

How Unique do we Move? Understanding the Human Body and Context Factors for User Identification

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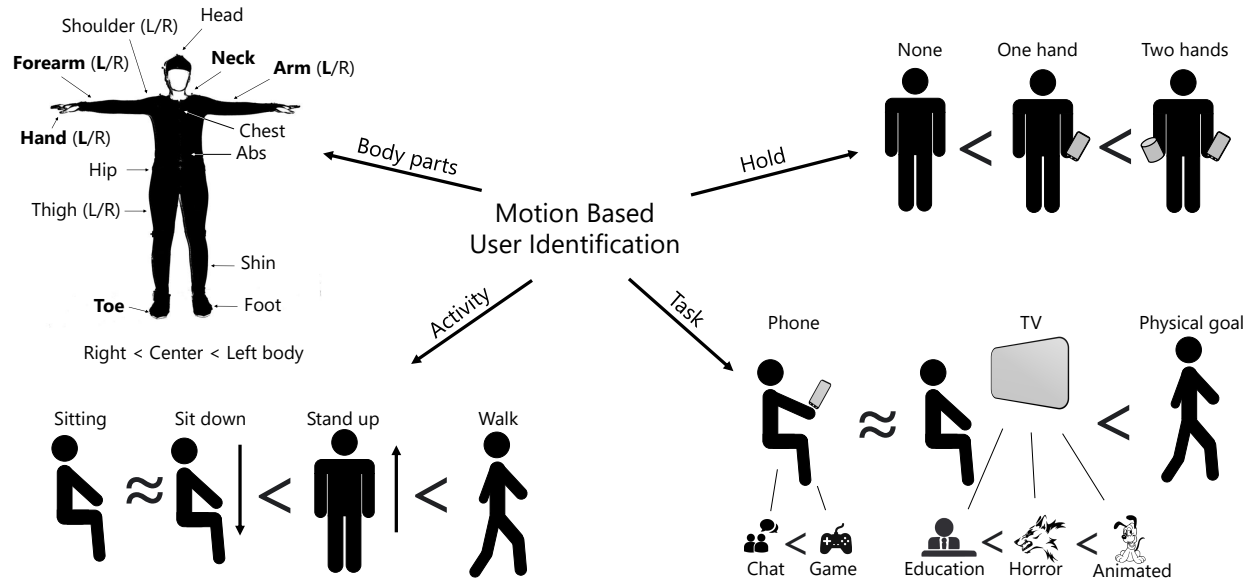


Figure 1: We assess the effects of four contextual factors on user identification: (1) Body parts, i.e. how different parts of the human body compare to identify. (2) Activity, i.e. how motion data collected in different physical activities affect identification quality. (3) Hold, i.e. the act of holding objects in one or two hands. (4) Task, i.e. how a task that the user performs elicits unique behavior. Insights on user identification quality are indicated by '<' and '≈', and the top 5 body parts are marked bold.

ABSTRACT

Past work showed great promise in biometric user identification and authentication through exploiting specific features of specific body parts. We investigate human motion across the whole body, to explore what parts of the body exhibit more unique movement patterns, and are more suitable to identify users in general. We collect and analyze full-body motion data across various activities (e.g., sitting, standing), handheld objects (uni- or bimanual), and tasks (e.g., watching TV or walking). Our analysis shows, e.g., that gait as a strong feature amplifies when carrying items, game activity elicits more unique behaviors than texting on a smartphone, and motion features are robust across body parts whereas posture features are more robust across tasks. Our work provides a holistic reference on how context affects human motion to identify us across a variety of

factors, useful to inform researchers and practitioners of behavioral biometric systems on a large scale.

CCS CONCEPTS

• Security and privacy → Human and societal aspects of security and privacy.

KEYWORDS

User Identification, Authentication, Full-body Motion, Context

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1 INTRODUCTION

Biometrics have a long history in security research to uniquely identify a person and enable authentication to a system [12, 45]. A

major advantage, compared to traditional authentication methods such as passwords or PINs, is that biometric data can be observed implicitly in the background for continuous and passive authentication during interaction [41, 42]. Suitable authentication scenarios relate to everyday activities, such as driving a car [13], interacting with a computer [4], talking on the phone [15], or on the go [10].

A plethora of research leverages *bodily motion* for identification, often utilizing features of the user’s feet and legs [11]. Other work focused on distinct parts of the human body, such as hand movement obtained by a smartwatch [23], touch operations on a smartphone [9], or head motion through head-worn devices [25, 39]. This research line can be enhanced multimodal [35], such as leveraging a set of body locations points obtained through a depth sensor [29] or combined hand and head motion in virtual reality [32].

While prior art contributes to the knowledge and utility of secure systems and authentication in the investigated scenario, the insights are often specifically tailored to the particular device setup and use case. However, there are many contextual factors with the potential to influence the assessment of unique user traits. For example, if a sensor is on a different part of the body, the user holds an object in the hand or performs a particular activity. Insights into these factors can become highly relevant for many of the investigated as well as future scenarios, to adapt a potential authentication system to a given context, and to inform under which circumstances the recognition may work better or worse. For example, Saad et al. have recently investigated shoe and floor variations for gait recognition, finding novel insights into how these contexts affect the data quality [36]. Yet, work exploring how such contextual factors may affect user recognition broadly is scarce, partly because it is challenging to study behavioral systems beyond the environment and the technology used (sensors, cameras).

We pursue an approach complementary to the device-specific nature of the prior art, by focusing on a *holistic human-centric approach*. Our objective is to understand (1) how the many parts of the human body contribute to the capability to identify a person, and (2) the influence of high-level contextual factors. As personal computing and sensing technologies are continuously evolving, human and biometric traits represent the constant across device and sensor landscapes. Our objective is to inform work leveraging body motion, e.g., for full-body authentication, using selected body sensors, or identification systems adaptive to varying contexts.

