HMOG: A New Biometric Modality for Continuous Authentication of Smartphone Users

Zdeňka Sitová† Jaroslav Šeděnka† Qing Yang‡ Ge Peng† Gang Zhou† Paolo Gasti† Kiran Balagani‡

†New York Institute of Technology – {sitovaz, sedenka}@mail.muni.cz, {pgasti, kbalagan}@nyit.edu
‡College of William and Mary – {qyang, gpeng, gzhou}@cs.wm.edu

Abstract—In this paper, we introduce Hand Movement, Orientation, and Grasp (HMOG), a behavioral biometric to continuously authenticate smartphone users. HMOG unobtrusively captures subtle micro-movement and orientation dynamics resulting from how a user grasps, holds, and taps on the smartphone. We evaluated the authentication and biometric key generation (BKG) performance of HMOG features on typing data collected from 100 subjects. Data was collected under two conditions: sitting and walking. We achieved authentication EERs as low as 6.92% (walking) and 10.20% (sitting) when we combined HMOG, tap, and keystroke features. We performed additional experiments to investigate why HMOG features perform well during walking. Our results suggest that this is due to the ability of HMOG features to capture distinctive body movements caused by walking, in addition to the hand-movement dynamics from taps. With BKG, we achieved EERs of 13.7% using HMOG combined with taps. In comparison, BKG using tap, key hold, and swipe features led to EERs between 31.3% and 36.7%. We also analyzed the energy consumption of HMOG feature extraction and computation. Our analysis shows that HMOG features extracted at 16Hz sensor sampling rate incurred a minor overhead of 7.9% without sacrificing authentication accuracy.

Index Terms—Behavioral biometrics, continuous authentication, biometric key generation, energy evaluation, HMOG.

I. INTRODUCTION

In this paper, we present Hand Movement, Orientation, and Grasp (HMOG), a new behavioral biometric for continuous authentication of smartphone users. HMOG uses accelerometer, gyroscope, and magnetometer readings to unobtrusively capture subtle hand micro-movements and orientation patterns generated when a user taps on the screen.

HMOG biometric is founded upon two core building blocks of human prehension [1]: stability grasp, which provides stability to the object being held; and precision grasp, which involves precision-demanding tasks such as tapping a target. We view the act of holding a phone as a stability grasp and the act of touching targets on the touchscreen as a precision grasp. We hypothesize that the way in which a user “distributes” or “shares” stability and precision grasps while interacting with the smartphone results in distinctive movement and orientation behavior. The rationale for our hypothesis comes from the following two bodies of research.

First, there is evidence (see [2,3,4]) that users have postural preferences for interacting with hand-held devices such as smartphones. Depending upon the postural preference, it is possible that the user can have her own way of achieving stability and precision—for example, the user can achieve both stability and precision with one hand if the postural preference involves holding and tapping the phone with the same hand; or distribute stability and precision between both hands, if the posture involves using both hands for holding and tapping; or achieve stability with one hand and precision with the other.

Second, studies in ergonomics, biokinetics, and human-computer interaction have reported that handgrip strength strongly correlates with an individual’s physiological and somatic traits like hand length, handedness, age, gender, height, body mass, and musculature (see, e.g., [5,6,7]). If the micro-movements caused by tapping reflect an individual’s handgrip strength, then the distinctiveness of HMOG may have roots, at least in part, in an individual’s distinctive physiological and somatic traits.

Motivated by the above, we designed 96 HMOG features and evaluated their continuous user authentication and biometric key generation performance during typing. Because walking has been shown to affect typing performance [8], we evaluated HMOG under both walking and sitting conditions.

A. Contributions and Novelty of This Work

New HMOG Features for Continuous Authentication. We propose two types of HMOG features: resistance features, which measure the micro-movements of the phone in response to the forces exerted by a tap gesture; and stability features, which measure how quickly the perturbations in movement and orientation, caused by tap forces, dissipate. Our extensive evaluation of HMOG features on a dataset of 100 users† who typed on the smartphone led to the following findings: (1) HMOG features extracted from accelerometer and gyroscope signals outperformed HMOG features from magnetometer; (2) Augmenting HMOG features with tap characteristics (e.g., tap duration and contact size) lowered equal error rates (EERs): from 13.99% to 11.68% for sitting, and from 14.62% to 8.12% for walking. This shows that incorporating tap information associated with micro-movements considerably improves HMOG-based authentication performance; and (3) HMOG features complement tap and keystroke dynamics features, especially for low authentication latencies at which

†We made the dataset available at http://www.cs.wm.edu/~qyang/hmog.html. We also described the data and its release in [9].
tap and keystroke dynamics features fare poorly. For example, for 20-second authentication latency, adding HMOG to tap and keystroke dynamics features reduced the equal error rate from 17.93% to 12.93% for walking and from 19.11% to 15.44% for sitting.

**Empirical Investigation Into Why HMOG Authentication Performs Well During Walking.** HMOG features achieved lower authentication errors (12.69% EER) for walking compared to sitting (17.88% EER). We investigated why HMOG had a superior performance during walking by comparing the performance of HMOG features during taps and between taps (i.e., the segments of the sensor signal that lie between taps). Our results suggest that the higher authentication performance during walking can be attributed to the ability of HMOG features to capture distinctive movements caused by walking in addition to micro-movements caused by taps.

**BKG with HMOG Features.** BKG is closely related to authentication, but has a different objective: to provide cryptographic access control to sensitive data on the smartphone. We believe that designing a secure BKG scheme on smartphones is very important, because the adversary is usually assumed to have physical access to the device, and therefore cryptographic keys must not be stored on the smartphone’s memory—but rather generated from biometric signals and/or passwords.

To our knowledge, we are the first to evaluate BKG on smartphones. We instantiated BKG using normalized generalized Reed-Solomon codes in Lee metric. (See section VII for formulation and evaluation.) We compared BKG on HMOG to BKG on tap, key hold, and swipe features under two metrics: equal error rate (EER) and guessing distance.

Our results on BKG can be summarized as follows: we achieved lower EERs with HMOG features compared to key hold, tap, and swipe features in both walking and sitting conditions. For walking, EER of HMOG-based BKG was 15%, vs. 31% with key hold and 37% with tap features. By combining HMOG and tap features, we achieved 13.7% EER. For sitting, we obtained an EER of 21% with HMOG features and 29% with tap features. In contrast, we obtained 34% EER with swipes. HMOG features also provided higher guessing distance (i.e., 3.1 for walking, and 2.8 for sitting) than all other features extracted from our dataset (1.5 for taps and 1.1 for key holds in walking and 1.4 for taps in sitting conditions).

**Energy Consumption Analysis of HMOG Features.** Because smartphones are energy-constrained, it is crucial that a continuous user authentication method consumes as little energy as possible, while maintaining the desired level of authentication performance. To evaluate the feasibility of HMOG-based continuous authentication on smartphones, we measured the energy consumption of accelerometer and gyroscope, sampled at 100Hz, 50Hz, 16Hz and 5Hz. We then measured the energy required for HMOG feature computation from sensor signals, and report the tradeoff between energy consumption and EER.

Our tradeoff analysis reveals that by sampling HMOG features at 16Hz, the energy overhead is 7.9%, compared to 20% with 100Hz sampling rate. Authentication accuracy was not affected by the reduced sampling rate. However, by further reducing the sampling rate to 5Hz, we observed a significant increase in EER.

**B. Organization**

We present the description of HMOG features in Section II and details on our dataset in Section III. In sections IV and V, we describe the authentication experiments and present results. We introduce and evaluate BKG on HMOG in Section VI. We analyze the energy consumption of HMOG features in Section VII. In Section VIII, we review related research. We conclude in Section IX.

