Sensor-based Continuous Authentication of Smartphones’ Users Using Behavioral Biometrics: A Survey

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Abstract—Mobile devices and technologies have become increasingly popular, offering comparable storage and computational capabilities to desktop computers allowing users to store and interact with sensitive and private information. The security and protection of such personal information are becoming more and more important since mobile devices are vulnerable to unauthorized access or theft. User authentication is a task of paramount importance that grants access to legitimate users at the point-of-entry and continuously through the usage session. This task is made possible with today’s smartphones’ embedded sensors that enable continuous and implicit user authentication by capturing behavioral biometrics and traits. In this paper, we survey more than 140 recent behavioral biometric-based approaches for continuous user authentication, including motion-based methods (27 studies), gait-based methods (23 studies), keystroke dynamics-based methods (20 studies), touch gesture-based methods (29 studies), voice-based methods (16 studies), and multimodal-based methods (33 studies). The survey provides an overview of the current state-of-the-art approaches for continuous user authentication using behavioral biometrics captured by smartphones’ embedded sensors, including insights and open challenges for adoption, usability, and performance.

Index Terms—Sensor-based Authentication, Continuous Authentication, Mobile Sensing, Smartphone Authentication.

I. INTRODUCTION

SMARTPHONES have been witnessing a rapid increase in storage and computational resources, making them an invaluable instrument for activities on the internet and a leading platform for users’ communication and interaction with data and media of different forms. Moreover, the current edge and cloud computing services available to users have increased the reliance on mobile devices for mobility and convenience, revolutionizing the landscape of technologies and methods of conducting transactions [1]. The continuous user authentication is an implicit process of validating the legitimate user based on capturing behavioral attributes by leveraging resources and built-in sensors of the mobile device. Users tend to develop distinctive behavioral patterns when using mobile devices, which can be used for the authentication task. These patterns are implicitly captured as users interact with their devices using behavioral features calculated from a stream of data, such as interaction and environmental information and sensory data. Continuous authentication methods are also called “transparent, implicit, active, non-intrusive, non-observable, adaptive, unobtrusive, and progressive” techniques [2], [3]. Traditionally, continuous authentication methods operate as a support process to the conventional authentication methods, e.g., using secret-based authentication or physiological biometrics, such as prompting users to re-authenticate when adversarial or unauthorized behavior is detected.

Recently, the field of continuous authentication has been gaining increasing interest, especially with the expansion of storage and computational resources and the availability of sensors that can make the implicit authentication very accurate and effective. Using sensors-based authentication methods offers convenient and efficient access control for users. This paper surveys recent and state-of-the-art methods for continuous authentication using behavioral biometrics. We aim to shed light on current state and challenges facing the adoption of such methods in today’s smartphones.

Conventional vs. Biometric Approaches. To date, vendors of mobile devices have adopted both knowledge-based schemes and physiological biometrics as the primary security method for accessing the device. Knowledge-based approaches rely on the knowledge of the user; i.e., the user must provide certain information such as numeric password, PIN, graphical sequence, or a picture gesture [4], to access a device [5]. Despite their simplicity, ease of implementation, and user acceptance, such approaches suffer from several shortcomings such as the inconvenience of frequent re-entering (especially when the knowledge used are long enough to convey strong security) and several adversarial attacks (e.g., shoulder surfing and smudge attacks) [6]–[10]. Another issue with knowledge-based authentication is the underlying assumption of having equal security requirements for all applications [11]. For example, accessing financial records and texting are given the same level of security. Using a knowledge-based authentication on smartphones falls short on delivering application-specific security guarantees [12], especially observing the recent emergence of adaptable biometric authentication that account for environmental factors to adapt and select the suitable sensors for authentication (e.g., using fingerprint sensor when the lighting condition does not allow for face recognition) [13]. Even when using more complicated implementations of knowledge-based approaches, e.g., Yu et al.’s [14] implementation of 3D graphical passwords which can be easier to remember and
Renaud demonstrated that 90% of the study’s participants are influential for user adoption since a survey by Crawford and behavioral biometrics-based authentication have shown to be abandonment protection, or when the legitimate user of behavioral biometrics, they are a suitable solution for user authentication methods that may incorporate physiological biometrics to harden security and boost the performance of the authentication scheme.

**Contribution.** This work contributes to the mobile continuous user authentication in several aspects:

- Survey more than 140 works on continuous user authentication methods, categorizing them into six behavioral and physiological biometrics groups (motion, gait, keystroke dynamics, gesture, voice, and multimodal).
- Present the studies of each biometric modality in a table format, comparing works by the modality, sensors, and the used authentication algorithm, in addition to the data collected, user sample size, and six evaluation metrics. Such comparison provides ease in understanding each work and how it compares to others in the field.
- Give insights and challenges for different biometric methods, highlighting the possible future work and existing common gaps within the literature.

**Organization.** This survey is organized as follows: we discuss the system design of continuous user authentication, including biometric modalities, user enrollment and verification techniques, and evaluation metrics in Section II. The user authentication system is categorized into six groups: motion-based authentication in Section III, gait-based authentication in Section IV, followed by keystroke dynamics-based authentication in Section V. Touch gesture-based and voice-based authentication methods are described in Section VI and Section VII, respectively. The multimodal-based authentication is described in Section VIII. Finally, we conclude in Section IX.

### II. Continuous Authentication: Design

Numerous studies have explored various methods for continuous user authentication leveraging modern mobile technologies and embedded sensors to model users’ behavior. The deployment of sensors on today’s mobile devices have enabled a variety of applications, such as modeling human behavior, user authentication, activity and action recognition, and healthcare monitoring, among others. In this paper, we show recent user authentication methods that use mobile sensory data to capture users’ behavioral biometrics.

#### A. Used Biometric Modalities

Several modalities are used for biometric-based authentication, including physiological biometrics (e.g., face, fingerprint, iris, etc.) and behavioral biometrics (e.g., keystroke dynamics, touch gestures, voice, motions, etc.). Figure 1 shows a categorization of used modalities for user authentication tasks. All these modalities are made possible by the embedded mobile sensors, e.g., camera, microphone, accelerometers,
and gyroscopes, which contribute to the enrolment phase and the verification part of the authentication process. Such sensors provide sufficient information for accurate and secure authentication, and adopting the proper utilization mechanism would play an essential role in delivering efficient and usable user authentication [35]. Using biometrics for authentication, there are enormous studies that demonstrated the benefits and security aspects of using such information to explore “on-the-move biometry” [36].

B. User Authentication

Biometric-based user authentication leverages users’ behavioral patterns for the identification or/and validation task using a pattern recognition method. The authentication is commonly referred to as a verification task in mobile security since the authentication method validates the legitimate user given certain biometrics. The general framework for the authentication system is illustrated in Figure 2.

Enrollment. There are two common approaches for user enrollment in the user authentication system. For simplicity purposes, we categorize enrollment techniques to 1 template-based enrollment and 2 model-based enrollment. For template-based enrollment, the user submits several samples to establish templates for future comparison. This method is popular among authentication methods using physiological biometrics, where features can be more robust to intra-class variations and more distinctive and scalable for a large population. Once users’ templates are established, a similarity-based technique is used to validate users after passing a similarity threshold. Many considerations should be taken to ensure the quality of templates for supporting the performance of the system, such as the robustness and distinguishability of features across users, removing outliers, and reducing noise and redundancy. Moreover, security concerns should be addressed to ensure the security and privacy of users’ templates, whether during enrollment and template registration, storing, retrieving, and processing for user authentication. For model-based enrollment, users’ biometrics are collected for training a machine learning model for user authentication, where the authentication model decides whether the input data belongs to the legitimate user. The common machine learning approach is used to establish users’ models, including data acquisition and preprocessing, feature extraction and selection, and modeling. The quality of features plays a significant role in the performance of model-based authentication. Therefore, most efficient methods include a feature evaluation and selection process to extract the most distinctive features across a large population. Recently, model-based approaches have been gaining success for the user authentication task. However, several challenges should be tackled for efficient adoption, such as data collection size, training time, model size and robustness against possible adversarial attacks.

User Verification. After the user enrollment, the system validates the legitimate user based on extracted features. The verification can be at the point-of-entry and continuously through the usage session. For continuous authentication, the user verification process occurs periodically to grant access to the legitimate user and to deny access to impostors. The frequency of verification should be carefully selected to allow sufficient biometric data acquisition and features extraction process and to manage energy consumption. Depending on the enrolment approach, the authentication algorithm follows a similarity-based or probability-based scheme for user validation. Similarity-based techniques are used for measuring the similarity of input data in comparison to a stored template for a certain user. Traditionally, the verification implies a match between a given data and a stored template to a certain degree. The authentication system is responsible for giving access to the legitimate user when presenting a biometric data that matches the supposed template with similarity check higher than a predefined threshold. The threshold is for accounting for environmental and processing errors that could affect the reading or calculating of the biometric data. Mathematically, a verification process can be viewed as $C = True$ if $f(x,y) \geq t$ and $False$ otherwise, where $f$ is a similarity measurement between an input $x$ and a template $y$, and $t$ is a predefined threshold. The genuine match is shown when $C$ evaluates to $True$, while the impostor match is when $C$ is $False$.