We present a holistic analysis of body motion for user identification across a range of contexts (cf. Figure 1). Our primary factor is the *body part* where we compare 18 different points across the body from head to toe. Second, we assess the *user’s activity*, particularly the physical activity ranging from sitting to walking in a room. Third, we analyze how *holding an object* in the hand allows unique behavior during walking to be elicited, which we vary for none, uni- and bimanual cases. Lastly, we compare different user *tasks*, from interacting with a smartphone or watching TV to having a physical goal. To accomplish this, we collected data from 22 users who were engaged across two sessions with these contexts. Users wore a full-body motion tracking suit to collect high-precision movement and position data. Furthermore, we compare different machine learning methods of user classification and report on parameter analysis.

Among others, we found that the most useful body parts to elicit unique behavior were the arm, forearm, hand, neck, and toe. Regarding activities, we found that when users stand up, the recognition is more accurate than when sitting (down), but overall walking led to the best user identification accuracy. More unique behavior was elicited when holding objects. In the investigated tasks, we found that there is no strong discrepancy between using a phone or watching TV (both sitting), but content matters. Games led to more unique behavior than chatting (on the phone) and animation was more effective than education and horror movies (TV).

Our contribution is threefold. First, we contribute a full-body motion dataset for 22 users across 11 different tasks involving various contextual factors. Second, we present an analysis of the data across the contextual factors for the purpose of user identification using several machine learning models. Third, we provide a set of insights, including how different body parts contribute to recognizing user identity, as well as the impact of motion, carrying objects as well as perceiving different content on a phone and TV.

2 RELATED WORK

Biometrics are widely used for user identification and authentication. Fingerprint, face recognition (i.e. FaceID), iris scan, and voice recognition are integral in smart devices. Various body parts have been focused on, such as ear and body contact [15], hand shape [38], or hand veins [21]. Fundamental categories are implicit and explicit approaches [3, 17, 40]. An implicit approach utilizes behavioral biometrics of the user in the background [12]. Orr et al. showed it is possible to identify people from their footstep force on a smart floor [31]. Keystroke dynamics have been used as a behavioral biometric for user identification [6, 19, 28]. Other modalities include eye movements as a response to visual stimuli on a display [33, 44], authentication when driving [13], keyboard typing on a computer [4], and mobile typing when the user is on the go [10].

Behavioral biometrics is often facilitated through body motion, a human mechanic inherent to physiological and behavioral traits. Gait is a prominent example of an unobtrusive biometric identification modality [11, 36]. Furthermore, the smartphone was explored for user identification, e.g., using the accelerometer for gait detection [11], or normal [8, 41] and altered touchscreen interactions [26]. Using depth cameras, Hayashi et al. identified users by hand waving [14] and Munsell and colleagues used skeleton points of the body [29]. Researchers identified users by continuously tracking and identifying hand movements on tabletop systems [2]. Wearables have been assessed to recognize users in physical, VR, and AR environments [22, 25, 32, 39], including contexts such as ball-throwing [22], overhead interactions [24, 30, 43] and walking [39].

Prior work shows how behavioral biometrics can serve to accurately identify users, but the research is fragmented across various sensors, devices, and activities. Although focused on a more technical perspective of the Internet of Things, Huang et al. accurately pointed out the issue: “*Traditional efforts [...] mainly rely on either dedicated sensors or specified user motions, impeding their widescale adoption*” [16]. We aim to go beyond these boundaries, exploring the variety of user motions that the human body can exhibit.

Additionally, our investigation can inform research on multimodal biometrics [5, 7, 35], where limitations of a single modality

may be overcome by including multiple sources of information to infer the identity [34, 35]. Recent work in virtual reality, which provides high-precision data across multiple sources, inspired our work. Pfeuffer et al. investigated how the combinations and spatial relations between hand, head, and eye movements can become useful as a behavioral biometric during the user's normal VR interactions [32]. They compared this across four tasks, and find that head leads to the most accurate results and that pointing and grabbing tasks led to better user authentication results than typing and walking. Liebert et al. studied two virtual gaming tasks for both hand and head motion as physiological biometric factors [25]. They achieved high accuracy especially when physiological features were normalized across users. More recently, Saad et al. have presented an investigation of gait identification that, similar to our work, regarded a set of contexts [36]. Their context factors included types of shoes, walking platforms, objects carried, and other activities, for a system based on a mobile phone IMU sensor. Our work complements their research by considering a large set of new context factors and by capturing the whole body with a variety of sensor locations.

Our work extends prior work on sensor- and context-specific studies investigating multiple body parts and potential tasks. What sets our work apart is taking a step back and considering the entirety of the human body beyond a head-worn or handheld device. Also, we investigate four context factors. This can inform future work on user identification and authentication systems at scale.

3 CONTEXT FACTORS AND USE CASES

Complementary to prior work on singular use cases and threat models, we focus broadly on the human body for motion-based identification to inform use cases where motion sensing is possible. In this section, we describe and motivate the four main contextual factors we analyze for this purpose. We also describe exemplary use cases for each factor. The context factors are illustrated in Figure 1.

3.1 Body Parts

As shown in related work, the majority of behavioral biometrics papers focus on a single or a small set of sensors related to positions on the human body. Complementary to these efforts, we explore the effects of various body parts across the whole body and how they are potentially useful to capture unique behavior.

To achieve this, we utilize a state-of-the-art motion tracking system where the body is tracked with a motion suit. This extends prior work on, e.g., perspective-based skeleton tracking [29] by enabling full 3D tracking in the environment. Our system enables inference of 18 distinct body parts (cf. Figure 1, top left). This also includes commonly considered body parts, and thus can be of interest to projects using head [39], hands [11], or feet [46] to understand how they compare to other body parts. Understanding the relative differences in user identification quality can be useful to inform use cases where only a part of the body may be sensed, e.g., when using only a few on-body sensors (head-worn device, smartwatch) or only parts of a person are visible to an external camera (e.g. user partially occluded by an object or inside a window/car).

3.2 Activity

Activity is one of the main factors of a user's context, especially for interaction with computers [37]. We focus on fundamental physical activity as it directly contributes to motion behavior and as it is part of many contexts of use. The main states are a person sitting or standing and walking to get to another position. Walking has been extensively investigated for gait recognition [11]. Therefore, it represents an ideal baseline to compare to other activities. We also explore the transition from standing up to sitting down.