**II. Description of HMOG Features**

We define two types of HMOG features: grasp resistance and grasp stability—that are computed from accelerometer, gyroscope, and magnetometer sensor readings. Because HMOG features aim to capture the subtle micro-movements and orientation patterns of a user while tapping on the screen, we extract HMOG features during or close to tap events.

Let \( X, Y, \) and \( Z \) represent the readings from a sensor (accelerometer, gyroscope, or magnetometer) in \( x, y, \) and \( z \) axes respectively. Let \( M = \sqrt{X^2 + Y^2 + Z^2} \) represent the magnitude of acceleration, angular speed, or magnetic field. Grasp resistance and stability features are computed as follows.

**A. Grasp Resistance Features**

Grasp resistance features measure the resistance of a hand grasp to the forces (or pressures) exerted by touch/gesture events. We quantify resistance as the change (or perturbation) in movement, orientation (i.e., angular velocity, and acceleration) and magnetic field caused by a tap event. We define grasp resistance features as follows:

1) Mean of \( X, Y, \) and \( Z \) during a tap event.
2) Standard deviation of \( X, Y, \) and \( Z \) during a tap event.
3) Difference between \( X, Y, \) and \( Z \) before and after a tap event.
as $\text{avg100msAfter}(Z) - \text{avg100msBefore}(Z)$, where $\text{avg100msBefore}(Z)$ is the average of $Z$ values in 100 ms window before tap start time and $\text{avg100msAfter}(Z)$ is the average of $Z$ values in a 100 ms window after tap end time.

4) **Mean change in $X$, $Y$, $Z$, and $M$ values caused by a tap.** We calculate this as $\text{avgTap}(Z) - \text{avg100msBefore}(Z)$, where $\text{avgTap}(Z)$ is the average of $Z$ values during a tap event.

5) **Maximum change in $X$, $Y$, $Z$, and $M$ values caused by a tap.** This is calculated as $\text{maxTap}(Z) - \text{avg100msBefore}(Z)$, where $\text{maxTap}(Z)$ is the maximum $Z$ value during a tap event.

We extracted the five grasp resistance features from three sensors and four types of sensor readings ($X$, $Y$, $Z$, and $M$), leading to $5 \times 3 \times 4 = 60$ features.

### B. Grasp Stability Features

Stability features quantify how quickly the perturbations caused by a finger-force from a tap event disappears after the tap event is complete. We compute grasp stability features as follows:

(Figure 2 illustrates variables used in features 1 through 3.)

1) **Time duration to achieve movement and orientation stability after a tap event.** Let $t_{\text{end}}$ denote the end time of the tap event, and $t_{\text{min}}$ the time when stability is achieved after the tap event has ended. This feature is calculated as $t_{\text{min}} - t_{\text{end}}$. While $t_{\text{end}}$ is obtained using the tap event handler, $t_{\text{min}}$ is calculated as follows.

Let $T = (t_1, \ldots, t_n)$ represent the series of timestamps collected between $t_{\text{end}}$ and $t_{\text{end}} + 200$ ms, and $R = (Z_1, \ldots, Z_n)$ the corresponding sensor readings. We define $\text{avgDiffs}(t_i) = \text{average}_{j=i,\ldots,n}(|Z_j - \text{avg100msBefore}(Z)|)$. $t_{\text{min}}$ is the timestamp such that $\text{avgDiffs}(t_{\text{min}}) = \min_{t \in T}(\text{avgDiffs}(t))$.

2) **Normalized time duration for mean sensor value to change from before tap to after tap event,** calculated as:

$$\Delta_{\text{duration}} = \frac{t_{\text{after\_center}} - t_{\text{before\_center}}}{\text{avg100msAfter}(Z) - \text{avg100msBefore}(Z)}$$

where $t_{\text{after\_center}}$ is the center of the 100ms window after a tap event, and $t_{\text{before\_center}}$ is the center of the 100ms window before the tap event.

3) **Normalized time duration for mean sensor values to change from $\text{maxTap}(Z)$ to $\text{avg100msAfter}(Z)$ in response to a tap event,** calculated as:

$$\Delta_{\text{max\_to\_avg}} = \frac{t_{\text{after\_center}} - t_{\text{max\_in\_tap}}}{\text{avg100msAfter}(Z) - \text{maxTap}(Z)}$$

where $\text{maxTap}(Z)$ is the maximum sensor value during a tap, and $t_{\text{max\_in\_tap}}$ is the time when this value occurred.

We extracted the above three grasp stability features for three sensors and four types of sensor readings ($X$, $Y$, $Z$, and $M$), for a total of $3 \times 3 \times 4 = 36$ features.

### III. Dataset

To evaluate HMOG features, we used sensor data collected from 100 smartphone users (53 male, 47 female) during eight free text typing sessions [9]. Users answered three questions, typing at least 250 characters for each answer. In four of the collection sessions, users typed while sitting; in the remaining four, they typed while walking in a controlled environment.

For each user, we collected an average of 1193 taps per session (standard deviation: 303) and 1019 key presses (standard deviation: 258). The average duration of a session was 11.6 minutes, with a standard deviation of 4.6 minutes. All data was collected using a Samsung Galaxy S4 smartphone.

We recorded accelerometer, gyroscope and magnetometer sensor readings (sampling rate 100 Hz) as well as raw touch data collected from the touchscreen, touch gestures (e.g., tap, scale, scroll, and fling), key press, and key release latencies on the virtual keyboard. Due to security concerns, Android OS forbids third-party applications to access touch and key press data generated on the virtual keyboard. Therefore, we designed a virtual keyboard for data collection that mimicked the look, feel, and functionality of default Android keyboard, including the autocorrect and autocomplete options, which the users were free to use.

During data collection users were allowed to choose the orientation of the smartphone (i.e., landscape or portrait). Because less than 20 users typed in landscape orientation, we performed all authentication experiments with data collected in portrait mode.

### IV. Evaluation of HMOG Features

#### A. Design of Authentication Experiments

**1-Class Verifiers.** We performed verification experiments using three verifiers [10]: scaled Manhattan (SM), scaled Euclidian (SE), and 1-class SVM. (Henceforth, we use “SVM” to refer to “1-class SVM.”) We chose these verifiers because previous work on behavioral authentication has shown that they perform well. For instance, SM and SVM were top performers in a study on keystroke authentication of desktop users by Killourhy and Maxion [10]. SVM performed well in experiments on touch-based authentication of smartphone

---

2Our dataset is available at [http://www.cs.wm.edu/~qyang/hmog.html](http://www.cs.wm.edu/~qyang/hmog.html)
users by Serwadda et al. [11], SE is a popular verifier in biometrics (see for example [12, 13]).

Parameter tuning was not required for SM and SE. However, for SVM [14], we used RBF kernel and performed a grid search to find the parameters (for \( \gamma \), we searched through \( 2^{-13}, 2^{-11}, 2^{-9}, \ldots, 2^{13} \); and for \( \nu \), we searched through 0.01, 0.03, 0.05, 0.1, 0.15 and 0.5).  

We did not include 2-class verifiers in our evaluation. To train a 2-class verifier, in addition to data from smartphone owner, biometric data from other users (non-owners) is required. Because sharing of biometric information between smartphone users leads to privacy concerns, we believe that 1-class verifiers are more suitable for smartphone authentication. (A similar argument was made in [15].)

**Training and Testing.** For experiments in sitting and walking conditions, we used the first two sessions for training and the remaining two for testing. We extracted HMOG features during each tap. Thus, each training/testing vector corresponded to one tap. With keystroke dynamics features, each training/testing vector corresponded to one key press on the virtual keyboard.

For SM and SE, the template consisted of the feature-wise average of all training vectors. We used user-wise standard deviations for each feature for scaling. We used all training vectors to construct the template (hypersphere) with SVM. Users with less than 80 training vectors were discarded from authentication. As a consequence, ten users failed to enroll (and were not included in our experiments).

