session data collection (*e.g.,* MDPdt1 or MDPdt2), the subjects is inclined to repeat her/his first MDP motion, which would lead a verification performance enhancement. While for the inter-session of MDPdt1& MDPdt2, because a week has passed, the usage habit and upper body morphology will play a more important role than the behavioral inertia. The positive verification performance of 6.13% EER demonstrates the proposed method is time constant. The verification performance on the mixed dataset of MDPdt1& MDPdt3 and MDPdt1& MDPdt2& MDPdt3 still have the same acceleration noise problem with intra-session result. Since the accuracy enhancement effect of behavioral inertia does not exist in the inter-session experiment, the performance is even worse than the intra-session result with MDPdt3.

Similar results can also be found in the TRM in column 6, Table 1. The EER of mixed dataset of MDPdt1& MDPdt3 and MDPdt1& MDPdt2& MDPdt3 are 24.69% and 24.34%. As explained, the reconstructed trajectory of stationary status and walking status varies for the acceleration impact, verification employing trajectory reconstruction method is not feasible since the EER is already as high as 24%.

To prove the performance reduction of dataset related to MDPdt3 is caused by the acceleration and to solve the moving status verification problem, we conduct experiment without accelerometer data and the result is shown in Table 2. The result in Table 2 are based on the 6-degree sensor data, including 3-axes ambient geomagnetic field, the 3-axes angular velocity. We can clearly observe from the result, although the accelerometer data is removed, the performance result increased rather than declined. Comparing to the stationary session result, the performance in the moving status session is not so good but still acceptable, which

Table 2. EER for different MDP motion dataset without accelerometer data under and different segmentation settings.

%	MDPdt1& MDPdt3	MDPdt1& MDPdt2& MDPdt3
5 segments	13.24	12.35
10 segments	13.67	13.67
15 segments	11.35	9.36
20 segments	10.27	9.62
Mean	12.13	11.25

compliment the demerit of the TRM.

6. Conclusion

This paper investigates the feasibility of a new behavioral biometric modality based on MDP motion. We propose two novel methods, a Statistic Method to intuitively apply classification algorithms on the smoothing sensor data; and a Trajectory Reconstruction Method to reconstruct the MDP motion trajectories utilizing Kalman filter and extract specific identity features from the reconstructed traces. We evaluate our proposed methods on a multi-session MDP motion dataset from 31 subjects. From the results, we found that the accuracy of the methods is declined in inter-session tests. Furthermore, user movements(e.g. walking) highly impacted the accelerometer data, and further decreased the inter-session results. To solve this, we have to emphasize gyroscope and magnetometer data in case extra motion is detected. Last, experimental results of MDP motion based verification are encouraging and point to the possibility of MDP motion based biometric systems in real world applications.

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