This factor can be interesting for several use cases. A behavioral biometrics system can consider the user's activity to decide which features to exploit. In a more dynamic environment like public transport or an office entrance, body motion can be useful as a behavioral biometric. For public transport, when users enter, e.g., a bus their ticket could be automatically validated. When users sit down on a train, a system could infer if the user is sitting at their booked seat. Office building entrances could automatically identify the employees and provide access to the building. This is also applicable to a smart home environment. When users are sitting on their couch to watch TV, the system can infer the user's identity to automatically log in to the Netflix account.

3.3 Hold

Similarly, a fundamental factor is holding an object in the hand. Especially, considering the well-documented research on gait, it is not clear whether holding an object in either one or two hands may affect the identification result. Therefore, we particularly focus on this factor for walking conditions. There are many potential use cases where this may occur. For example, in an office environment users may walk to a meeting room with documents, a laptop, or a cup of coffee held. When they enter the room, they could be authenticated and automatically logged onto their devices, and other users can be notified who entered. Another use case where users often carry things is shopping. After shopping, users may walk to their car with bags in their hands. The car could infer who is approaching and provide easier access to the user. Behavioral authentication systems should infer in what conditions users are walking, and consider how these may affect identification quality.

3.4 Task

The user's task, typically directed towards a particular objective, is likely to have a substantial effect on user behavior. However what constitutes a task is impacted by many factors, such as the user device, the activity involved, and the goal the user aims to accomplish. As a first high-level approach, we consider three categories for tasks. Two categories are defined by the device used, a smartphone, or a large display, which are commonly used in many contexts. The other task is related to physical activity, where the user is tasked to walk to a particular position. Within the devices, we further vary the task. For the smartphone, we consider a chat and a game task as two frequently used applications in mobile interaction that are however distinct in their nature. For the TV display, we consider three distinctive genres in television: watching an educational video, a horror video, and an animated movie.

Potential use cases are broad. Interaction with a phone is a common activity that can accompany many security scenarios, from

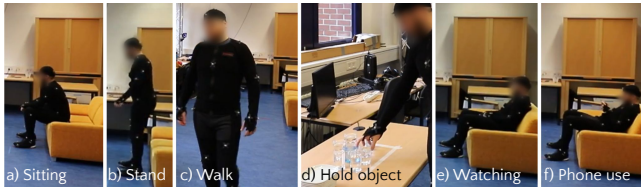


Figure 2: Pictures showing the tasks of the study participants: walking (a-d), watching (e), and phone use (f).

(second-factor) authentication to the actual device, or to authenticate users in a hospital waiting room (to avoid having to register manually by waiting in a long queue). Previous work has shown that phone interactions on their own can be used as a behavioral biometric, e.g. when typing [9]. We extend these works at a higher level of task, by analyzing the body motion around the use of the phone allows us to make further user inferences. Such systems could be complemented with body-based features, if additional body tracking is available or data usage on the phone may not be desirable (e.g., for privacy reasons). In these cases, the app and interface on the phone can potentially be designed to elicit unique user behavior; an authentication scheme specific to the hospital waiting room, for instance, could be a health learning game that users can play to authenticate. A large TV scenario, on the other hand, lends itself more to typical home cinema scenarios, as well as public waiting scenarios such as when waiting at a bus or train station and viewing content on a public display.

4 DATA COLLECTION STUDY

We collect user motion data¹ across 2 sessions and the contextual factors outlined above. The goal is to build the base for a follow-up investigation of user identification related to motion and context.

4.1 Task and Study Design

To include the context factors as outlined in the previous section, we designed a study with 11 tasks that occurred counterbalanced across participants. The 11 tasks were divided in 3 categories: walking, watching TV, and smartphone use. We chose a within-subjects study design with repeated measures, over two sessions with at least 2 days in between. The category order as well as the tasks in each category were counterbalanced across participants. The three categories are described in more detail below.

4.1.1 Walking. For this task participants would sit down on a sofa, stand up again and get an object from a large table about 4 meters away, return, and sit down again. The approximate walking path is indicated as a dotted line in Figure 3. This process is repeated for each of the following 4 conditions 10 times: walking with (1) empty glasses, (2) water-filled glasses (3) empty glasses and plates (4) without carrying an object. Ten plates and ten glasses (either empty or filled with water) were prepared before each condition on the table to accommodate the 10 repetitions. The activities standing up and sitting down were derived post-hoc (see Section 4.5).

¹The dataset is publicly available at <https://go.unibw.de/unique-body-moves>

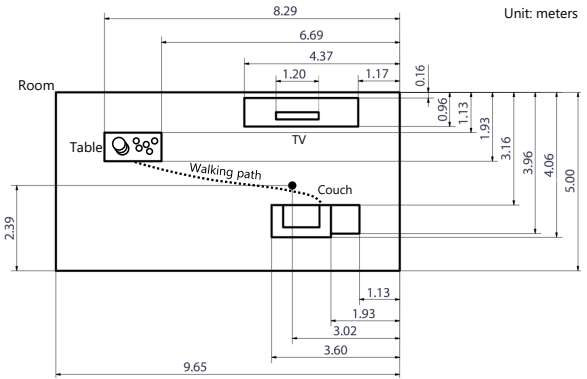


Figure 3: Top view of our study setup showing the object location and room size with dimensions.

4.1.2 Watching TV. Participants would sit down on the sofa and watch different videos. We showed three different videos: (1) an animation video (2) a learning video from Youtube and (3) a snippet from a horror movie. Participants were not given any hints on what kind of video they would be watching to elicit unique personal reactions. All videos were between three and five minutes long.