We created authentication vectors by averaging test vectors sampled during \( t \)-seconds scan. We report results for authentication scans of \( t = 20, 40, 60, 80, 100, 120 \) and 140 seconds. We chose these scan lengths to cover both low and higher authentication latencies. Our preliminary experiments showed that for scans longer than 140 seconds, there is minimal improvement in authentication performance.

**Quantifying Authentication Performance.** We generated two types of scores, genuine (authentication vector was matched against template of the same user) and zero-effort impostor (authentication vector of one user was matched against the template of another). We used population equal error rate (EER) to measure the authentication performance.

**Key Hold Features.** Key hold latency is the down-up time between press and release of a key. We used 89 key hold features, each corresponding to a key on the virtual keyboard.

**Digraph Features.** Digraph latency is the down-down time between two consecutive key presses. We used digraph features for combinations of the 35 most common keys in our dataset. Thus we have \( 35^2 = 1225 \) digraph features.

**Score-level Fusion.** To determine whether HMOG features complement existing feature sets, we combined tap, key hold, digraph and HMOG features using weighted sum score-level fusion. We chose this method because it is simple to implement, and has been shown to perform well in biometrics [17]. We used the technique of Locklear et al. [13] to ensure that weights sum to one and proportion of weights is preserved when scores from some feature sets were missing (e.g. due to lack of accelerometer data). We used grid-search to find the weights which led to the best authentication performance.

**C. Feature Selection, Preprocessing, and Transformation**

To improve authentication performance, we performed feature selection, feature transformation with Principal Component Analysis, and outlier removal. All procedures described in this section were performed on training data and were tried with the three verifiers, different feature sets from feature selection and for sitting and walking conditions.

**Feature Selection.** We evaluated two feature selection methods: Fisher score [19], and minimum-Redundancy Maximum-Relevance (mRMR) [20]. Fisher score ranking was computed independently for each feature as the ratio of between-user to within-user variance. The higher the Fisher score, the higher the discriminability of the corresponding feature. We experimented with feature subsets whose sum of Fisher scores accounted for 85, 90, 95, 98 and 100% of the sum of Fisher scores of all features. Our preliminary experiments showed that Fisher score performed better for HMOG features, while mRMR performed well with tap features. With key hold and digraph features, the best performing feature set contained all the features.

We selected HMOG features for each verifier separately. The following parameters for Fisher score ranking provided the best authentication results: 98% (39 features) for SM and SVM during sitting; 98% (37 features) for SM during walking; and 95% (28 features) for SVM during walking. For SE, we achieved lowest EER by including resistance features only, compared to the feature subset obtained from feature selection. Figure 3 reports the ranking of the features during sitting (3(a)) and walking (3(b)).

For tap features, with SM verifier we achieved the best results with 3 features chosen by mRMR (threshold 0) and

\[ \begin{align*}
\text{duration of the tap} & \\
\text{Contact size features: mean, median, standard deviation, } & \\
& \quad \text{1st, 2nd and 3rd quartile, first contact size of a tap, minimum and maximum of the contact size during the} \\
& \quad \text{tap (9 features)} \\
& \quad \text{Velocity (in pixels per second) between two consecutive} \\
& \quad \text{press events belonging to two consecutive taps.}
\end{align*} \]
In Figure 3, we show the EERs of all verifiers under sitting and walking conditions, when the authentication scans varied between 20 and 140 seconds. Among the three verifiers, SM overall had lower EERs for both sitting and walking conditions, when the authentication scans varied between 20 and 140 seconds. Among the three verifiers, SM overall had lower EERs for both sitting and walking conditions, and therefore we present the results only with SM hereafter.

In this section, we report authentication performance of HMOG features. We compare the performance of HMOG with keystroke and tap features and report results with fusion. Finally, we present our findings on why HMOG features achieve lower EERs during walking.

A. Performance of HMOG Features

With SM and SVM verifiers, HMOG features extracted from both accelerometer and gyroscope outperformed those extracted from individual sensors (see Table I for EERs). With SE, HMOG features from gyroscope generally outperformed all other sensors and sensor combinations. HMOG features from magnetometer performed consistently worse than accelerometer and gyroscope features with all verifiers, in both sitting and walking conditions. Combining magnetometer features with features from accelerometer and gyroscope did not improve performance.

Resistance features outperformed stability features in both walking and sitting conditions (and also had higher Fisher score, see Figure 3). This suggests that the ability of resistance features to discriminate between users is higher than that of stability features. We achieved the lowest EERs when we used both resistance and stability features and performed feature selection. In some cases, using PCA after feature selection further lowered EERs. In Table I, we indicate when feature selection and PCA led to the lowest EERs.

In Figure 4, we show the EERs of all verifiers under sitting and walking conditions, when the authentication scans varied between 20 and 140 seconds. Among the three verifiers, SM overall had lower EERs for both sitting and walking conditions, and therefore we present the results only with SM hereafter.

### Feature Transformation

We used Principal Component Analysis (PCA) to transform original features into principal components, that were subsequently used in authentication experiments. Our motivation for using PCA are: (1) to remove correlation between features to meet the assumptions in SE and SM, and (2) to reduce dimensionality by using only those principal components, which explain most of variance in data. We performed PCA under two settings: (1) on all features (except magnetometer features, which performed poorly), and (2) on a subset of features selected using Fisher score and mRMR. We experimented with components explaining 90%, 95%, 98% and 100% of total variance in order to find threshold for dimensionality reduction. PCA improved EER for HMOG features with SE when performed on resistance features and with SVM in sitting when performed on features selected by feature selection. PCA performed on all tap features improved results with SM and SE.

### V. Authentication Results

For key hold and digraph latencies, using only outlier removal and not performing feature selection or transformation led to the best results. Outlier removal was done using two parameters: (1) latencies longer than $l$ ms were discarded and (2) if a feature occurs less than $m$ times in a user’s template, the feature was discarded. The values evaluated for $l$ were 100, 200, 300, 400, 500 and 1000 for key hold and 200, 350, 500, 650 and 800 for digraph. For $m$, we experimented with 2, 5, 10, 15, 20, 40 and 60. The best $l$ value was 200 for key hold, and between 350–500 for digraph; the best $m$ value was between 2–60 for key hold and between 2–5 for digraph.

**Outlier Removal.** For HMOG and tap templates, we evaluated the interquartile outlier removal (i.e., different subsets of the values from the first and fourth quartile are removed). Experiments with SM verifier showed that outlier removal does not improve authentication accuracy, so we did not consider it further in our experiments.

For key hold and digraph latencies, using only outlier removal and not performing feature selection or transformation led to the best results. Outlier removal was done using two parameters: (1) latencies longer than $l$ ms were discarded and (2) if a feature occurs less than $m$ times in a user’s template, the feature was discarded. The values evaluated for $l$ were 100, 200, 300, 400, 500 and 1000 for key hold and 200, 350, 500, 650 and 800 for digraph. For $m$, we experimented with 2, 5, 10, 15, 20, 40 and 60. The best $l$ value was 200 for key hold, and between 350–500 for digraph; the best $m$ value was between 2–60 for key hold and between 2–5 for digraph.