Probability-based algorithms are used for model-based enrollment, where the authentication model signals a probability for granting access to the legitimate user based on the input data, the verification process is similar to the template-based algorithm, expect of using a pre-trained model for decision making. The decision of the model $C = True$ if $g(x) \geq th$ and $False$ otherwise, where $g$ is the objective function of the probability-based algorithm and $th$ is a predefined threshold. The user verification process runs periodically for continuous user authentication, however, the frequency $f_{req}$ higher bound is limited by minimum verification time $t_{v}$, where $f_{req} = \frac{1}{t_{v}}$, and $t_{v} = t_{d} + t_{p} + t_{c}$, where $t_{d}$ is the time needed to acquire sufficient data for verification, $t_{p}$ refers to the time required for data preprocessing, and $t_{c}$ is classification period. While $t_{c}$ can be mitigated by overlapping $t_{d}$ and $t_{p}$ with $t_{c}$, it should be taken into account the computational power and battery consumption needed for the verification process.
C. Authentication Evaluation Metrics

Biometric-based authentication systems are evaluated by their ability to generalize to a large population. This emphasis becomes more obvious when addressing mobile security since the authentication system should account for a very large and different population. There are several evaluation metrics for evaluating authentication system performance. The three most common metrics are the false accept rate (FAR), the false reject rate (FRR), and the equal error rate (EER). For the authentication task on a mobile device, a false accept indicates that false access is granted to an intruder, while a false reject indicates that the legitimate user is denied access to the device. FAR is represented as \( \frac{Number\ of\ False\ Acceptance}{Total\ Number\ of\ Attempts} \) and FRR is equal to \( \frac{Number\ of\ False\ Rejections}{Total\ Number\ of\ Attempts} \). The EER is where the FAR is roughly similar to the FRR, and it is a very popular metric for interpreting system error.

Additional evaluation metrics for the authentication system include true positive rate, true negative rate, false positive rate, false negative rate, accuracy, precision, recall, and F1-score. True positive rate and true negative rate indicate the rate of correctly validating a legitimate user and denying an imposter, respectively. False positive rate and the false negative rate is the rate of which the system denies access for the legitimate user and allows access for the imposter, respectively. Accuracy is the proportion of true positives and negatives to the overall tested data, including (true positives, true negatives, false positives, and false negatives). Precision indicates how frequently the system correctly produces positive classifications, which is calculated as the ratio of true positives to both true and false positives. Recall indicates how frequently the system correctly validates positive data, which is calculated as the ratio of true positives to both true positives and false negatives.

D. Behavioral Biometrics

Behavioral biometrics enable efficient implementation of an authentication system that operates beyond the point-of-entry access and continuously authenticate users without explicitly asking their input. Therefore, behavioral biometrics improve mobile security by providing user continuous and transparent authentication process throughout the entire routine session. An efficient implementation of behavioral biometric-based authentication method should account for hardware- and software-independent operation and network connectivity differences to allow for successful system adoption [37]. Various techniques have been proposed for mobile user authentication using behavioral usage and features by taking advantage of the embedded sensors. Using sensory data, a background process continuously and implicitly captures user’s behavior to perform an active and transparent authentication, e.g., using motion patterns [22], [38], [39], gait [29], [40]–[44], touch gestures [38], [45]–[48], electrocardiography (ECG) [27], keystroke dynamics [19], [47], [49], [50], voice [51]–[53], signature [54]–[56], and profiling [23], [25], [57].

Since today’s smartphones are well-equipped with a variety of embedded sensors, such as motion sensors (e.g., gravity, accelerometer, gyroscope, and magnetometer), environmental sensors (e.g., light, temperature, barometer, and proximity), and position sensors (e.g., GPS and compass), numerous studies have leveraged these sensors for user authentication [22], [25], [58], [59]. A study by Crawford et al. [60] shows that behavioral biometrics reduce the demand for legitimate authentication by 67% in comparison to knowledge-based methods, i.e., adding a remarkable improvement in usability. In terms of exploiting access privilege, the authors showed that an intruder could perform more than 1,000 tasks if successfully gain access to a mobile device using a knowledge-based authentication scheme; however, the intruder can hardly achieve one task if the mobile device uses a multimodal behavioral biometrics-based method [60].

III. Motion-based Authentication

Most of today’s mobile devices are equipped with motion sensors such as accelerometers and gyroscopes, which can be a valid source for modeling users’ behavior. The accelerometer provides the gravitational acceleration in three spatial dimensions (axes), \( x \), \( y \), and \( z \), measured in meter per second squared, where the axes denote the vertical, and left-to-right dimensions [76]. The gyroscope measures the angular rotation
require the user input and are secret—fail to offer covert, transparent, or continuous authentication, and their performance when the smartphone is placed at five different locations on the user’s body. Amini et al. [58] introduced DeepAuth, an LSTM-based user authentication method, which uses sensory data extracted from the accelerometer and gyroscope to model users’ behavioral patterns. The experiments, which were carried out on data collected from 47 users with 10–13 minutes each, have shown an average accuracy of 96.7% for 20 seconds authentication window. Zhu et al. [81] introduced a technique based on users’ phone-skating behavior captured by motion sensors. The experiments reported an average EER of 1.2% using data of 20 users. Lee et al. [73] introduced an SVM-based system for user authentication using readings from three motion sensors to achieve an average accuracy of 90% when using data collected from four participants.

Exploring the effects of using different sensory data augmentation process, Li et al. [74] examined five data augmentation methods to authenticate users with SensorAuth. The overall results of SensorAuth have shown an EER of 4.66% when using 5 seconds window.

Using different motion-based modality, Zhang et al. [26] introduced an eye movement-based implicit authentication method based on eye movement in response to visual stimuli when using a VR headset. The authors reported imposters’ detection accuracy of 91.2% within 130 seconds. Song et al. [75] conducted a similar study on smartphones to track individual eye movement with the built-in front camera to investigate using gaze patterns for user authentication [75]. The authors reported an average system accuracy of 88.7% in three dimensions, \( x, y, \) and \( z \), in radians per second along the axes [68]. Such sensory data provides a feature space that enables the modeling of users’ movement and usage; therefore, a variety of methods revolve around utilizing such data for authentication and security.

Early exploitation of motion sensors includes air-written signatures [39], [69] for which the user holds the device and performs an air-written signature as the application is running and recording the user’s motion. Traditionally, signatures are well-known behavioral biometric commonly used for conducting official or commercial transactions [77]–[79]. However, air-written signatures, while providing a valid method for user authentication, they operate as a point-of-entry authentication and fail to offer covert, transparent, or continuous authentication. Laghari et al. [39] showed that a motion-based signature had achieved a 1.46% FAR and 6.87% FRR when tested on a dataset collected from motion sensors of ten participants’ smartphones. While such methods are robust against shoulder surfing attacks [80], they \( 1 \) require the user input and engagement once authentication is required, \( 2 \) fail to offer a continuous transparent authentication, and \( 3 \) are secret- and knowledge-based since the user must memorize the used signature. Similar implementations include waving gestures [61], free-form gestures [68], and “picking-up” movement (i.e., picking the phone and raising it for answering a call) [62].

Ehatisham et al. [22] proposed a continuous authentication system that identifies mobile users based on their activity patterns using embedded sensors, i.e., accelerometer, gyroscope, and magnetometer. The authors reported an analysis of the system performance when the smartphone is placed at five different locations on the user’s body. Amini et al. [58] introduced DeepAuth, an LSTM-based user authentication method, which uses sensory data extracted from the accelerometer and gyroscope to model users’ behavioral patterns. The experiments, which were carried out on data collected from 47 users with 10–13 minutes each, have shown an average accuracy of 96.7% for 20 seconds authentication window. Zhu et al. [81] introduced a technique based on users’ phone-skating behavior captured by motion sensors. The experiments reported an average EER of 1.2% using data of 20 users. Lee et al. [73] introduced an SVM-based system for user authentication using readings from three motion sensors to achieve an average accuracy of 90% when using data collected from four participants.

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when tracking users’ eye movement for 10 seconds.

The summary of the related work associated with motion-based user authentication is listed in Table I. Most of the studies use embedded motion sensors such as accelerometer, gyroscope, and orientation sensors. Using motion-based methods for user authentication allowed an authentication accuracy of up to 99.13% using SVM trained on sensory data collected from motion sensors [63].