4.1.3 Smartphone Use. The last task was the use of smartphones. Participants were asked to sit on the sofa and use a smartphone under two conditions: (1) playing a game², and (2) texting using a common application (Whatsapp). Each of the two tasks was finished after five minutes. For the game, the participants were provided with a smartphone with the game "Cut the Rope". The choice of the level to play was left to the participants themselves, and there were also no restrictions towards the number of levels or the score. In the chat condition, participants were asked to use their own smartphones so they could use their normal keyboard layout and smartphone size which affects how they hold it. The chat partner for this task was always a researcher. The theme of the chat was casual small talk. In addition, the researcher had a list of questions to aid the conversation flow if necessary.

4.2 Setup and Apparatus

We use an OptiTrack system³ with 20 cameras for full body tracking along with 37 markers on the suit used to derive 18 distinct body parts. The markers were distributed as instructed by the tracking software to create a full body model⁴. We logged the positions of all markers on the suit at a frame rate of 90 Hz using a C# script. The environment included a sofa (170 × 90 × 62 cm) placed opposite to a television (55 inches) on a table with height 1 m and 2.2 m away from the sofa and 94 cm from the rear wall holding the cameras. A top view of the setup can be seen in Figure 3. A table (80 × 80 cm) with objects for the walking task was placed on the left. 10 plates and 10 glasses were placed on top at previously marked positions to ensure reproducibility. Participants used an LG G6 smartphone.

²<https://play.google.com/store/apps/details?id=com.zeptolab.ctr.ads&hl=en> (last accessed 21/06/2023)

³<https://optitrack.com/> (last accessed 21/06/2023)

⁴Marker distribution: 3 on the head, 1 on each shoulder, 1 on the chest, 3 on the back, 3 on each arm, 3 one on each hand, 4 on each leg, 2 on each foot, and 2 on the front and rear pelvic bone

Each body part was tracked as coordinates (x, y, z) according to the 3D tracked space. There are five body part features that are available for both the left and right sides. Due to a tracking error in the software, only one side is available for the shin, toe, and foot. As illustrated in Figure 1, we tracked the following body parts:

- *Left body side*: Shoulder, arm, forearm, hand, thigh.
- *Right body side*: Shoulder, arm, hand, forearm, thigh.
- *Other*: Hip, abs, chest, neck, head, shin, toe, foot.

4.3 Procedure

In the first session, all participants received a brief introduction and filled in the demographics and consent forms. After that, participants were asked to put on the full motion tracking suit (pants, jacket, headpiece and shoe) and one of the researchers attach the required markers. Once the participants wore the suit the tracking system was calibrated. Next participants performed the 11 tasks as described in Section 4.1. At the end, we asked if they had seen the videos or if they had already played the game before. The study lasted between 45–60 minutes including breaks between tasks.

4.4 Participants

We recruited 22 participants (13 female) between 18 and 36 years ($M : 23.73, SD : 3.93$) using the university mailing lists and social media platforms. Participants were either students from the local university or employees with mixed backgrounds and were compensated with 10 Euros. Users had little experience with motion tracking ($M: 1.41, SD: 0.58$) as indicated on an experience scale from 1 (no experience) to 5 (very experienced).

4.5 Data Preprocessing for Activities

Active walking tasks included standing up, walking, potentially fetching items and sitting down again. Start and end are identical in all walking conditions (participants placed the objects they were supposed to carry on a table before sitting down again). To separate walking from sitting and standing tasks, we use the participants' absolute position relative to the couch using a proximity and height threshold. We found that on average, sitting down took 0.89 s (session 1) and 0.9 s (session 2), and standing up took 0.83 s and 0.85 s respectively. Walking took on average 8.12 s in the first and 7.67 s in the second session. This aligns with our expectations and fits a typical time to perform these activities.

4.6 Dataset Limitations

This user study provides a high precision dataset on body motion across tasks with the following limitations. The motion tracking system could wrongly detect the posture of a user due to insufficient visibility of the infrared markers. This can happen when users sit down and the markers at their back are hidden or due to fast walking speed. However, such an issue was consistent for each user, with no effect on the analysis across users. Ecological validity may be limited, as the study took place in our lab environment with users wearing a motion suit. This is a compromise we take to be able to study users at high precision and compare the many context factors without external influence. To better quantify this effect, we asked how normal users were able to behave in our setting (1:

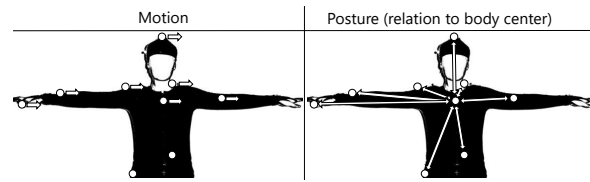


Figure 4: Types of features for the identification analysis

not normal to 7: normal). Users provided an average rating of 5.64 ($SD=0.98$), indicating only little deviation from normality. Finally, a larger number and diversity of participants would potentially allow better identification accuracy estimates. However, we do not aim for the highest possible accuracy – prior work showed such results and this strongly depends on the dataset too. Our focus is on understanding the context factors, where relative differences between the conditions matter most.

5 MODELING AND EVALUATION METHOD

To facilitate identification we map a feature vector computed from a time window of data to one of the classes corresponding to the task and user. We compare *Random Forest (RF)*, *K-Nearest Neighbors (KNN)*, *Support Vector Machine (SVM)* and *Multilayer Perceptron (MLP)*. For *RF*, *KNN* and *SVM* we use the implementation of the *scikit-learn* library. For *MLP* we used *Keras* with *tensorflow* backend. We report *accuracy* as the number of correct predictions (target class received highest score) divided by the total number of predictions made. The data was split into two equal halves (corresponding to the first and second sessions) as training and testing sets. Data modeling depended on the task: 10 seconds were used for the seated tasks, and we used the full duration (at 90 Hz) for the rest.

5.1 Extracted Features

We derive two feature types from the 18 body part positions to model the spatial behavior of the user (Figure 4). We consider *motion* as a descriptor of how the user physically performs activities such as walking, sitting, or standing. It is computed as the delta of two consecutive frames. Second, we consider *posture* as a metric that describes how the user's body parts are situated in relation to each other. This can be useful to better describe users in static activities, such as sitting. We compute this by subtracting all body parts from a reference point (users' chest). Posture is interesting as it more explicitly describes the physical features of the user's body, e.g. relative length of the arms.