**Comparison of HMOG with Keystroke Dynamics and Tap Features.** HMOG and tap features performed better than keystroke dynamics features in both sitting and walking conditions (see Figure 5). HMOG features outperformed tap features in walking condition, while tap outperformed HMOG in sitting. The performance of tap and keystroke dynamics features did not change significantly between sitting and walking.
TABLE I  
SUMMARY OF LOWEST EERS ACHIEVED WITH INDIVIDUAL HMOG FEATURES.

| Verifier                  | Best Performing Motion Sensors | Best Performing Features                                                                 | Sitting  | Walking   |
|---------------------------|-------------------------------|------------------------------------------------------------------------------------------|----------|-----------|
| Scaled Manhattan Accelerometer + Gyroscope | Resistance + Stability (w/ FS) | 17.88%                                                                                   | 12.69%   | 13.88% (w/ PCA) |
| Scaled Euclidean Gyroscope | Resistance                    | 19.15% (w/ PCA)                                                                           | 13.88% (w/ PCA) |
| 1-Class SVM Accelerometer + Gyroscope | Resistance + Stability (w/ FS) | 22.43% (w/ PCA)                                                                           | 14.65%   |

TABLE II  
SUMMARY OF LOWEST EERS ACHIEVED WITH SCORE-LEVEL FUSION OF HMOG, TAP, AND KEYSTROKE DYNAMICS (KD) FEATURES.

| Score-Level Fusion with SM Verifier | Sitting  | Walking  |
|-------------------------------------|----------|----------|
| HMOG, Tap, and Keystroke Dynamics   | 10.20%   | 6.92%    |
| Tap and KD                          | 11.68%   | 8.12%    |
| Tap and KD                          | 10.86%   | 10.51%   |

Fig. 4. Comparison of HMOG features in sitting and walking conditions for three verifiers. The reported EERs are with PCA for SE – sit, SE – walk, and SVM – sit, and without PCA for SM – sit, SM – walk, and SVM – walk. Y-axis shows authentication time in seconds.

Fig. 5. Comparison of EERs of HMOG with keystroke dynamics (i.e., key hold and digraph) and tap features with SM verifier. Y-axis shows authentication time in seconds.

However, the performance of HMOG improved considerably (up to 5.52%) during walking.

**Fusion of HMOG, Tap, and Keystroke Features.** We used SM verifier and performed score-level fusion with the following feature combinations: {HMOG, tap, keystroke dynamics}; {tap, keystroke dynamics}; and {tap, HMOG}. Detailed fusion results for sitting and walking conditions are presented in figures 6(a) and 6(b) respectively. The lowest EERs achieved with fusion are summarized in Table II.

Our results show that: (1) for both walking and sitting conditions, score-level fusion of all signals led to the lowest EER; and (2) fusing HMOG with tap features led to a decrease in EERs and either outperformed (in the case of walking and shorter scans in sitting) or was comparable (in the case of longer scans in sitting) to fusion of tap and keystroke dynamics (see figures 6(a) and 6(b)). Both (1) and (2) indicate that HMOG provides additional distinctiveness to tap and keystroke dynamics, especially in walking condition.

**B. Why HMOG Features Perform Better During Walking**

We investigated why HMOG features performed better during walking. Specifically, we investigated whether the high
Experiment setup. We extracted 64 HMOG features from two segments of an accelerometer/gyroscope signal: (1) during tap, as discussed in previous sections; and (2) between taps, in which HMOG features were extracted when the user was not tapping the screen (see Figure 7). In (2), the signal between taps was segmented into non-overlapping blocks of 91 ms; one HMOG feature vector was extracted from each block. We selected 91 ms as the block size because it was the median duration of a tap in our training data. This ensured that the number of sensor readings used to extract a HMOG feature vector between and during tap remained same.

HMOG features extracted during taps use sensor readings from 100 ms before and 200 ms after a tap event (see Section II). We extracted HMOG features between taps starting 300 ms after a tap until 300 ms before the next tap, to avoid any overlap between during and between HMOG features.

The average number of the training vectors per user for HMOG during taps was 1122 for sitting, and 1186 for walking. For between taps, it was 7692 for sitting and 7462 for walking. The average number of testing vectors per user for HMOG features during taps was 897 for sitting and 972 for walking. For between taps, it was 5885 for sitting and 5768 for walking.

Verification experiments were performed using SM.

Performance of HMOG Features Extracted During vs. Between Taps. We compared HMOG features extracted during taps with the same features extracted between taps for sitting and walking conditions. For sitting, HMOG features extracted during taps performed consistently better than those extracted between taps (see EERs in Figure 8). This indicates that HMOG features were able to capture distinctive hand micro-movement patterns when the users tapped on the phone. Similarly, for walking, HMOG features extracted during taps performed better than those extracted between taps (see EERs in Figure 8). This again indicates that HMOG features capture user’s distinctive hand micro-movement patterns when the user is tapping, regardless of the motion condition.

Impact of Walking on HMOG Features Extracted Between Taps. HMOG features extracted between taps during walking outperformed the same when extracted during sitting (see between tap EERs for sitting and walking in Figure 8). This indicates that HMOG features capture distinctive movements induced by walking, even in the absence of tap activity.

Supported by the above results, the high authentication accuracies achieved by HMOG features during walking can be jointly attributed to: (a) the distinctiveness in hand movements caused by tap activity and (b) the distinctiveness in movements caused by walking.

VI. BIOMETRIC KEY GENERATION FROM HMOG FEATURES

In this section, we evaluate the performance of HMOG features for biometric key generation (BKG). For this purpose, we introduce our BKG construction, which extends and generalizes the fuzzy commitment scheme of Juels et al. [21]. While the technique in [21] operates on features represented using a single bit, our BKG construction represents features as symbols of an alphabet of arbitrary prime size $p$. Our BKG relies on Reed-Solomon error correcting codes [22] in Lee metric [23].

Preliminaries. BKG uses biometric information to prevent unauthorized access to cryptographic keys; these keys can then be used, e.g., to encrypt/decrypt sensitive information. The
process of protecting a key is referred to as committing, and the outcome of this process is a commitment. Given a commitment, the cryptographic key is reconstructed by decommitting (or opening) it, using information from a biometric signal. Informally, a BKG construction is secure if a key committed using a biometric signal $s$ can be opened only using a signal $s' \approx s$, and both $s$ and $s'$ are from the same user.

BKG techniques use error-correcting codes to address natural variations among different biometric samples from the same users. An error-correcting code is defined as a set $C$ of codewords. Typically, there are two functions associated with a code: $\text{encode}()$ and $\text{decode}()$. The former maps a message to a codeword; the latter—a possibly perturbed codeword to the original codeword. The $\text{decode}()$ function is designed to maximize the probability of correct decoding.

A. Our Construction

Scaling and Discretization. BKG techniques work on discrete values, instead of real values. Therefore, the user first performs scaling and discretization of the feature vector representing her biometric. Each feature $F_i$ is assigned a discretization range $[0, \text{d}_{\text{max}}F_i]$, where $\text{d}_{\text{max}}F_i \in \{(p - 1)/2, \ldots, p - 1\}$ is negatively correlated to the standard deviation $\sigma_i$ of $F_i$ (i.e., if $\sigma_i < \sigma_j$, then $\text{d}_{\text{max}}F_i > \text{d}_{\text{max}}F_j$).

Let $x_i$ be an instance of $F_i$, and $\text{min}_{F_i}$ and $\text{max}_{F_i}$ be respectively the typical minimum and maximum value of $F_i$. Discretization and scaling are performed as:

$$\text{DS}_{F_i}(x_i) = \begin{cases} 0 & x_i < \text{min}_{F_i} \\ \left\lfloor \frac{x_i - \text{min}_{F_i}}{\text{max}_{F_i} - \text{min}_{F_i}} \right\rfloor \text{min}_{F_i} \leq x_i \leq \text{max}_{F_i} \\ \text{d}_{\text{max}}F_i & x_i > \text{max}_{F_i} \end{cases}$$

Committing a Key. To commit a cryptographic key using $n$ biometric features, the user selects a random codeword $c$ of length $n$ from $C \subset (Z_p)^n$. The key is computed as $k = \text{PRF}_c(z[0])$, where PRF is a pseudorandom function family, $z$ is a system-wide public constant and \{} denotes string concatenation. (BKG can be augmented with a second authentication factor by setting $z$ to a user-provided password.) $c$ is then committed using the user’s biometrics as discussed next. Let $x = (x_1, \ldots, x_n)$ be a scaled and discretized feature vector. The user computes $\delta = (x - c) = (x_1 - c_1, \ldots, x_n - c_n)$ and publishes commitment $\gamma = (\text{PRF}_c(z[1]), \delta)$.