**Insights and Challenges.** While motion-based user authentication methods can detect and classify legitimate users, it has been shown that it is not sufficient to use the motion alone, achieving relatively low accuracy (up to 96.87%) given the criticality of the application. Additionally, such methods are hard to implement for continuous authentication, or at least with high frequency, as secret in-air handwriting may be required. Recent studies have incorporated motion-based user authentication methods within wearable and augmented reality devices, requiring more hardware to function, which is not generally feasible for IoT devices. On the technical side, capturing the motion of the user is challenging, especially for the user behavior variations and imperfection in motion tracking on large-scale datasets. In particular, using the gyroscope sensor to detect the motion presents a sub-millimeter precision challenge, where a slight movement of the sensor adds noise to the user data, lowering the overall accuracy. Similarly, in-air handwriting and gestures are easy to be exposed, as a malicious user may mimic the legitimate user behavior by observing his movement, introducing another channel of vulnerability to the user authentication system.

IV. GAIT-BASED AUTHENTICATION

Gait recognition has gained increased interest in recent years, especially with the vast adoption of mobile and wearable sensors. Gait recognition is defined as the process of identifying an individual by the manner of walking using computer vision and/or sensory data collected from environmental and wearable sensors [98]. Computer vision approaches for gait recognition include segmenting the individual’s images while walking and capturing the features that enable accurate recognition [82]. While using sensory data, include (1) adopting floor sensors that gait-related features are captured once the person walks on them [83], [84], (2) adopting wearable sensors that aims to collect information that enables gait recognition [83]. For mobile security and authentication, gait recognition is usually done using wearable sensors, especially the reading of the motion sensors (e.g., accelerometer) of the mobile device, to enable continuous transparent authentication.

The general approach to gait recognition includes four steps, (1) data acquisition step in which the device is placed in a certain way that enables the walk activity recording, (2) data preprocessing step for reducing the introduced noise by the data collection method or other environmental factors, (3) walk detection step using either traditional cycle or machine learning techniques, and (4) analysis step [76]. Handling the data acquisition process requires accurate readings from motion sensors as the user places the device in a predefined manner such as carrying the device inside of a pouch [90], in the pants pocket [76], [91], or in hand [92]. Studies conducted for mobile security using gait-based biometrics usually include data collection from a population of size equal to or less than 50 participants [90]–[92], and processed in controlled conditions to minimize the effects of outside factors [93]. Even though some studies have attempted to capture gait-related metrics from a real-world collection of sensory data, such as the study by Nickel and Busch [93], generally, the data collection requires an ideal setting at least in one aspect (e.g., walking patterns or floor condition) [3].

The second step after acquiring the data, the preprocessing step takes place to clean, reduce the noise, and normalize the data. The major task in this regard is the noise reduction considering various possible noise sources, such as environmental and gravitational factors, floor conditions, and the users’ shoes or other wearable materials. Since the gait-related features rely heavily on readings from motion sensors, such as the accelerometer, which are very sensitive, the adopted method should account for further noise [91]. Such noises can be handled using linear interpolation and filtering techniques, while environmental noise adds much complexity to the walk detection task, which can be minimized using activity recognition to remove any irrelevant data [90]. For the walk detection, cycles (i.e., the time between two paces bounded by maximum and minimum threshold across the three axes) or machine learning techniques are both utilized in the literature. Cycle-based approaches are commonly used since the average cycle length is easily and simply calculated to detect cycles by moving forward or backward in intervals of the average cycle length with some correction measurement. On the other hand, machine learning-based approaches have shown to be accurate for automatic walk detection [93]. Such techniques require readings of sensory data, preprocessing phase to reduce the noise and normalize the data, and a walk detection model that leverages the lowest and highest values for thresholding and decision.

The final step of gait recognition is the analysis on the time intervals, frequencies, or both. Using time intervals analysis, some metrics can be extracted and studied, such as cycle statistics, including the minimum, average, maximum acceleration values, and cycle lengths and frequencies. Moreover, cycle variance and stability are measured by acceleration moments [76], [98]. Using frequency analysis, usually conducted using Discrete or Fast Fourier Transforms, it has been shown that the first few coefficients resulting from each conversion are highly relevant for detecting distinctive gait patterns [76].

Wang et al. [82] and Gafurov et al. [83] used k-NN model to classify legitimate users using gait-based features, where Wang et al. uses the camera to capture the user movement, and Gafurov et al. captures the user movement using cyclic rotation metric device attached to different places of the body (ankle, hip, pocket, arm). Both studies achieved an accuracy of above 85%, with EER of 3.54% and 5%, respectively. Multiple studies used accelerometer as a standalone sensor to capture the user movement for user authentication task [76], [85]–[93].

Both Thang et al. [85] and Hoang et al. [86] collected data of 11-14 users and used SVM-based models for capturing user patterns, achieving a nearly same accuracy of 92%. In
addition, Hoang et al. [91] achieved an EER of 3.5% by using a fuzzy commitment algorithm on a study sample of 38 users, outperforming its counterparts. Others [94]–[97] incorporated different sensors to capture the motion aspects of the users, achieving an accuracy of up to 96% by using accelerometer, gyroscope, compass, piezoelectric energy harvester, and electromagnetic energy harvester [94]. The summary of the gait-based user authentication methods is shown in Table II.

**Insights and Challenges.** Similar to motion-based user authentication methods, gait-based methods do not achieve high accuracy and precision in user authentication tasks. Most studies use the accelerometer for user authentication, while it can provide continuous authentication, it fails to operate when no data is captured (the user is not moving). In general, gait-based user authentication methods are feasible in limited applications, particularly in wearable sports devices. Moreover, such authentication requires external devices with sensors that are not common in the IoT device. Observing the gait-based patterns for user authentication have many limitations, such as the user state at the enrollment stage, as a user over time behavior may change and is highly dependent on the user’s physical state when capturing the data. Such challenges may explain the low accuracy of gait-based authentication methods.

V. KEYSTROKE-BASED AUTHENTICATION

One of the earliest behavioral authentication methods is based on studying the keystroke dynamics. Most keystroke dynamics-based methods are cost-effective and do not require additional modules to operate [110]. During the usage of the device, when a key input is required (e.g., texting), the keystroke dynamics-based authentication method continuously validates the user since behavioral dynamics can be distinctive across users. Conducting authentication via keystroke dynamics requires analyzing and capturing the distinctive features and patterns of users’ keystrokes when using the device [111], [112]. Common features include: 1) Keypress frequency, which calculates the frequency of keypress events. 2) Key release frequency, which calculates the frequency of key release events. 3) Latency and hold time, which calculates the rates of press-to-press, press-to-release (which is also known as the hold time), release-to-release, and release-to-press events. 4) Finger’s pressure while touching the screen. 5) Pressed area size by the user’s fingers. 6) Error rate, which is the frequency of using backspaces or deletion option.

Using keystroke dynamics for authentication or user validation has been adopted on traditional computers before their application to smartphones [99]. Even though it seems to be an easier task to implement a keystroke dynamics-based authentication method continuously validates the user since behavioral dynamics can be distinctive across users. Conducting authentication via keystroke dynamics requires analyzing and capturing the distinctive features and patterns of users’ keystrokes when using the device [111], [112].
to improve the authentication accuracy, especially when the key-based input is unavailable [113], [114]. Another distinction between applying keystroke dynamics-based methods on smartphones and computers is the large space of key-based input in the smartphone since it includes touches and swipes that meant for interacting with the applications without typing textual content [101]. Several studies have addressed the generalization of these methods to different types of input. For instance, McLoughlin et al. [101] showed that using key press and release frequencies and the latency between two presses contribute greatly to establishing distinctive keystroke behavior for users. The authors showed that the application should account for the inconsistencies in recorded data by introducing weights based on the variance of data (i.e., lower variance gets higher weights). Their results show an accuracy of more than 90%, establishing the validity of using keystroke dynamics as a biometric for authentication with minimal computational overhead and increased usability.

Burio et al. [115] designed an authentication scheme based on the user’s hand movements and timing features as they enter ten keystrokes. The authors conducted experiments using data collected from 97 participants and reported an authentication accuracy of 85.77% and FAR of 7.32%. Similarly, Zahid et al. [102] studied keystroke behavior of 25 users, including features such as the hold time, error rate, and latency. The authors suggested a fuzzy classifier to account for the diffused features space and argued that presenting the classification task of keystroke behavior as an optimization problem benefits the robustness of the model when compared to similarity-based methods [103]. Using a fuzzy classifier with Particle Swarm Optimization and Genetic Algorithms, their proposed method showed 0% FRR and 2% FAR, suggesting high security and usability potential. However, keystroke dynamics are often incorporated with other modalities for improving performance and accuracy. For instance, Hwang et al. [104] suggested including rhythm and tempo as components for studying keystroke dynamics, i.e., a user is required to follow a distinct and consistent timing pattern for accurate keystroke-based authentication. For example, a given term can be entered digit by digit separated with subsequent short and long pauses that are controlled by tempo cues, e.g., a metronome for counting pause intervals. In their study, the authors showed an average improvement of about 4% in the EER evaluation metric when using artificial rhythmic input with tempo cues in comparison to natural rhythms. However, adopting such methods adds complexity to the usability aspect.