5.2 Time Window Selection

Each frame contains the motion $m_b = (x, y, z)$ of all body parts b . To capture the temporal aspect we concatenate the motion data from Δt frames $f_t, f_{t+1}, \dots, f_{t+\Delta t-1}$, to form a new sample, hence modeling motion of body parts over Δt frames. Compared to the common abstraction of computing features on time windows (e.g. avg, SD, min, max) this approach allows us to retain the raw data. To find the optimal time window Δt per task, we trained *RF* with $n_{estimators}=30$ models using all body parts and several time windows Δt . We then computed the average accuracy per time window across features. Table 1 shows the optimal time window Δt .

Table 1: Optimal time windows across tasks

| Task | Δt (frames) |
|---------------------------|---------------------|
| All walking tasks | 70 |
| Stand up | 40 |
| Sit down | 30 |
| Texting | 15 |
| Play game; watch animated | 30 |
| Watch horror movie | 15 |
| Watch learning video | 10 |

5.3 Multi-class Classifier and Parameters

We trained a multi-class classifier (i.e. one class per participant) for each body part, and all body parts, with optimized time windows Δt . For training, we used *RF* with $n_{estimators}=30$. Other hyperparameters had default values.

5.4 Feature Optimization & Classifiers

To investigate optimized feature sets per task, we used *greedy top-down* feature selection [20]. We start training with all features, repeatedly iterating over all remaining features, and training models without the chosen feature. If one of those models achieves a higher accuracy, the respective feature is removed from the feature set and the process is repeated. It stops if none of the features leads to an improvement in accuracy when dropped from the feature set or when only one feature remains. For training, we used *RF* with $n_{estimators}=50$. Table 2 shows feature optimization results with the determined best feature set and resulting accuracy. We then compared the user identification accuracy between different classifiers. Time windows for all classifiers are based on Table 1. For *RF* we optimized $n_{estimators}$ from the set [100, 200, 300, 400, 500]. For *KNN* we optimized the number of nearest neighbors k from the options [5, 10, 15]. For *SVM* we chose the optimizing parameter C from the options [0.1, 1.0, 10], and for *MLP* we tried different numbers of layers and units per layer. Results can be seen in Table 3.

6 RESULTS

If not stated otherwise, we report and compare the results with regard to user identification accuracy with the *RF* classifier as it yielded the highest accuracy among the models. The diagrams show the mean of the identification accuracy across the presented factors, and the error bars denote 95% CI of the given conditions. We use accuracy as our main metric. With 22 users the guessing baseline is $1/22 = 4.54\%$, which is surpassed by all results.

6.1 User Identification Across Tasks

Figures 5 and 6 show accuracy across tasks for motion and posture features. We describe the main findings below:

Motion features may identify users better: Comparing motion and posture features, we find that motion features achieve a higher accuracy (Max = 59.21% in walking) in several tasks than posture features (Max = 34.95%). However, this difference is not statistically significant as shown by repeated measures ANOVA, $P > .05$.

Identification most accurate when walking: Using the motion features, a substantially higher accuracy can be achieved for walking

tasks (40.75% to 59.21%) than, e.g., static tasks (chatting with 6.64% or watching learning video with 9.45%). Among the posture features, walking tasks are more accurate as well although the discrepancy is less pronounced (e.g., 13.52% for chatting vs. 32.36% for walking). For the motion features, a repeated measures ANOVA showed a statistically significant effect of the task on the classification accuracy ($\chi^2(10) = 2060, P < .001$). In the watching task, the stimuli, animated movie ($M = 13.8; SD = 1.9$), horror movie ($M = 9.7; SD = 2.2$), and news ($M = 9.44; SD = 1.67$) showed statistically significant effect on the classification accuracy, ($\chi^2(2) = 48.49, P < .001$). Pairwise comparisons showed a significant effect on each pair with $P < .001$. In addition, repeated measures ANOVA also showed a significant effect of the walking tasks ($M = 47.7; SD = 2.46$) and sitting tasks ($M = 9.9; SD = .95$) on accuracy ($\chi^2(1) = 4069.23, P < .001$).

For the posture features repeated measures ANOVA showed a statistically significant effect of the task on the classification accuracy, ($\chi^2(10) = 32.69, P < .001$). However, no effect was found for the stimuli in the watching tasks on the classification accuracies, $P > .05$. Finally, we found a significant effect of the walking ($M = 32.1; SD = 7.6$) and sitting tasks ($M = 19.6; SD = 3.98$) on the classification accuracy, ($\chi^2(1) = 83.5, P < .001$).

Walking identification is higher with objects: Within the walking conditions we found accuracy to increase with the number of items held. The highest accuracy was achieved for walking with glasses on a plate at 59.21%, which is the most mass users carried. This is closely followed by walking with filled (56.63%) and empty glasses (53.01%). All these tasks have a larger margin to the baseline walking task without any handheld objects at 40.75%. Repeated measures ANOVA showed statistically significant effect of the number of items on the accuracy of the number of items (no items ($M = 40.75; SD = 2.75$), empty glasses ($M = 53; SD = 3.21$), filled glasses ($M = 56.83; SD = 3.58$), glasses and plates ($M = 59.21; SD = 2.93$)) on the accuracy of the classification, ($\chi^2(1) = 377.38, P < .001$). A pairwise comparison also showed statistically significant difference between all pairs with, $P < 0.05$.

For static tasks, posture is more accurate than motion: Considering the 7 tasks where users were sitting, posture features led to better identification. Accuracy was higher for chatting (+6.77%), sitting down (+18.99%), watching a learning video (+7.91%), watching a horror movie (+8.38%), playing a game (+14.65%), watching an animated movie (+5.1%) and standing up (+3.54%). The aggregated results in Figure 9 show the trend of static vs. movement-based tasks. However, we could not find statistically significant differences using paired sample T-test, $P > .05$, this suggests that more investigation has to be carried out.