The user computes $k$ from $\gamma$ and her biometric signals (and possibly a password $z$) as follows. She extracts biometric features from the signal, and encodes them as $y = (y_1, \ldots, y_n)$. Then, she computes $\delta' = \text{decode}(y - \delta)$. If $\text{PRF}_c(z[1]) = \text{PRF}_c(z[0])$ with overwhelming probability, security of our construction is analyzed in Appendix A.

Using Lee-metric Decoding for BKG. Distance between feature vectors is defined using the Lee distance [23]—a discrete approximation of SM:

Definition 1 (Lee weight). Let $p$ be an odd prime. The Lee weight of element $x \in Z_p$ is defined as $w_L(x) = \min |x'|$, for $x' \equiv x \mod p$. The Lee weight of vector $x = (x_1, \ldots, x_n) \in (Z_p)^n$ is defined as the sum of Lee weights of its elements, i.e., $w_L(x) = \sum_{i=1}^{n} w_L(x_i)$.

Definition 2 (Lee distance). The Lee distance of vectors $x, y \in Z_p$ is the Lee weight of their difference, i.e., $d_L(x, y) = w_L(x - y)$.

In $Z_2$, the Lee weight coincides with Hamming weight. We used normalized generalized Reed-Solomon codes from [22], presented next, to implement the $\text{encode}()$ and $\text{decode}()$ functions.

Definition 3. Let $k \leq n$ and $n \leq p$. A linear $[n, k]$-code over $Z_p$ is a $k$-dimensional vector subspace of $(Z_p)^n$. A normalized Reed-Solomon $[n, k]$-code over $Z_p$ is a linear $[n, k]$-code over $Z_p$ with parity-check matrix:

$$H = \begin{pmatrix} 1 & 1 & \cdots & 1 \\ 1 & 2 & \cdots & n \\ 1 & 2^2 & \cdots & n^2 \\ \vdots & \vdots & \ddots & \vdots \\ 1 & 2^{n-k-1} & \cdots & n^{n-k-1} \end{pmatrix}$$

and generator matrix:

$$G = \begin{pmatrix} v_1 & v_2 & \cdots & v_n \\ v_1 & 2v_2 & \cdots & nv_n \\ v_1 & 2^2v_2 & \cdots & n^2v_n \\ \vdots & \vdots & \ddots & \vdots \\ v_1 & 2^{k-1}v_2 & \cdots & n^{k-1}v_n \end{pmatrix}$$

The rows of $G$ form a basis of the nullspace of $H^T$.

To obtain a random codeword from $C$, we select a $k$-tuple $m = (m_1, \ldots, m_k) \in (Z_p)^k$ uniformly at random, and encode $m$ as $c = mG$. The Lee distance of $C$ is $2(n - k)$, so for any error $e = (e_1, \ldots, e_n)$ with $w_L(e) < n - k$, $\text{decode}(c + e) = c$.

B. Evaluation of HMOG Features on BKG

To evaluate HMOG features for BKG, we determined their authentication accuracy and security against population attacks. We then compared our results with HMOG features to that of tap, key hold, and swipe features under the same metrics.

Biometric Accuracy. Figures 9(a) and 9(b) summarize the results of our experiments, performed on our 100-user dataset. We evaluated BKG using the features that performed best for authentication. We used 37 and 39 HMOG features in sitting and walking conditions, respectively (see Figure 3). For sitting, reliable key generation was not possible with key hold features, and with HMOG features combined with tap features.

We ran experiments on four different feature subsets: (1) HMOG-only features; (2) 11 tap-only features; (3) 12 (sitting) and 8 (walking) key hold-only features; and (4) HMOG and 3 best-performing tap features. For walking experiments, feature subset (4) provided the best results, i.e., 12% EER with two-minute feature collection windows. Using one-minute windows, the EER increased to 14%. For sitting experiment, key generation was not possible with (3) and (4), as the within-user variability of the biometrics signals was too high. Best result was achieved using HMOG features with 21% EER for both two-minute and one-minute scans.
Šeděnka et al. [24] showed that Linear Discriminant Analysis (LDA) [25] improves BKG accuracy on desktop keystroke dynamics. However, HMOG, tap, and key hold features on a virtual keyboard did not benefit from LDA. Therefore we do not report BKG results with LDA for these features.

**Security Against Population Attacks.** EER computed via zero-effort attacks provides limited information on the security of a BKG scheme, because it does not take into account all the information readily available to the adversary. In particular, with BKG the adversary has access to: (1) the commitment \( \gamma \); and (2) an approximation of the distribution of the user’s biometric signals, in the form of population data.

Access to \( \gamma \) allows the adversary to test whether a particular feature vector decommits the key. The adversary can perform this test offline, i.e., with no restrictions on the number of attempts performed (within the limits of the available resources). Therefore, the hardness of “guessing” a user’s feature vector given \( \gamma \) is an upper bound on the security of a BKG scheme.

The adversary can use (2) to guess the user’s feature vector more efficiently, under the assumption that biometric signals from different users are not completely independent. To this end, Ballard et al. [26] proposed the notion of guessing distance. It is defined as the logarithm of the number of guesses necessary to open a commitment using feature vectors from multiple impostors.

We instantiated guessing distance in our setting as follows. First, we built a commitment \( \gamma_i = (\text{PRF}_z(z[1], \delta_i) \) from the feature vector of each user \( i \). Then, we used the biometric sample from user \( j \) to open all \( \gamma_i \) such that \( i \neq j \), and ranked users according to how many commitments they were able to open. Finally, for each user \( i \) we select users \( j \neq i \) following to this ranking, and determined how many attempts were required to open \( \gamma_j \). Guessing distance was computed as the binary logarithm of this value. There might be users \( i \) for which no feature vector from other users could open \( \gamma_i \). We refer to the commitments of these users as non-guessed.

Table III summarizes the results of our experiments for one minute scans. The lowest EER was achieved by combining HMOG features with the tap features selected by mRMR. Overall, HMOG outperformed tap features for biometric key generation. Nevertheless, our results show that most commitments can be guessed using population data.

**Comparison of HMOG and Swipe Features.** Because there is no previous work on BKG using touch-, accelerometer-, or gyroscope-based features, we compared BKG on HMOG with BKG on touch features extracted from swipes (swipe features hereafter). For this purpose, we computed swipe features from the datasets of Serwadda et al. [11]. As in [11], we used the whole first session for computing commitments and ten swipes from the second session to perform impostor/genuine open attempts. Results are reported in Table III.

We also performed experiments on the touch dataset of Frank et al. [10]. However, a large majority of the users could not reliably decommit their own keys. This was due to the large variance between the vectors used to build the commitment, and the one used to open it. Therefore, we did not include these results in this paper.

**VII. ENERGY CONSUMPTION OF HMOG FEATURES**

We measured the energy consumption of two basic modules involved in extracting HMOG features: (1) sensors (i.e., accelerometer and gyroscope); and (2) feature computation (i.e., calculation of a HMOG feature from raw sensor readings). Our main finding from energy consumption analysis is that decreasing sensor sampling rate (from 100Hz to as low as 16Hz) considerably reduced the energy overhead without impacting the authentication performance of HMOG features.

**A. Experiment Setup and Design**

We developed an Android application that collects and processes sensor data at different sampling rates. Our application allows us to selectively enable sensors and HMOG features. We extracted the best-performing 37 features for sitting (i.e., top-ranked 37 features in Figure 3a) and 39 HMOG features for walking (i.e., top-ranked 39 features in Figure 3b). The union of these two feature sets resulted in 42 HMOG features. Because none of these feature were extracted from magnetometer, we did not measure its energy consumption. Experiments were performed using a Samsung Galaxy S4 smartphone running Android 4.4.