Using smartphone embedded sensors to support keystroke dynamics-based authentication has been repeatedly suggested to improve the performance and to provide transparent authentication. [105] proposed incorporating velocity-related metrics to reach an accuracy of 98.6% for classifying data from ten users using an SVM classifier. Similarly, Giuffrida et al. [106] proposed incorporating keystroke data with motion sensors data, namely, accelerometer and gyroscope, to conclude that metrics obtained from the accelerometer data are more useful than those obtained from the gyroscope. The authors showed that combining features from motion sensors with keystroke metrics provides similar results as adopting only the motion sensors-related features alone, i.e., the study shows that sensor-related features can be more useful than keystroke dynamics in terms of authentication. However, obtaining and analyzing high-frequency sensory data can be power consuming. Table III shows a list of authentication methods based on keystroke dynamics. The proposed approaches show a promising direction for using this modality for user authentication, achieving an accuracy of up to 99% by Cilia et al. [19].

**Insights and Challenges.** Keystroke dynamics is one of the earliest modalities used for implicit authentication utilizing

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**TABLE III**

Summary of the related work for keystroke dynamics-based user authentication. Each work is identified by the used modalities, utilized sensors, dataset, modeling algorithm, and their performance.

| Study | Modalities | Sensors | Methods | # Users | EER | FAR | FRR | TPR | Accuracy | Auth. Time |
|-------|------------|---------|---------|---------|-----|-----|-----|-----|----------|------------|
| [99]  | Keystroke Dynamics | NA      | k-NN    | 63      | x   | x   | x   | x   | 83.22–92.14% | x          |
| [100] | Keystroke Dynamics | NA      | Matching | 33      | x   | x   | x   | x   | 0.25% 16.36% | x          |
| [101] | Keystroke Dynamics | NA      | Distance & Cl | 3     | x   | x   | x   | x   | 86%       | x          |
| [102] | Keystroke Dynamics | NA      | RBFN    | 25      | x   | x   | x   | x   | 36% 26.6% | x          |
| [103] | Keystroke Dynamics | NA      | Distance | 15     | x   | x   | x   | x   | 12.97% 2.25% | x          |
| [104] | Keystroke Dynamics | NA      | Distance | 25     | 4%  x | x   | x   | x   | 19.0% 2% | 632-2151ms |
| [105] | Keystroke Dynamics | NA      | SVM     | 10      | x   | x   | x   | x   | 0.08% 98.7% | x          |
| [106] | Keystroke Dynamics | Ac, Gy  | k-NN    | 20      | x   | x   | x   | x   | 86%       | x          |
| [107] | Keystroke Dynamics | NA      | MLP     | 32      | x   | x   | x   | x   | 6.33% 4.89% | x          |
| [108] | Keystroke Dynamics | Ac      | SVM     | 24      | x   | x   | x   | x   | 1.42% 2% | 95.1% 99%  |
| [109] | Keystroke Dynamics | Ac      | MLP     | 13      | x   | x   | x   | x   | 5.1% 2% 1% | 94.8% 99%  |
| [110] | Keystroke Dynamics | DAE-SR  | SVM     | 64      | x   | x   | x   | x   | 86%       | x          |

Ac: Accelerometer, Gy: Gyroscope, Cl: Confidence Interval, RBFN: Radial Basis Function Network, PSO: Particle Swarm Optimization, GA: Genetic Algorithm, DAE-SR: Deep Auto Encoder and Softmax Regression, MCF: Multi-Classifier Fusion, SVM: Support Vector Machine, k-NN: k-Nearest Neighbor, MLP: Multilayer Perceptron.
keystroking features. The features include time, e.g., the latency between pressing and releasing of a key, and latency between releasing one key and pressing another, device orientation, finger pressure size [48]–[50], and others. Keystroke dynamics-based methods have shown high efficiency in user authentication tasks, achieving an overall accuracy of 99%. However, it only works when the user interacts with the keyboard [2], [57]. Implementing keystroke dynamics-based approach is challenging, for instance, feature selection is a critical process, as the selected features should not only enable identifying and validating legitimate users, but also should be robust against noise and variations, especially temporal behavioral changes over time. The selected features should be a suitable representation of the user identity and behavior, ensuring distinctiveness of the characteristics, this is done by minimizing the external effects such as physical, emotional, and over time behavioral changes (i.e., deviation of the feature data as environment changes) on the extracted features. Other factors may play a major role in the authentication task, such as selecting a suitable machine learning algorithm to learn patterns and sequences for user authentication with minimized complexity. In addition, mobile devices support multi-language functionality, and there is a lack of addressing the changes in user behaviors when using multiple languages.

VI. TOUCH GESTURE-BASED AUTHENTICATION

Using touch gestures as a biometric modality extend landscape of transparent authentication applications to include a variety of devices with touchscreen unit (e.g., smartwatches, digital cameras, navigation systems, and monitors) [3]. Several studies have investigated the touch gestures as a behavioral biometrics for continuous authentication since it can be convenient and cost-effective. Touch gestures include swipes [116], [133], flicks [117], [118], [121], slides [119]), and handwriting [134]. The distinction between keystroke dynamics and touch gestures can be summarized in the input form for users and the method of input. The commonalities between the two modalities are the space of improvement when accounting for motion sensors [117], [120]. Therefore, many studies have incorporated motion-based features to gesture-based methods [121]. Considering features from touch gestures enable accurate authentication with an accuracy reaching to 99% and minimal EER such as 0.03% when applying k-Nearest Neighbors classifier or other distance-based classifiers [120].

Leveraging the abundance of information generated by the operating system of smartphones, a large number of features can be extracted from touch gestures such as the reading from the accelerometer, pressure, gravity, velocity, touch area, and time-related measurements. Such features allow for accurate calculation of the gesture statistics and developing patterns for user authentication [122]–[125], [135]. Antal et al. [126] extended the feature space of swipe gestures to include touch duration, trajectory length, acceleration, average speed, touch pressure, touch area, and gravity readings. Using data from 40 users, including 58 samples, the authors performed one and two-class classification using multiple classifiers such as Bayes Net, k-Nearest Neighbor, and Random Forests. The authors reported that Random Forests showed an EER of 0.004%. Their results showed that the device motion and positioning are important factors in distinguishing users.

Since touch gestures are commonly known as soft biometrics that could enable the recognition of gender and proportional measures such as physical attributes including hand size, forearm length, and height, they are beneficial in criminal investigations. Miguel et al. [136] proposed studying the swipe gesture for sex prediction using a variety of features including the swipe’s length, width, touch area, pressure, velocity, acceleration, start-to-end angle, and others. The authors showed that applying a multilinear logistic regression classifier for sex prediction achieves an accuracy of 71% when the direction of the swipe is down-to-up. Using a fusion of swipe direction-based decision, the accuracy reaches 78%. Similarly, Bevan and Fraser [137] investigated the relationship between swipe gestures, thumb length, and gender. Using data from 178 users performing one-hand gestures using the thumb, the authors collected 21,360 samples of swipes in various directions. Among the calculated features, the results showed a strong correlation between thumb length and gestures, and they reflected in the velocity, acceleration, and completion time. Moreover, the study also showed that male users completed the gestures at a higher speed than female users.

The landscape of using touch gestures as behavioral biometrics for user authentication includes devices designed for users with disabilities. For example, Azenkot et al. [138] proposed PassChords, which designed for authenticating users with vision impairments using a predefined sequence of screen taps. Another application is proposed by [45] for users with finger injuries, which uses the finger’s trajectory and posture before touching the screen using its positioning and proximity. For this application, the direct touch gesture (i.e., the contact with the screen) is not fully required, and only the proximity-related measurement is possibly feasible to authenticate users.

Several studies have shown that gesture-based authentication schemes are application-dependant, and data of touches can vary significantly from one application to another, which makes the generalization aspect of gesture-based schemes for continuous authentication across different applications is limited [127]–[129], [139]. Therefore, a “context-aware” approach is a potential solution to generalize gesture-based methods. Khan and Hengartner [12] showed that the performance of gesture-based methods could be improved by allowing context-aware implementation where different applications control the tuning of features. To this end, the authors used the Kullback-Leibler (KL) divergence metric, which is shown to differ by application indicating the importance of accounting and tuning the features based on the used application. Using data of 32 users who were instructed to use four different applications during the data collection process, the experimental results showed that using the “context-aware” approach improves the accuracy of the device-centric approach.