On the mobile phone, games identify users better than chatting behavior: We found that for both motion and posture features, playing a game led to higher identification accuracy than chatting. The effect is, however, more pronounced for posture (+11.45%) than motion (+3.58%). Games potentially induce a more unique behavior through their game-play dynamics, compared to chatting which is quite standardized (i.e., fingers are mostly on a predefined area). A repeated measures ANOVA test showed a statistically significant effect of the application type on the classification accuracy for the chatting ($M = 6.73; SD = .90$) and games applications ($M = 10.32; SD = 1.46$), ($\chi^2(1) = 199.92, P < .001$).

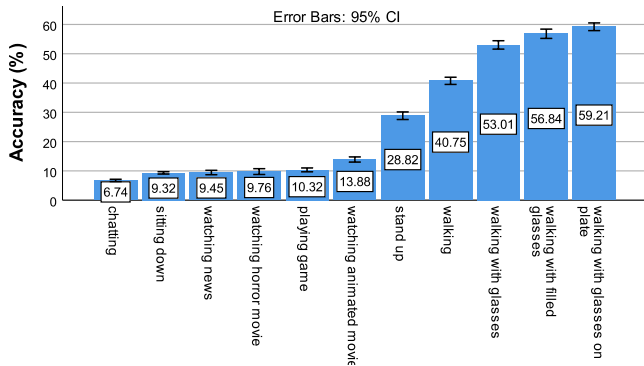


Figure 5: ID accuracy of *motion* features per task

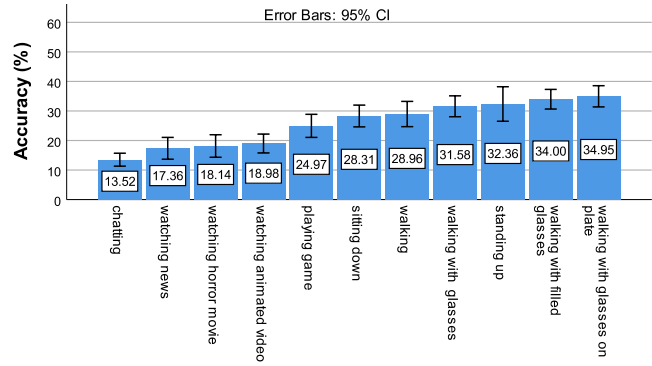


Figure 6: ID accuracy of *posture* features per task

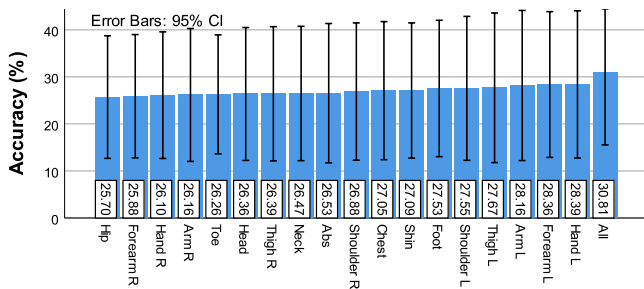


Figure 7: ID accuracy of *motion* features per body part

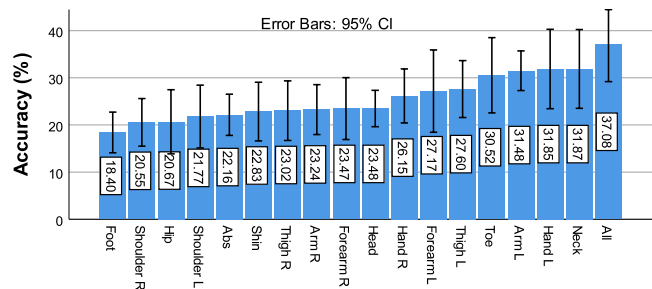


Figure 8: ID accuracy of *posture* features per body part

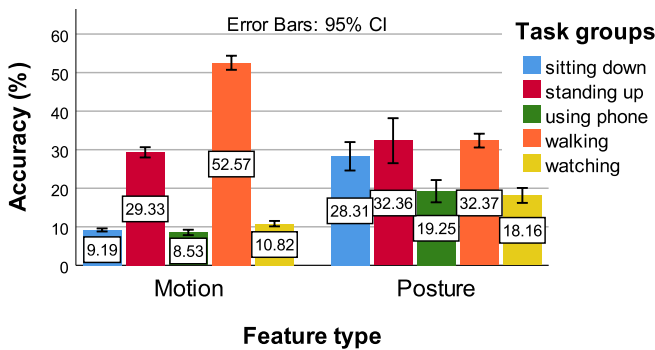


Figure 9: ID accuracy grouped by tasks

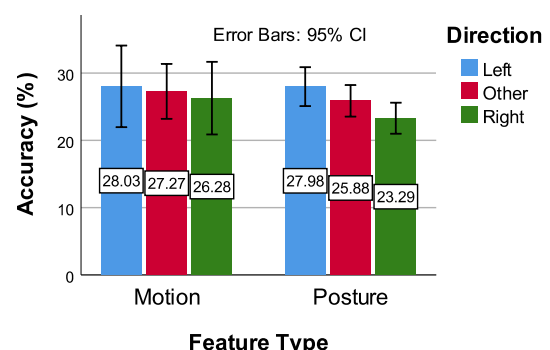


Figure 10: ID accuracy grouped by body group

Standing up is more consistent for user identification than sitting down: Looking at the stand/sit tasks, we find that similar accuracy is obtained for standing up for both motion (28.82%) and posture features (32.36%). However, for sitting down, there is a large gap between motion and posture (9.32% vs. 28.31%), indicating that standing up may trigger more unique motion behavior. A potential reason is that users were free to choose where to stand up while sitting down on the same couch (i.e. same height and position). This was also proven statistically where repeated measures ANOVA shows statistically significant effect of the task standing up ($M = 28.81; SD = 2.9$) and sitting down ($M = 9.32; SD = .89$) on the classification accuracy ($\chi^2(1) = 945.67, P < .001$).