To obtain consistent and repeatable results, we terminated all other applications and all Google services on the smartphone. Additionally, we switched off WiFi, Bluetooth,
TABLE III
SECURITY OF BKGO BASED ON HMOG, TAP, KEY HOLD, AND SWIPE FEATURES.

| Dataset                | Features       | EER  | Average       | Non-guessed | log2(codewords) |
|------------------------|----------------|------|---------------|-------------|-----------------|
|                        |                |      | guessing      | commitments |                 |
|                        |                |      | distance      |             |                 |
| Our dataset-sitting    | HMOG           | 21.1%| 2.8           | 1%          | 21              |
|                        | Tap            | 29.4%| 1.4           | 1%          | 28              |
|                        | HMOG with 3 tap| 15.1%| 3.1           | 1%          | 52              |
|                        | Tap            | 13.7%| 2.7           | 8%          | 21              |
|                        | Key hold       | 31.3%| 1.1           | 3%          | 31              |
| Serwadda et al. [11]   | portrait       | 34.2%| 3.3           | 0%          | 39              |

cellular radios. The screen was turned on during the experiments. Automatic brightness adjustments were disabled, and brightness was set to the lowest level. We used the Monsoon Power Monitor [27] to measure the phone’s energy consumption.

We performed the energy consumption experiments as follows. First, we measured baseline energy consumption by running our application with all sensors and features disabled. Then, we enabled accelerometer and gyroscope, and evaluated the corresponding energy consumption. Our application is designed to sample sensors at all supported frequencies. In the case of Galaxy S4, the available sampling rates are: 5Hz, 16Hz, 50Hz, and 100Hz. We used authentication windows of 60 and 120 seconds. Our results report the average and standard deviation of ten experiments in each setting. Finally, we quantified the energy overhead of computing 42 HMOG features from sensor readings acquired during data collection.

Calculation of EERs at Lower Sampling Rates. We originally collected our data at 100Hz sampling rate. In order to obtain the EERs for lower sampling rates, we use downsampling. For example, to simulate 16Hz sampling rate, we choose every sixth sensor reading from the original sensor data. Then, using the downsampled data, we performed HMOG-based authentication with SM verifier for 60- and 120-second scans using the same evaluation process as in Section IV.

B. Energy Consumption of HMOG Authentication

EERs vs. Energy Consumption. Figure [10] shows that EERs for 16Hz sampling rate are comparable to those of 50Hz and 100Hz for both sitting and walking, while the EERs for 5Hz are considerably worse than 16Hz, 50Hz, and 100Hz.

On the other hand, Table [IV] shows that energy overhead over the baseline is low (between 6.2% and 7.9%) for 5Hz and 16Hz sampling rates and, in comparison, high (between 12.8% and 20.5%) for 50Hz and 100Hz.

Thus, during the active authentication with HMOG, we can choose 16Hz instead of 100Hz as the sensor sampling rate, which would lower the energy overhead of sensor data collection by about 60% without sacrificing EER.

Energy Consumption for Feature Computation. The energy overhead for computing 42 features is very low compared to energy overhead of sensor data collection. The energy consumption for computing all 42 HMOG features is 0.28 joules, which corresponds to 0.64% overhead for the 60-second and 0.32% for 120-second scans. This low overhead can be attributed to the fact that HMOG features are time-domain features. (As suggested by previous research [28, 29], computing time-domain features consumes less energy than computing frequency-domain features.) Further, because HMOG feature computation involves simple arithmetic calculations, they can be processed very quickly by the smartphone’s CPU (on average 37ms per feature, in our case).

**TABLE IV**
ENERGY CONSUMPTION MEASUREMENT RESULTS.

| Dataset     | Features       | EER  | Average       | Non-guessed | log2(codewords) |
|-------------|----------------|------|---------------|-------------|-----------------|
|             |                |      | guessing      | commitments |                 |
|             |                |      | distance      |             |                 |
| Our dataset-sitting | HMOG | 21.1%| 2.8           | 1%          | 21              |
|             | Tap            | 29.4%| 1.4           | 1%          | 28              |
|             | HMOG with 3 tap| 15.1%| 3.1           | 1%          | 52              |
|             | Tap            | 13.7%| 2.7           | 8%          | 21              |
|             | Key hold       | 31.3%| 1.1           | 3%          | 31              |
| Serwadda et al. | portrait | 34.2%| 3.3           | 0%          | 39              |

VIII. RELATED WORK

Continuous Authentication Using Taps. Because HMOG features are collected during taps, we review existing work that uses tap activity to authenticate smartphone users. (Other work on continuous smartphone user authentication includes swipe-based [16, 11] and gait-based [36, 37] behaviors.) In Table [V],
TABLE V

| Work          | Condition | Free text | Motion-based features | Tap features | Keystroke features | Authentication vector | # of owners | # of imposters per owner | Vender    | Training data source | Best FAR | Best FRR |
|---------------|-----------|-----------|-----------------------|--------------|-------------------|-----------------------|-------------|--------------------------|----------|-----------------------|---------|---------|
| Toyoda et al. | sit       | X         |                       |              |                   | SVM (Gaussian kernel) | 0.85        | 0.85                     | unknown  | unknown               | 0.85    | 0.85    |
| Li et al.     | regular smartphone usage |          | pressure, contact size (both at press and release) | key hold, key interval | 5-60 char. window | linear SVM | 12          | 305                   | owner    | owner & impostor       | EER = 3.65% | 3.65%   |
| Zheng et al.  | sit       | X         | pressure              | key hold, key interval | 5-60 char. window | linear SVM | 12          | 305                   | owner    | owner & impostor       | EER = 3% | 3%      |
| Feng et al.   | sit       | X         | pressure              | key hold, key interval | 5-60 char. window | linear SVM | 12          | 305                   | owner    | owner & impostor       | EER = 1% | 1%      |
| Gascon et al. | sit, walk | X         | mean magnitude of acceleration and angular velocity during tap | coordinate, pressure, duration | features extracted from time window | linear SVM | 12          | 305                   | owner    | owner & impostor       | EER = 1% | 1%      |
| Bo et al.     | sit, walk |          | pressure              | key hold, key interval | 5-60 char. window | linear SVM | 12          | 305                   | owner    | owner & impostor       | EER = 1% | 1%      |
| This work     | sit, walk |          | Pressure and stability features extracted from tap, using accelerometer, gyroscope, and magnetometer | contact time of (X), duration, velocity between two taps | key hold | 5-60 char. window | linear SVM | 12          | 305                   | owner    | owner & impostor       | EER = 1% | 1%      |

we summarize the state-of-the-art in tap-based authentication[4] and highlight various aspects of each work, such as: (1) how the taps were collected—did the user compose free-text or type predefined fixed-text; (2) which body motion conditions (e.g., sitting and walking) were considered; (3) number of subjects (partitioned into owners and impostors, wherever appropriate); (4) how the verifier was trained; (5) how the authentication vector was created; and (6) which features were used (e.g., motion-sensor-, tap-, or keystroke-based).