Table IV shows a list of proposed gesture-based authentication methods using varieties of touch gestures and machine learning models. Random forest, in particular, is among the top achieving and adopted models in this modality-based method, with an accuracy above 99% as shown in [131] and [45].
Text-independent approach in which users are authenticated based on the matching of spoken words. This approach allows higher flexibility, especially in offering transparent authentication, where users are unaware of the service. However, accurate text-independent authentication accuracy faces different challenges due to the dynamic changes in the feature space of voice input accounting for the state of the user condition and other environmental factors. Speaker recognition using voice features follows the typical pattern recognition system, starting from data collection and preprocessing, going through the feature extraction and selection, and ending with the modeling and pattern recognition. Similar to conventional machine learning-based systems, the quality of features contributes considerably to the accuracy of the system [151], [152]. For speaker recognition, such features include short-term spectral features, temporal and rhythmic, voice source, prosodic, and conversation-level features [3]. Short-term spectral characteristics represent the resonance attributes of the vocal tract and often extracted with high frequency from 20 to 30 ms timeframes. Prosodic and temporal traits include intonation and rhythmic patterns extracted from long timeframes. Conversation-level features are high-level properties extracted from the textual contents of spoken words, such as word or phrase frequencies. The quality of features is measured by their distinctive nature and their robustness against possible introduced noise (e.g., the user condition and environment) [153]. In this regard, a study by Reynolds [150] showed that spectral features provide high-quality, simple, and discriminative feature space.

Using the extracted features, a variety of models are utilized for voice/speaker recognition such as SVM and Gaussian mixture models [153]. Early applications for voice recognition include access control, personalization, and forensic and criminal investigations [150]. The application landscape has increased to include online banking (i.e., conducting a transaction via voice communication as the voice recognition system transparently and continuously authenticate the

| Study | Modality | Sensors | Methods | # Users | EER | FAR | FRR | TPR | Accuracy | Auth. Time |
|-------|----------|---------|---------|---------|-----|-----|-----|-----|----------|-----------|
| [116] | Swipe Gesture | NA | ANN-CPPAN | 71 | × | 0.08% | 0 | × | × | × | 92.8% | × |
| [117] | Flick Gesture | AC, Gy | SOM | NA | × | × | × | × | 99.9% | × |
| [118] | Flick Gesture | Or | k-NN | 16 | 6.85% | ✓ | ✓ | ✓ | ✓ | 100ms | × |
| [119] | Slide Gesture | NA | SVM | 60 | 0.01–0.02% | × | × | × | × | 0.3s | × |
| [120] | Swipe Gesture | Ac, Or | MHD | 104 | 0.31% | ✓ | ✓ | ✓ | ✓ | 9.2% | × |
| [121] | Flick Gesture | Ac | Naïve Bayes | 10 | × | 1.3% | 8% | 92% | 98% | × |
| [122] | Touch & keystroke | NA | k-NN | 10 | 1% | × | × | × | 99% | 20ms | × |
| [123] | Keystrokes/Touch/Handwriting | NA | SVM-RBF | 32 | 0.75–8.67% | × | × | × | ✓ | × |
| [124] | Gesture | NA | MGGM | 20 | ✓ | ✓ | × | × | × | 89% | 53ms |
| [125] | Gesture | NA | PSO-RBFN | 20 | 1% | × | × | × | × | × |
| [126] | Swipe Gesture | Or | RF | 10 | 0.2% | × | × | × | × | 1% |
| [127] | Swipe Gesture | NA | RF | 34 | 16.22–22.94% | × | × | × | × | 12.6s |
| [128] | Touch Gesture | NA | DTW-k-NN | 23 | ✓ | × | × | × | × | 91% | × |
| [129] | Touch Gesture | NA | RF | 71 | 1.8% | × | × | × | 18.52% | × | 0.77s |
| [130] | Touch Gesture | NA | RF | 71 | 5.4% | × | × | × | × | 5% |
| [131] | Touch Gesture | NA | RF | 30 | 2.54% | 1.98% | × | × | 99.68% | × |
| [132] | Touch Gesture | NA | Matching | 30 | × | × | × | 93.01% | 93.76% | × |
TABLE V
SUMMARY OF THE RELATED WORK FOR VOICE-BASED USER AUTHENTICATION. EACH WORK IS IDENTIFIED BY THE USED MODALITIES, UTILIZED SENSORS, DATASET, MODELING ALGORITHM, AND THEIR PERFORMANCE.

| Study  | Modalities | Sensors | Methods       | # Users | EER   | FAR  | FRR  | TPR  | Accuracy | Auth. Time |
|--------|------------|---------|---------------|---------|-------|------|------|------|----------|------------|
| [140]  | Voice      | Ca, Mi  | Matching      | 27      | x     | x    | 3%   | x    | 93%      | < 24.7s    |
| [141]  | Voice      | Sp, Mi  | CC            | 21      | 1%    | 1%   | x    | x    | 99.34%   | 0.5s       |
| [142]  | Voice      | Sp, Mi  | GMM           | 104     | x     | x    | 99%  | 95%  | x        |            |
| [143]  | Voice      | Mi      | PCA-SVM       | 18      | 5.4%  | 2%   | 93%  | 93.5%| x        |            |
| [144]  | Voice      | Mi      | DTW           | 15      | x     | 1%   | 15%  | 88.6%| x        |            |
| [145]  | Voice      | Mi      | GMM           | 50      | 6.24% | x    | x    | x    | 10.76s   |            |
| [146]  | Voice      | Mi      | GMM           | 48      | 6%    | x    | x    | x    | x        |            |
| [147]  | Voice      | Mi      | Similarity    | 12      | 1.01% | 1%   | 99%  | 99.3%| x        |            |

Ca: Camera, Mi: Microphone, Sp: Speaker, GMM: Gaussian Mixed Model, PCA: Principle Component Analysis, CC: Cross-Correlation, SVM: Support Vector Machine, DTW: Dynamic Time Wrapping, HMM: Hidden Markov Model.

While voice-based user authentication methods capture the voice using the microphone, different works can be distinguished by the data preprocessing and the utilized machine learning algorithm. Zhang et al. [141] achieved an accuracy of 99.34% with EER and FAR of 1% using the cross-correlation method with an authentication time of half a second on a sample size of 21 users. Additionally, using gaussian mixed model, Kim et al. [145] and Johnson et al. [146] achieved similar EER of around 6% on a sample size of 50 and 48 respectively. Similarly, Lu et al. [142] achieved an accuracy of 95% and TPR of 99% in conducting user authentication tasks using a gaussian mixed model with a sample size of 104 users. Multiple machine learning methods may be incorporated for user authentication tasks, Wang et al. [143] used principle components analysis with support vector machine to train data collected from 18 users, achieving an EER of 5.4% and overall accuracy of 93.5%. Using a simple approach may outperform powerful machine learning algorithms in user authentication tasks, as Zhang et al. [147] achieved an accuracy of 99.3% with EER of 1.01% and FAR of 1% using sample similarity method. Table V shows several voice-based user authentication methods. The listed voice-based methods show the validity of using this modality for the user authentication task.

Insights and Challenges. Voice-based methods can be used as a baseline for the feature extraction process in user authentication systems with high accuracy of around 99.3%, eliminating the need to remember passwords and challenging hackers to spoof biometric traits. However, technical limitations may exist. For instance, background noise and illness (i.e., throat related diseases) may affect the quality of the captured sound, increasing the false acceptance and false rejection rates of the implemented approach. Moreover, the voice signature is likely to change according to the distance between the microphone and the mouth, resulting in additional challenges to be highlighted. In general, continuous voice-based user authentication methods are hard to be implemented, as voice commands and signatures should be entered to the system periodically, downgrading the usability and user experience.

VIII. MULTIMODAL AUTHENTICATION

Multimodal authentication systems have become increasingly popular since relying on multiple modalities on offer robust and accurate results in comparison to unimodal systems that consider only a single biometric modality. Such systems offer hardened security, especially against adversarial attacks, and deliver a flexible method for authentication considering possible changes of the input data that result in problems in the enrollment and validation phase [77], [173].

The implementation of multimodal authentication could require a fusion of multiple data sources, extracted features, and/or used algorithms and models. The literature shows that multimodal biometric-based authentication schemes have used different fusion approaches such as feature-level fusion, used modeling algorithms fusion, and decision-level fusion.

1. Feature-level fusion includes combining features from different modalities to be considered together as an input to the modeling algorithm. Accounting for possible heterogeneous resulting feature space from different sources, a normalization process usually takes place.

2. Algorithm-level fusion includes constructing an ensemble of models that are built based on an individual of multiple biometric modalities. The ensemble combines outputs by considering matching scores or voting mechanism to help with the decision.

3. Decision-level fusion occurs when decisions are generated by individual modalities separately. The final decision considers all outputs and adopts certain rules or voting to generate the final output.