6.2 User Identification across Body Parts

Figures 7 and 8 show the identification accuracy for each feature type, split by body part. As the posture data was computed relative to the chest, we exclude the chest feature here. The results point to the following findings:

All features lead to highest identification accuracy: Across both feature types of motion and posture, the best identification results were achieved using all features. However, we find that for motion, single features such as the left arm or hand, are only marginally less accurate. This indicates that a system can potentially only track e.g. the hand and thus substantially decrease tracking complexity. For posture only, all features (37.08%) have a slightly higher gap to the second highest (31.87%), indicating that for this type of feature,

Table 2: Feature sets with the highest accuracy determined by a top-down greedy algorithm for each task.

| Activity | Body part set |
|----------------------------|---|
| Walk+no object (52.79%) | Hip, abs, chest, neck, arm L+R, forearm L+R, hand L+R, shoulder R, thigh L, shin, foot, toe |
| Walk+empty glass (62.40%) | Hip, chest, neck, head, shoulder L+R, arm L+R, forearm L+R, hand L+R, thigh L+R, shin, foot, toe |
| Walk+filled glass (67.49%) | Hip, chest, neck, shoulder L+R, arm L+R, forearm L+R, hand L, thigh L, shin, foot, toe |
| Walk+glass+plate (69.73%) | All body parts |
| Stand up (35.92%) | Hip, abs, chest, neck, head, shoulder L+R, arm L+R, hand L+R, forearm R, thigh L+R, shin, foot, toe |
| Sit down (11.15%) | Hip, abs, chest, neck, head, shoulder L+R, arm L+R, hand L+R, forearm R, thigh L+R, shin, foot, toe |
| Texting (9.52%) | Abs, chest, neck, shoulder L+R, arm L+R, forearm L+R, hand L+R, thigh L+R, shin, foot, toe |
| Play game (14.89%) | Hip, abs, chest, neck, head, shoulder L+R, arm L+R, hand L+R, forearm R, shin, thigh R, foot, toe |
| Watch animated (19.36%) | Hip, abs, chest, neck, head, arm L+R, hand L+R, shoulder R, forearm R, thigh L+R, shin, foot, toe |
| Watch horror (13.34%) | Ab muscle, chest, neck, head, shoulder L+R, arm L+R, forearm R, hand R, thigh L, shin, foot |
| Watch learning (14.40%) | Hip, ab muscle, chest, neck, head, shoulder L+R, arm L+R, hand L+R, forearm R, shin, thigh R, toe |

it may be indeed better to combine features. Overall, we could not find statistically significant differences in the accuracies when using different body parts for both motion and posture features, $P > .05$.

Best body parts: The range of differences between body parts is more pronounced for posture features (18.4 - 37.08%) than for motion features (25.7 to 30.81%). The best features were left hand, forearm, and arm as well as the thigh (center).

The left side achieved higher accuracy than the right: Among the top features are often features that belong to the left side of the user’s body. Figure 10 shows the results aggregated by the left, center, and right sides of the body. It further shows that for motion features, the left/right difference is marginal. For the posture features, a slightly higher discrepancy is visible, with the left side achieving a higher user identification score of 4.69%. However, we could not find statistically significant differences between the left and the right body parts on the classification accuracies, $p > .05$

Motion is robust to body parts; posture is robust to tasks: We find that when using motion-based features, the various body parts result in similar accuracy scores on a range between 25.7 to 30.81%. The high error bars also indicate that the task has a stronger effect on motion than the actual body part, as we discussed in the previous section (c.f., Fig. 5). On the other hand, for posture-based features, we see a stronger effect of the body parts, ranging between 18.4% to 37.08%. Thus, this points to posture feature being more robust to task variations. From a high-level perspective, it can be expected that motion is more affected by tasks that vary in their physical exertion. Our analysis confirms this.

6.3 Best Feature Sets

Multimodal features [35] have the potential to a higher identification quality than individual aspects. We conducted feature optimization for the motion feature type. Table 2 shows the best feature set for all tasks. We achieved the best accuracy (69.73%) for walking while carrying glasses and plates where all (18) body parts were involved in the task. Next up comes walking with glasses (67.49%) where 14 body parts were involved in the motion. For walking with empty glasses we achieved 62.40%. The least accurate activities were chatting (9.52%) and sitting down (11.15%) with 16 and 17 body parts involved in the recognition. These accuracy scores

Table 3: Hyperparameter optimization results across RF, KNN, SVM and MLP (bold denotes best per task, numbers in brackets denote model parameters used) in percentages

| Task | RF | KNN | SVM | MLP |
|----------------|--------------------|-------------------|-------------------|-------|
| Walk | 57.39 (500) | 52.71 (5) | 29.79 (10) | 45.65 |
| Walk + glasses | 67.02 (500) | 72.74 (5) | 60.09 (10) | 51.24 |
| Walk + filled | 71.58 (400) | 74.32 (5) | 67.34 (10) | 62.34 |
| Walk + plate | 74.67 (500) | 73.12 (5) | 63.47 (10) | 57.28 |
| Stand up | 37.73 (400) | 33.25 (5) | 41.84 (1) | 32.37 |
| Sit down | 11.67 (400) | 9.27 (5) | 13.37 (10) | 9.52 |
| Chatting | 10.22 (300) | 11.27 (10) | 4.80 (10) | 6.17 |
| Play game | 15.06 (500) | 6.00 (5) | 1.92 (10) | 6.97 |
| Watch anim. | 20.74 (400) | 10.40 (5) | 5.06 (1.0) | 8.66 |
| Watch horror | 14.74 (500) | 8.70 (15) | 6.27 (0.1) | 8.20 |
| Watch learning | 16.28 (500) | 12.93 (10) | 5.99 (10) | 7.96 |

are the highest that was achieved in our analysis, indicating that multimodal user identification is superior in our tested cases. To complement these results, we trained all of the mentioned algorithms with these feature sets and tested several hyperparameters (see Table 3). The results show RF performing best for most of the tasks (55% of the tasks), followed by KNN (27%) and SVM (18%).