Among previous papers[32, 33, 35], which have used motion sensors for user authentication, Zheng et al. [32] used fixed pins while Gascon et al. [34] used fixed phrases. The only work that used free-text typing and also the only one to authenticate users under walking condition is the paper by Bo et al. [35]. Therefore, we believe that this is closest work to our paper, and highlight the differences between our paper and [35] as follows: (1) we performed experiments on a large-scale dataset containing 100 users (90 users qualified as genuine, and 92 or more as impostors), while [35] used only 10 genuine users and 50 impostors (on average) from a dataset of 100 subjects. Because the genuine population size in [35] is too small, it is difficult to assess how accurately the reported FARs/FRRs represent the achievable authentication error rates with movement-based features, given that the number of users is a critical factor in assessing the confidence on empirical error rates of biometric systems[43]; (2) we introduced and evaluated a wide range of movement features, while [35] used only two (i.e., mean magnitude of acceleration and mean magnitude of angular velocity, during a gesture). Our results clearly reveal that certain types of movement features (e.g., resistance) perform better than others (e.g., stability), while [35] does not distinguish between different types of movement features; (3) our evaluation is comprehensive and includes detailed comparison and fusion with additional features such as touchscreen tap and keystroke. This allowed us to report how fusion with different types of features impacted authentication and BKG performance. In contrast, [35] do not compare different types of features; and (4) HMOG features performed well in both sitting and walking condition, while [35] had resorted to gait features for authentication during walking.

Biometric Key Generation. To our knowledge, there is no previous work on BKG on smartphones. Here, we review some important work related to BKG in general.

Introduced by Juels et al. [21], BKG implemented via fuzzy commitments uses error correcting codes to construct cryptographic keys from noisy information. Features are extracted from raw signals (e.g., minutiae from fingerprint images); then, each feature is encoded using a single bit. Cryptographic keys are committed using features; subsequently, commitments are opened using biometric signals from the same users. Error-correcting techniques are applied to noisy biometric information in order to cope with within-user variance.

Ballard et al. [20] provided a formal framework for analyzing the security of a BKG scheme, and argued that BKG should enjoy biometric privacy (i.e., biometric signals cannot be reconstructed from biometric keys) and key randomness (i.e., keys look random given their commitment). They also formalized adversarial knowledge of the biometric by introducing guessing distance—the logarithm of the number of guesses necessary to open a commitment using feature vectors from multiple impostors.

Energy Consumption Analysis. Bo et al. [35] showed that energy consumption can be reduced by selectively turning off motion sensors based on two factors: (1) the sensitivity of the app being used—non-sensitive applications, such as games, require no authentication; and (2) the probability that the smartphone is handed to another user. This probability is calculated using historical smartphone usage data. In their experiments, Bo et al. were able to turn off the sensors 30-90% of the time, while maintaining reasonable authentication performance. However, they did not report how they performed energy consumption measurements, nor listed the energy consumption associated with determining if the phone was being held by its owner or handed to another user.

Feng et al. [44] introduced TIPS—a continuous user authentication technique that relies on touch features exclusively. By collecting energy usage data, the authors reported average energy consumption of 88 mW, which corresponds to less than 6.2% overhead. Like [35], Feng et al. [44] also do not describe
how energy measurements were performed.

Khan et al. presented Itus [45], a framework that helps Android application developers to deploy various continuous authentication mechanisms. Energy evaluation was performed using PowerTutor [46]—an Android application that reports energy measurements performed by the smartphone. Overall energy overhead of the tested continuous authentication techniques varied between 1.2% and 6.2%.

Compared to previous research, our work provides a more complete picture of energy overhead of continuous authentication using HMOG. In fact, we highlighted the tradeoffs of energy usage for different sensor sampling rates and authentication scan lengths, versus authentication accuracy. In comparison to our work, existing literature did not analyze fine-grained energy consumption brought by individual components such as motion sensors. To our knowledge, we are the first to report the relationship between sensor sampling rates and accuracy for continuous authentication.

IX. Conclusion and Future Work

In this paper we introduced HMOG, a novel behavioral biometric for continuous authentication of smartphone users. We evaluated HMOG from three perspectives—continuous authentication, BKG, and energy consumption. Our evaluation was performed on multi-session data collected from 100 subjects under two motion conditions (i.e., sitting and walking).

Results of our evaluation can be summarized as follows. By combining HMOG with tap features, we achieved 8.12% authentication EER during walking and 11.68% during sitting, which is lower than the EERs achieved individually with tap or HMOG features. Further, by fusing HMOG, tap and keystroke dynamic features, we achieved the lowest EERs (6.92% in walking and 10.20% in sitting). Our results demonstrate that HMOG is well suited for continuous authentication of smartphone users, because the performance of HMOG improves during walking—a common smartphone usage scenario. For BKG, HMOG features provide lower EER (15.1%) than swipe features (34.2%). Moreover, fusion of HMOG, tap and keystroke dynamics features provide the best combined performance, with 13.7% EER. Additionally, the energy overhead of sample collection and feature extraction is small (less than 8% energy overhead when sensors were sampled at 16Hz). This makes HMOG well suited for energy-constrained devices such as smartphones.

For future work, we will investigate to what extent walking impacts the performance of HMOG features by collecting ground truth data on walking. We will also determine how HMOG features perform on activities that do not involve typing, such as web browsing and map navigation.

References

[1] J. Napier, “The prehensile movements of the human hand,” Journal of bone and joint surgery, vol. 38, no. 4, 1956.
[2] A. Karlson and B. Bederson, “Studies in one-handed mobile design: Habit, desire and agility;” in ERCIM Workshop on User Interfaces for All (UHALL), 2006.
[3] S. Azenkot and S. Zhai, “Touch behavior with different postures on soft smartphone keyboards,” in MobileHCI, 2012.
[4] J. Wobbrock, B. Myers, and H. Aung, “The performance of hand postures in front- and back-of-device interaction for mobile computing,” Int. J. Hum.-Comput. Stud., vol. 66, no. 12, 2008.
[5] I. Fiebert, K. Roach, J. Fromdahl, J. Moyer, and F. Pfeiffer, “Relationship between hand size, grip strength and dynamometer position in women,” Journal of Back and Musculoskeletal Rehabilitation, vol. 10, no. 3, 1998.
[6] S. Chatterjee and B. Chowdhuri, “Comparative grip strength and isometric endurance between the right and left hands of men and their relationship with age and other physical parameters.” Journal of human ergology, vol. 20, no. 1, 1991.
[7] K.-E. Kim, W. Chang, S.-J. Cho, J. Shim, H. Lee, J. Park, Y. Lee, and S. Kim, “Hand grip pattern recognition for mobile user interfaces,” in National Conference on Artificial Intelligence, vol. 21, no. 2, 2006.
[8] S. Mizobuchi, M. Chignell, and D. Newton, “Mobile text entry: Relationship between walking speed and text input task difficulty,” in International Conference on Human Computer Interaction with Mobile Devices and Services. ACM, 2005, pp. 122–128.
[9] Q. Yang, G. Peng, D. Nguyen, X. Qi, G. Zhou, Z. Sitová, P. Gasti, and K. Balagani, “A multimodal data set for evaluating continuous authentication performance in smartphones,” in SenSys, 2014.
[10] S. Killourhy and R. Maxion, “Comparing anomaly-detection algorithms for keystroke dynamics,” in Intl. Conf. on Dependable Systems and Networks, 2009.
[11] A. Serwadda, V. Phoha, and Z. Wang, “Which verifiers work?: A benchmark evaluation of touch-based authentication algorithms,” in BTAS, 2013.
[12] M. Blanton and P. Gasti, “Secure and efficient protocols for iris and fingerprint identification,” in ESORICS, 2011.
[13] S. Govindarajan, P. Gasti, and K. Balagani, “Secure privacy-preserving protocols for outsourcing continuous authentication of smartphone users with touch data,” in BTAS, 2013.
[14] C.-C. Chang and C.-J. Lin, “LIBSVM: A library for support vector machines.” ACM Transactions on Intelligent Systems and Technology, vol. 2, 2011.
[15] C. Shen, Z. Cai, X. Guan, Y. Du, and R. Maxion, “User authentication through mouse dynamics,” TIFS, vol. 8, no. 1, 2013.
[16] M. Frank, R. Biedert, E. Ma, I. Martinovic, and D. Song, “Touchalytics: On the applicability of touchscreen input as a behavioral biometric for continuous authentication,” IEEE Trans. Inf. Forensics Security, vol. 8, no. 1, 2013.
[17] A. Jain and A. Ross, “Information fusion in biometrics,” Pattern Recognition Letters, vol. 24, 2003.
[18] H. Locklear, S. Govindarajan, Z. Sitová, A. Goodkind, D. Brizan, A. Rosenberg, V. Phoha, P. Gasti, and K. Balagani, “Continuous authentication with cognition-centric text production and revision features,” in IJCB, 2014.
[19] R. Duda, P. Hart, and D. Stork, Pattern Classification. 2nd Edition. Wiley-Interscience, 2001.
[20] H. Peng, F. Long, and C. Ding, “Feature selection based on mutual information: criteria of max-dependency, max-relevance, and min-redundancy,” IEEE Trans. Pattern Anal. Mach. Intell., vol. 27, 2005.
[21] A. Juels and M. Wattenberg, “A fuzzy commitment scheme,” in CCS, 1999.
[22] R. Roth, Introduction to Coding Theory. Cambridge University Press, 2006.
[23] C. Lee, “Some properties of nonbinary error-correcting codes,” Information Theory, IRE Transactions on, vol. 4, no. 2, 1958.
[24] J. Šeděnka, P. Gasti, V. Phoha, and K. Balagani, “Privacy-preserving population-enhanced biometric key generation from free-text keystroke dynamics,” in IJCB, 2014.
[25] R. A. Fisher, “The use of multiple measurements in taxonomic problems,” Annals of Eugenics, vol. 7, no. 2, 1936.
[26] L. Ballard, S. Kamara, and M. Reiter, “The practical subtleties of biometric key generation.” in USENIX Security Symposium, 2008.
[27] “Monsoon power monitor.” [http://www.msoon.com/LabEquipment/PowerMonitor/ accessed: 2014-11-12].
[28] A. Krause, M. Ihnig, E. Rankin, D. Leong, S. Gupta, D. Siewiorek, A. Smialowicz, M. Deisher, and U. Sengupta, “Trading off prediction accuracy and power consumption for context-aware wearable computing,” in International Symposium on Wearable Computers, 2005.
[29] Z. Yan, V. Subbaraju, D. Chakraborty, A. Misra, and K. Aberer, “Energy-efficient continuous activity recognition on mobile phones: An activity-adaptive approach,” in International Symposium on Wearable Computers, 2012.
[30] M. Trojahn and F. Ortmeier, “Biometric Authentication Through a Virtual Keyboard for Smartphones,” International Journal of Computer Science & Information Technology, vol. 4, no. 5, 2012.
APPENDIX A
SECURITY ANALYSIS OF OUR BKG SCHEME