Using multimodal authentication on smartphones is a feasible solution since today’s devices are equipped with a variety of sensors that support the reading of several biometrics [154]. However, several challenges should be considered when implementing multimodal authentication, such as the input data quality generated by different sources since poor data results in poor performance, and the inclusion of multiple data sources requires reading from different sensors, which could be computationally-hungry and energy-expensive [174]. Addressing such challenges effectively allows multimodal authentication to offer robust and secure access control [175].

Vildjoumaita et al. [92] proposed combining gait and voice biometrics to increase the performance of user validation. Using data samples of 31 users, the authors reported a decrease in the error rates from 2.82%–43.09% and 13.7–17.2% using the individual voice and gait recognition, respectively, to 1.97%–11.8% for adopting a multimodal system incorporating...
both biometrics. However, the proposed method is event-
dependant and performs differently when the user motion
or speaking is different since the results show that such a
method is ineffective if the user is not speaking or speaking.
Zhu et al. [171] proposed an SVM-based method called
RiskCog that can validate users within 3.2 seconds using
sensory data collected from mobile and/or wearable devices
including readings of the accelerometer, gyroscope and gravity
sensors. The authors reported an average system accuracy of
93.8% and 95.6% for steady and moving users, respectively,
using a large dataset of 1,513 users. Lee et al. [59] proposed
combining sensors’ readings from the user’s smartphone and
other wearable devices to improve authentication accuracy.
Their experiments on a dataset of 35 users have shown an
accuracy of 98.1%, FRR of 0.9%, and FAR of 2.8% by
combining data from users’ smartphones and smartwatches
when adopting an authentication window of six seconds.

Gofman et al. [154] suggested using face and voice bio-
metrics to tackle input data quality and training data scarcity
for mobile authentication. Considering the nature of the data
acquisition process on mobile devices, the authors argued that
data quality is usually in poor condition due to environmental
factors or the utilization of low-cost sensors. Moreover, the
authors stated mobile authentication systems face a training
data scarcity problem since users tend to provide small training
samples during the enrolment phase. Using a multimodal
system, the authors addressed these issues and enhanced the
potential of acquiring high-quality data samples during user
enrollment. The proposed approach incorporated the Fisher-
face method for face recognition since it is shown to be ef-
efective under changing environmental conditions, and Hidden
Markov Models (HMM) and Linear Discriminant Analysis
(LDA) for voice recognition (HMM was used for algorithm
score-level fusion and LDA was used for feature-level fusion).
The authors used a quality-based weighting method to adjust to
samples’ quality and limit the impact of poor-quality samples
on the performance of the system. The results showed a
decrease in error rates from 4.29% for the face recognition
module and 34.72% for the voice recognition module to 2.14%
for the feature-level fused multimodal system. Similar work
has been proposed by Morris et al. [56] for combining voice,
face, and signature modalities for personal digital assistant
devices. The authors reported a decrease in error rates when
combining all three modalities from 3.38%-29.87% to 0.56%,
which is considered a considerable improvement in the system
performance. Their implementation adopts a text-dependent
voice authentication approach since text-independent can bring
much complexity when addressing phonetic variations, which
can computationally-expensive and energy-draining when run-
ning locally on the device.

Kayacik et al. [164] proposed a data-driven approach with
an ensemble of classifiers to enable the authentication system

| Study | Modalities | Sensors | Methods | # Users | EER | FAR | FRR | TPR | Accuracy | Auth. Time |
|-------|------------|---------|---------|---------|-----|-----|-----|-----|----------|------------|
| [53]  | Face/Voice | Ca, Mi  | LDA-HMM | 54      | 21.58% | x   | x | ✓  | ✓  | 0.39s |
| [145] | Teeth Images/voice | Ca, Mi | HMM/GMM | 50 | 2.13% | ✓ | ✓ | ✓ | ✓ | 10.76s |
| [154] | Face/Voice | NA     | LDA-Matching | 54 | 2.14% | x | x | ✓ | ✓ | 1.57s |
| [56]  | Face/Voice/Signature | NA | GMN | 60 | 0.56% | 0.97% | 0.69% | x | ✓ | ✓ | 3.1s |
| [155] | Touch/Gaze | To, Ca | MLP-RBF | 30 | 3.3% | x | x | x | x | 2-10m |
| [157] | App/Bluetooth/Wi-Fi | NA | k-NN | 200 | 0% | x | x | x | x | 85% |
| [113] | Keystroke/Sensor dynamics | To, Ac, Gy | k-NN | 20 | 0.14% | x | ✓ | ✓ | ✓ | x |
| [114] | Keystroke/Motion/Orientation | To, Ac, Gy | PCA-SVM | 20 | 7.16% | ✓ | ✓ | ✓ | ✓ | 20s |
| [158] | Face/Peripheral/Iris | Ca | FA-NN | 78 | 0.68% | ✓ | ✓ | ✓ | ✓ | x |
| [159] | Face/Peripheral | Ca | Matching | 73 | 1.34% | 0.01% | x | x | 94.66% |
| [160] | Face/Peripheral | Ca | CNN | 246 | x | x | x | x | 98.5% |
| [161] | Keystroke/Gait | To, Ac | MLP | 20 | 1% | 0.68% | 7% | x | x | 99.11% |
| [162] | App/Bluetooth/Wi-Fi/other | NA | FPOS | 33 | x | ✓ | ✓ | ✓ | ✓ | 98.3% |
| [163] | Touch/Motion/App/other | To, Ac, Gy, Ma, Li | SVM | 48 | ✓ | ✓ | ✓ | ✓ | ✓ | 97.1% |
| [164] | App/Motion/Wi-Fi/other | Ac, WiFi, Li, other | Ensemble | 7 | x | x | x | x | 99.4% | 122s |
| [165] | Motion/Gesture | Ac, Gr, Or, Ma | n-gram | 20 | 0.8-3.6% | x | x | x | x | 4.96s |
| [166] | Face/Touch/Motion | Ca, To, Ac, Gy, Ma | Ensemble | 100 | 31.1% | x | x | x | x | 71.30% |
| [167] | Touch/Motion/other | To, Ac, Gy, Ma, other | Compound-Voting | 30 | x | 0 | 0 | x | 100% |
| [168] | Touch/Motion | To, Ac, Gy | SVM | 100 | 15% | x | x | x | x | 88% |
| [169] | Touch/Motion | To, Ac, Gy | SVM | 48 | ✓ | 5.01% | 6.85% | x | x | ✓ |
| [18]  | Face/Voice | Ca, Mi | CNN-SVM | 10 | x | x | x | 88.84% | 94.07% | 30ms |
| [170] | Touch/Motion | Ac, Gy, Ma | CNN-SVM | 90 | x | x | ✓ | ✓ | x | 97.8% | 1s |
| [25]  | Touch/Motion | To, Ac, Gy, Ma, Or | HMM | 102 | 4.74% | 3.98% | 5.03% | x | x | 8s |
| [59]  | Wearable/Sensor dynamics | Ac, Gy, Or, Li | KRR | 15 | ✓ | 2.8% | 0.9% | x | x | 98.1% |
| [171] | Wearable/Sensor dynamics | Ac, Gy, Or | SVM | 1,513 | x | x | x | x | 73.28% | 95.57% | 3.2s |
| [172] | Healthcare readings | HWS | SVM-RBF | 37 | 2.6% | 7.6% | 9.6% | ✓ | ✓ | x |

Fa-NN: Fast Approximate Nearest Neighbor, CNN: Convolutional Neural Network, FPOS: Frequent Pattern Outlier Score, KRR: Kernel Ridge Regression.

HWS: Healthcare Wearable Sensors, LDA: Linear Discriminant Analysis, HMM: Hidden Markov Model, GMM: Gaussian Mixed Model, MLP: Multilayer Perceptron, RBF: Radial Basis Function, k-NN: k-Nearest Neighbor, PCA: Principal Component Analysis, SVM: Support Vector Machine, HMM: Hidden Markov Model, GMM: Gaussian Mixed Model.
to be temporally and spatially aware of the user behavioral usage and surroundings by taking advantage of several hard and soft sensors such as the accelerometer, WiFi, light sensor, and others. The proposed method requires more than 122 seconds to allow the data to be collected for authenticating users and about 717 seconds to detect an imposter. However, the experiments report a high authentication accuracy of 99.4%. Similar work has been proposed by Li and Bours [176] that incorporates sensory data of smartphones and WiFi information for enabling users to access an application within three seconds, with an average EER of 9.19%. Similar studies combinations of multiple biometrics to incorporate face, iris, and periocular recognition [158], [177], eye gaze, and touch gestures [155], and user behavioral profiling, keystroke dynamics, and linguistic features [156]. Another direction of research studied users’ behavioral patterns using their usage of applications and Wi-Fi traffic [157]. Table VI shows the multimodal-based user authentication methods by using multiple modalities and machine learning algorithms.