7 DISCUSSION

In this work, we investigated behavioral biometrics for user identification, and present the detailed quantification of the effects of context factors on the uniqueness of behavioral traits exhibited through motion. Some of the findings confirm prior findings, some are as expected and now documented, and others can be considered novel. In the following, we reflect on the main findings, and then discuss on the human-centric approach and future work directions.

7.1 Main Findings & Insights

Gait-based user recognition improves when holding objects: Across our walking conditions, we find clear evidence that user identification improves when users are holding one object, and further with both hands occupied. This reminded us of a finding from Buschek et al.’s work [9], that focused on a different setting (touchscreen

biometrics), but came to a similar insight. Targets on the screen that is more difficult to select, such as those close to the screen's border, are allowed to elicit more unique user behavior. Our work supports their insights and points to the more general property of user identification that if the task is designed with more difficulty, users are as well identified better.

Motion and posture data types depend: There is a trade-off between feature types used for identification when a user can remain still or in movement. In all our walking tasks, we find that motion is best to identify users. In contrast, in the tasks where users were mainly sitting, such as using their phone, we find absolute posture information of the user's body to be more unique. Here the posture information is more useful to make inferences about the user. In conclusion, a potential user identification system may ideally adapt the used feature type to the user's activity.

Why standing up may elicit more unique behavioral traits than sitting down: Standing up and sitting down are brief and in our tested conditions we found that standing up leads to more promising identification features. This may be accounted to the fact that users are more free to choose how they stand up towards the open space, contrasting sitting down to a specific location; something that demands further study.

Device content matters: We also find that user identification accuracy varies depending on the used smartphone app. We tested two smartphone apps used in a seated position: playing a game and chatting. We find that in a game, users were easier to identify than from chatting, indicating the effect of the application and its UI design on identification quality. Playing a game involves an aspect of engagement to the user, that users may approach more individually than chatting. Another potential influential factor is the mobile UI, as typing usually has a conforming, standard layout compared to dynamic game elements which may lead to more unique behaviors. Potentially, a similar effect occurs when users watched an animated film compared to others, but these results are yet inconclusive.

7.2 Limitations

There are a few caveats that must be considered when interpreting our findings. We focus on identification accuracy, leaving out other important metrics around false positives and negatives. We found that accuracy led to the most distinctions between the factors. We thus omitted other metrics for brevity. In our work, we achieved identification accuracies in the range of 30 to 75%. This is insufficient for real-world application. However, we believe it is sufficient for understanding how different contextual factors compare. In addition, the findings are inherently based on the given dataset, which involved many factors but can also include effects from the laboratory and motion tracking environment.

Further, our best feature sets describe the highest accuracy gained with a particular context in mind. This is useful when the system can assume that context information is available. However, if this is not clear, the accuracy is likely to degrade. We note that the focus of this work is not to achieve a working system, but to understand the potential effects that differing contexts can have. Our findings clearly show that accuracy is highly depending on contextual data, and future authentication systems have the potential to greatly improve if a better context recognition is used.

Yet, collectively our findings represent an extensive coverage of the many factors and the relations of our body to inform those interested in the design of motion-based behavioral biometric systems. Our work serves as the first groundwork in this matter (though not exhaustive [37]) that is broad and transcends sensors and technology through the focus on a human-centric approach.

7.3 Future Work

Concrete next steps can follow from the boundaries inherent to our work. We focus on user identification and it is open whether the findings translate to user authentication scenarios. Our work can also be extended to how potential attacks on behavioral biometric authentication can be mitigated, for instance how and to what extent each of the context factors and the body parts may be susceptible to imitation attacks [1, 27]. It could be insightful to understand whether some movements are easier to imitate, whereas others are more dependent on anatomy than behavior. Furthermore, in the cases that involve the detection of an attacker, the analysis needs to consider different classifiers than the multi-class variant that we used to train on the known set of users. Beyond these important extensions, there are further challenges with the potential to expand the theme of our holistic analysis:

7.3.1 Fine-grained Analysis of User Interaction. With increasing precision of motion sensors, it can become possible to focus on more fine-grained user interactions such as how users interact in the real world with their hands when grabbing and moving objects, when gesturing, or in the interaction with computing devices. Past work has already extensively explored specific devices, such as the interaction centered around smartphones [9, 15], yet these often focus on the user's touch input or motion sensors internal to the device. Although this already led to promising results, it is potentially only marginally catching the user behavior that may underlie the user's finger, hand, and arm motion. Manual interaction is a vast space, whether the user is interacting with an object, and whether it is digital and/or interactive. This could also be interesting with regards to more user-intrinsic physiological factors such as the eye gaze of a user [32, 33], that is inherently coordinated with the manual action [18] and in turn could amplify user identification as a multimodal biometric.

7.3.2 Analysis of Device-centric User Identification. Our human body focus was motivated by the prior strong focus on devices. But we also felt that the corresponding prior art is scattered across many research efforts. Although there are several surveys providing extensive reviews [6, 42], a holistic analysis of available devices and how they compare for the purpose of identification would clearly complement our work.

7.3.3 Deployment & Real-world Validation. In the long run, the technological advances of VR and AR devices may lead to full body motion integrated into the user's experience; it would then be interesting to deploy a user identification system and validate our findings. Such environments may allow obtaining motion data of multiple people, which opens further questions as user behavior may change when interacting and collaborating with others.

8 CONCLUSION

This work presented a holistic analysis of body motion for user identification that can be considered orthogonal to the prior device-specific research. We conducted a data collection of high-precision full-body motion with four context factors for 22 users across 18 body parts. This dataset was used for an extensive analysis of the motion and posture information of the user as a metric to understand the unique traits of persons. We provide an extensive analysis of features useful for user identification, which features are more descriptive based on which task and part of the user's body. Our findings highlight various factors for when users are still, in movement, using their phone, or watching TV, and complement the analysis with further classifier optimizations. Our work is useful to better understand how people move uniquely, and what parameters are useful to consider for behavioral biometric systems in smart environments that can track user motion, to make systems more secure as well as adapt the interface towards identified users.

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