We prove that our BKG technique meets the requirements from [26]—namely, that cryptographic keys are indistinguishable from random given the commitment (key randomness), and that given a cryptographic key and a commitment, no useful information about the biometric can be reconstructed (biometric privacy).

We assume that the biometric is modeled by an unpredictable function. This captures the idea that a user’s biometric is difficult to guess. Informally, an unpredictable function $f(\cdot)$ is a function for which no efficient adversary can predict $f(x^*)$ given $f(x_i)$ for various $x_i \neq x^*$. Formally:

**Definition 4.** A function family $(C, D, R, F)$ for $\{f_c(\cdot) : D \rightarrow R\}_{c \in C}$ is unpredictable if for any efficient algorithm $A$ and auxiliary information $z$ we have:

$$\Pr[f^*(x^*), f_c(x^*) \leftarrow A^{f_c(\cdot)}(z) \text{ and } x^* \notin Q] \leq \text{negl}(\kappa)$$

where $Q$ is the set of queries from $A$, $\kappa$ is the security parameter and negl$(\cdot)$ is a negligible function.

In order to define security of biometric key generation systems, Ballard et al. [26] introduced the notions of Key Randomness (REQ-KR), Weak Biometric Privacy (REQ-WBP) and Strong Biometric Privacy (REQ-SBP). We formalize the notion of key randomness by defining Experiment $\text{IND-KR}_A(\kappa)$:

**Experiment IND-KR}_A(\kappa):**

1) $A$ is provided with a challenge $(\text{PRF}_c(z[1], \delta), k_0$ and $z$, where $k_0 = \text{PRF}_c(z[0])$ and $k_1 \leftarrow_R \{0, 1\}^\kappa$ for a bit $b \leftarrow_R \{0, 1\}$, corresponding to user $i$.

2) $A$ is allowed to obtain biometric information $x_j$ for arbitrary users $j$ such that $j \neq i$.

3) $A$ outputs a bit $b'$ as its guess for $b$. The experiment outputs $1$ if $b = b'$, and $0$ otherwise.

**Definition 5.** We say that a biometric key generation scheme has the Key Randomness property if there exist a negligible function $\text{negl}(\cdot)$ such that for any PPT $A$, $\Pr[\text{IND-KR}_A(\kappa) = 1] \leq 1/2 + \text{negl}(\kappa)$.

**Theorem 1.** Assuming that the PRF is a pseudo-random function family and that biometric vector $x = (x_1, \ldots, x_n)$ is unpredictable, our Fuzzy Commitment scheme has the Key Randomness property.

**Proof of Theorem 1 (Sketch).** Because $c = x - \delta$, and $x$ is assumed to be unpredictable, $c$ is unpredictable given $\delta$. We now show that any PPT adversary $A$ that has advantage $1/2 + \Delta(\kappa)$ to win the IND-KR$_A(\kappa)$ experiment can be used to construct a distinguisher $D$ that has similar advantage in distinguishing PRF from a family of uniformly distributed random functions.

$D$ is given access to oracle $O(\cdot)$ that selects a random codeword $c$ and a random bit $b$, and responds to a query $q$ with random (consistent) values if $b = 1$, and with $\text{PRF}_c(q)$ if $b = 0$. $D$ selects a random $z$, a codeword $c'$ and a feature vector $x'$, and sets $\delta' = x' - c'$. Then $D$ sends $\gamma' = (O(z[1]), \delta')$ and $O(z[0])$ to $A$.

If $b = 0$, then pair $(\gamma', \text{PRF}_c(z[0]))$ is indistinguishable from $(\text{PRF}_c(z[1]), \delta)$. Therefore, $\gamma'$ is unpredictable given $\delta$ and thus both PRF$_c(z[1])$ and PRF$_c(z[0])$ are indistinguishable from random. If $b = 1$, then $O(\cdot)$ is a random oracle, so $(\gamma', O(z))$ is indistinguishable from the pair $(\text{PRF}_c(z[1]), \delta)$, and $O(z[0])$: $c$ is unpredictable given $\delta$, therefore PRF$_c(\cdot)$ is indistinguishable from random.

Eventually, $A$ outputs $b'$, and $D$ outputs $b'$ as its guess. It is easy to see that $D$ wins iff $A$ wins, so $D$ is correct with probability $1/2 + \Delta(\kappa)$. Therefore, $\Delta(\cdot)$ must be a negligible function.

REQ-WBP states that the adversary learns no useful information about a biometric signal from the commitment and the auxiliary information, while REQ-SBP states that the adversary learns no useful information about the biometric given auxiliary information, the commitment and the key. For our BKG algorithms, REQ-SBP implies REQ-WBP. In fact, $\text{PRF}_c(z[0])$ (which is part of the commitment) is known to the adversary, and therefore $k = \text{PRF}_c(z[0])$ does not reveal any additional information. From the unpredictability of $x$,
it follows that the output of $\text{PRF}_c$ does not reveal $c$, so $\text{PRF}_c(z|1)$ and $k$ do not disclose information about $x$. 