Insights and Challenges. Multimodal-based user authentication methods are designed by implementing several modalities (behavioral and physiological biometrics), such as the face, voice, and keystroke dynamics, to operate user authentication tasks. The performance of a system is related to the quality of the collected samples, as a good-quality biometric sample is critical for accurate identification. Due to unreliable features that could be caused by a single biometric (i.e., the changing emotional or physical state of the user or poor data acquisition), and to overcome performance degradation caused by these limitations, researchers have moved from unimodal biometrics to multimodal biometrics. For instance, combining face recognition and keystroke dynamics for user authentication will outperform the performance of each modality alone and mitigate the limitations of each modality. However, multimodal-based methods counter several challenges, while it utilizes several modalities to increase the performance, the authentication algorithm becomes critical since it should learn the user’s pattern across different modalities. To overcome this issue, researchers utilize an ensemble of machine learning models enabling different pattern recognition per legitimate user. However, this caused a longer training time, extending the required user enrollment stage time and processing, model size, prediction time, and data collection and preprocessing. Further, using multiple sensors and components may interrupt the user’s experience and usage of the device.

IX. CONCLUSION

Mobile devices have become the most common platform for communication and accessing the internet. The rapid enhancements of embedded technologies and resources of mobile devices have enabled users to conduct varieties of activities and transactions. Therefore, secure and accurate access control is essential. To date, mobile devices’ manufacturers have implemented knowledge-based and physiological biometric-based authentication methods as the primary access control scheme. While both approaches offer simplicity, efficiency, and precision, they assume the same level of security to all applications and fall short on delivering authentication beyond the point-of-entry. Moreover, these approaches require overt recognition, where the user explicitly enters the pass-secret or the used biometrics, making them fail in delivering implicit, transparent, and continuous authentication. Recently, behavioral biometrics are used to offer efficient continuous authentication on smartphones by leveraging the readings of a variety of embedded sensors. This survey aims to highlights methods, approaches, benefits, and challenges associated with using behavioral biometrics for user authentication. We surveyed around 150 studies that conducted a behavioral-based authentication and pointed out their used techniques, sensors, performance measurements, and time needed for authentication. As this field is rapidly evolving, there is still a need to explore security-related aspects and implementation considerations beyond familiar standards.

REFERENCES

[1] C. Jung, J. Kang, A. Mohaisen, and D. Nyang, “Digitalself: a transaction authentication tool for online and offline transactions,” in 2018 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP). IEEE, 2018, pp. 6956–6960.
[2] A. Al Abdulwahid, N. Clarke, I. Stengel, S. Furnell, and C. Reich, “Continuous and transparent multimodal authentication: Reviewing the state of the art,” Cluster Computing, vol. 19, no. 1, Mar. 2016.
[3] T. J. Neal and D. L. Woodard, “Surveying biometric authentication for mobile device security,” Journal of Pattern Recognition Research, vol. 1, pp. 74–110, 2016.
[4] Z. Zhao, G.-J. Ahn, and H. Hu, “Picture gesture authentication: Empirical analysis, automated attacks, and scheme evaluation,” ACM Transactions on Information and System Security (TISSEC), vol. 17, no. 4, p. 14, 2015.
[5] D. Nyang, A. Mohaisen, and J. Kang, “Keylogging-resistant visual authentication protocols,” IEEE Transactions on Mobile Computing, vol. 13, no. 11, pp. 2566–2579, 2014.
[6] D. Nyang, H. Kim, W. Lee, S.-h. Kang, G. Cho, M.-K. Lee, and A. Mohaisen, “Two-thumbs-up: Physical protection for pin entry secure against recording attacks,” computers & security, vol. 78, pp. 1–15, 2018.
[7] A. De Luca, A. Hang, F. Brudy, C. Lindner, and H. Hussmann, “Touch me once and i know it’s you!: implicit authentication based on touch screen patterns,” in proceedings of the SIGCHI Conference on Human Factors in Computing Systems. ACM, 2012, pp. 987–996.
[8] N. L. Clarke and S. M. Furnell, “Authentication of users on mobile telephones—a survey of attitudes and practices,” Computers & Security, vol. 24, no. 7, pp. 519–527, 2005.
[9] R. Amin, T. Gaber, G. Elraweel, and A. E. Hassanien, “Biometric and traditional mobile authentication techniques: Overviews and open issues,” in Bio-inspiring cyber security and cloud services: trends and innovations. Springer, 2014, pp. 423–446.
[10] H. Crawford and K. Renaud, “Understanding user perceptions of transparent authentication on a mobile device,” Journal of Trust Management, vol. 1, no. 1, p. 7, 2014.
[11] S. Furnell, N. Clarke, and S. Karatzouni, “Beyond the pin: Enhancing user authentication for mobile devices,” Computer fraud & security, vol. 2008, no. 8, pp. 12–17, 2008.
[12] H. Khan and U. Hengartner, “Towards application-centric implicit authentication on smartphones,” in Proceedings of the 15th Workshop on Mobile Computing Systems and Applications. ACM, 2014, p. 10.
[13] A. Wójcikiewicz and K. Joachimiak, “Model for adaptable context-based biometric authentication for mobile devices,” Personal and Ubiquitous Computing, vol. 20, no. 2, pp. 195–207, 2016.
[14] Z. Yu, I. Olade, H.-N. Liang, and C. Fleming, “Usable authentication mechanisms for mobile devices: An exploration of 3d graphical passwords,” in 2016 International Conference on Platform Technology and Service (PlatCon). IEEE, 2016, pp. 1–3.
[15] K.-I. Shin, J. S. Park, J. Y. Lee, and J. H. Park, “Design and implementation of improved authentication system for android smartphone users,” in 2012 26th International Conference on Advanced Information Networking and Applications Workshops. IEEE, 2012, pp. 704–707.
B. Zhou, Z. Xie, and F. Ye, “Multi-modal face authentication using deep visual and acoustic features,” in ICC 2019-2019 IEEE International Conference on Communications (ICC). IEEE, 2019, pp. 1–6.

D. Cilia and F. Inguanez, “Multi-modal authentication using keystroke dynamics for smartphones,” in 2018 IEEE 9th International Conference on Consumer Electronics-Berlin (ICCE-Berlin). IEEE, 2018, pp. 1–6.

C. A. Miles and J. P. Cohn, “Tracking prisoners in jail with biometrics: An experiment in a navy brig,” National Institute of Justice Journal, vol. 253, 2006.

K. B. Schaffer, “Expanding continuous authentication with mobile devices,” Computer, vol. 48, no. 11, pp. 92–95, 2015.

M. Ehtisham-ul Haq, M. Awais Azam, U. Naem, Y. Amin, and J. Loo, “Continuous authentication of smartphone users based on activity pattern recognition using passive mobile sensing,” J. Netw. Comput. Appl., vol. 109, no. 3, May 2018.

H. F. Nweke, Y. W. Teh, M. A. Al-Garadi, and U. R. Alo, “Deep learning algorithms for human activity recognition using mobile and wearable sensors: State of the art and research challenges,” Expert Systems with Applications, 2018.

M. N. Aman, M. H. Basheer, and B. Sikdar, “Two-factor authentication for iot with location information,” IEEE Internet of Things Journal, vol. 6, no. 2, pp. 3335–3351, 2019.

C. Shen, Y. Li, Y. Chen, X. Guan, and R. A. Maxion, “Performance analysis of multi-motion sensor behavior for active smartphone authentication,” IEEE Trans. Information Forensics and Security, vol. 13, no. 1, pp. 48–62, 2018.

Y. Zhang, W. Hu, W. Xu, C. T. Chou, and J. Hu, “Continuous authentication using eye movement response of implicit visual stimuli,” Proc. ACM Interact. Mob. Wearable Ubiquitous Technol., IMWUT, 2018.

J. S. Arteaga-Falconi, H. A. Osman, and A. El-Saddik, “ECG authentication for mobile devices,” IEEE Trans. Instrumentation and Measurement, vol. 65, no. 3, pp. 591–600, 2016.

Z. Ba, S. Piao, X. Fu, D. Koutsouknikolas, A. Mohaisen, and K. Ren, “Acb: enabling smartphone authentication with built-in camera,” in 25th Annual Network and Distributed System Security Symposium, NDSS 2018, 2018.

M. Zeng, L. T. Nguyen, B. Yu, O. J. Mengershoel, J. Zhu, P. Wu, and J. Zhang, “Convolutional neural networks for human activity recognition using mobile sensors,” in 6th International Conference on Mobile Computing, Applications and Services, MobiCASE, 2014, pp. 197–205.

G. B. Del Pozo, C. Sanchez-Avila, A. De-Santos-Sierra, and J. Guerra-Casanova, “Speed-independent gait identification for mobile devices,” International Journal of Pattern Recognition and Artificial Intelligence, vol. 26, no. 08, p. 1260013, 2012.

R. Damaševičius, R. Maskeliūnas, A. Venčkauskas, and M. Woźniak, “Smartphone user identity verification using gait characteristics,” symmetry, vol. 8, no. 10, p. 100, 2016.

Y. Lu, Y. Wei, L. Liu, J. Zhong, L. Sun, and Y. Liu, “Towards unsupervised physical activity recognition using smartphone accelerometers,” Multimedia Tools Appl., vol. 76, no. 8, Apr. 2017.

C. Shen, Y. Li, Y. Chen, X. Guan, and R. A. Maxion, “Performance analysis of multi-motion sensor behavior for active smartphone authentication,” IEEE Trans. Information Forensics and Security, vol. 13, no. 1, pp. 48–62, 2018.

Y. Zhang, W. Hu, W. Xu, C. T. Chou, and J. Hu, “Continuous authentication using eye movement response of implicit visual stimuli,” Proc. ACM Interact. Mob. Wearable Ubiquitous Technol., IMWUT, 2018.

J. S. Arteaga-Falconi, H. A. Osman, and A. El-Saddik, “ECG authentication for mobile devices,” IEEE Trans. Instrumentation and Measurement, vol. 65, no. 3, pp. 591–600, 2016.

Z. Ba, S. Piao, X. Fu, D. Koutsouknikolas, A. Mohaisen, and K. Ren, “Acb: enabling smartphone authentication with built-in camera,” in 25th Annual Network and Distributed System Security Symposium, NDSS 2018, 2018.

M. Zeng, L. T. Nguyen, B. Yu, O. J. Mengershoel, J. Zhu, P. Wu, and J. Zhang, “Convolutional neural networks for human activity recognition using mobile sensors,” in 6th International Conference on Mobile Computing, Applications and Services, MobiCASE, 2014, pp. 197–205.

G. B. Del Pozo, C. Sanchez-Avila, A. De-Santos-Sierra, and J. Guerra-Casanova, “Speed-independent gait identification for mobile devices,” International Journal of Pattern Recognition and Artificial Intelligence, vol. 26, no. 08, p. 1260013, 2012.

R. Damaševičius, R. Maskeliūnas, A. Venčkauskas, and M. Woźniak, “Smartphone user identity verification using gait characteristics,” symmetry, vol. 8, no. 10, p. 100, 2016.

Y. Lu, Y. Wei, L. Liu, J. Zhong, L. Sun, and Y. Liu, “Towards unsupervised physical activity recognition using smartphone accelerometers,” Multimedia Tools Appl., vol. 76, no. 8, Apr. 2017.

C. Nickel, H. Brandt, and C. Busch, “Classification of acceleration data for biometric gait recognition on mobile devices,” Proceedings of the Biometrics Special Interest Group, BiOSIG, 2011.

V. Zaliva, W. Melicher, S. Saha, and J. Zhang, “Passive user identification using sequential analysis of proximity information in touchscreen usage patterns,” in 2015 Eighth International Conference on Mobile Computing and Ubiquitous Networking (ICMU). IEEE, 2015, pp. 161–166.

A. J. Aviv, K. L. Gibson, E. Mossop, M. Blaze, and J. M. Smith, “Smudge attacks on smartphone touch screens,” in 4th USENIX Workshop on Offensive Technologies, WOOT, 2010.

J. Wu and Z. Chen, “An implicit identity authentication system considering changes of gesture based on keystroke behaviors,” IJDSN, vol. 11, pp. 470 274–1/470 274/16, 2015.

A. Buchoux and N. L. Clarke, “Deployment of keystroke analysis on a smartphone,” in Australian Information Security Management Conference, 2008, p. 48.

S. Mondal and P. Bours, “Person identification by keystroke dynamics using pairwise user coupling,” IEEE Transactions on Information Forensics and Security, vol. 12, no. 6, pp. 1319–1329, June 2017.

G. Kambourakis, D. Damopoulos, D. Papamartzivanos, and E. Pavlidakis, “Introducing touchstroke: keystroke-based authentication system for smartphones,” Security and Communication Networks, vol. 9, no. 6, pp. 542–554, 2016.

D. A. Reynolds, T. F. Quatieri, and R. B. Dunn, “Speaker verification using adapted gaussian mixture models,” Digital signal processing, vol. 10, no. 1-3, pp. 19–41, 2000.

H. Lu, A. J. B. Brush, B. Priyantha, A. K. Karlson, and J. Liu, “Speakerverse: Energy efficient unobtrusive speaker identification on mobile phones,” in Proceedings of the 9th International Conference on Pervasive Computing, 2011, pp. 188–205.

M. I. Gofman, S. Mitra, and N. Smith, “Hidden markov models for feature-level fusion of biometrics on mobile devices,” in 2016 IEEE/ACS 13th International Conference of Computer Systems and Applications (AICCSA). IEEE, 2016, pp. 1–2.

N. L. Clarke and A. Mekala, “The application of signature recognition to transparent handwriting verification for mobile devices,” Information management & computer security, vol. 15, no. 3, pp. 214–225, 2007.

M. Martinez-Diaz, J. Fierrez, J. Galbally, and J. Ortega-Garcia, “Towards mobile authentication using dynamic signature verification: useful features and performance evaluation,” in 19th International Conference on Pattern Recognition, 2008, pp. 1–5.

A. C. Morris, S. Jassim, H. Sellahewa, L. Allano, J. Ehlers, D. Wu, J. Koreman, S. Garcia-Salicetti, B. Ly-Van, and B. Dorizzi, “Multimodal person authentication on a smartphone under realistic conditions,” in Mobile Multimedia/Image Processing for Military and Security Applications, vol. 6250. International Society for Optics and Photonics, 2006, p. 62500D.

A. Alzubaidi and J. Kalita, “Authentication of smartphone users using behavioral biometrics,” IEEE Communications Surveys and Tutorials, vol. 18, no. 3, pp. 1998–2026, 2016.

S. Amini, V. Noroozi, A. Pande, S. Gupte, P. S. Yu, and C. Kanich, “Deepauth: A framework for continuous user re-authentication in mobile apps,” in Proceedings of the 27th ACM International Conference on Information and Knowledge Management, CIKM, 2018, pp. 2027–2035.
Y. Li, H. Hu, and G. Zhou, “Using data augmentation in continuous...

W. Lee and R. B. Lee, “Multi-sensor authentication to improve smart...

A. K. Jain, A. Ross, S. Prabhakar, and R. V. Prasad, “Multimodal biometric person authentication system using speech and signature features,” in TENCON 2008-2008 IEEE Region 10 Conference. IEEE, 2008, pp. 1–6.

F. Hong, M. Wei, S. You, Y. Feng, and Z. Guo, “Waving authentication: your smartphone authenticate you on motion gesture,” in Proceedings of the 33rd Annual ACM Conference Extended Abstracts on Human Factors in Computing Systems. ACM, 2015, pp. 263–266.

T. Feng, X. Zhao, and W. Shi, “Investigating mobile device picking-up motion as a novel biometric modality,” in 2015 IEEE Sixth International Conference on Biometrics: Theory, Applications and Systems (BTAS). IEEE, 2013, pp. 1–6.

J. Wu and Z. Chen, “An implicit identity authentication system considering changes of gesture based on keystroke behaviors,” International Journal of Distributed Sensor Networks, vol. 11, no. 6, p. 470274, 2015.

F. Hong, S. You, M. Wei, Y. Zhang, and Z. Guo, “Mgra: Motion gesture recognition via accelerometer,” Sensors, vol. 16, no. 4, p. 530, 2016.

D. Lu, D. Huang, Y. Deng, and A. Alshamrani, “Multifactor user authentication with in-air-handwriting and hand geometry,” in 2018 International Conference on Biometrics (ICB). IEEE, 2018, pp. 255–261.

Q. Xia, F. Hong, Y. Feng, and Z. Guo, “Motionhacker: Motion sensor based eavesdropping on handwriting via smartwatch,” in IEEE INFOCOM 2018-IEEE Conference on Computer Communications Workshops (INFOCOM WKSHPS). IEEE, 2018, pp. 468–473.

J. Yan, Y. Qi, Q. Rao, and S. Qi, “Towards a user-friendly and secure hand shaking authentication for smartphones,” in 2018 17th IEEE International Conference On Trust, Security And Privacy In Computing And Communications 12th IEEE International Conference On Big Data Science And Engineering (TrustCom/BigDataSE). IEEE, 2018, pp. 1170–1179.

A. L. Fantana, S. Ramachandran, C. H. Schunck, and M. Talamo, “Biometric authentication with smartphones,” in 2015 International Carnahan Conference on Security Technology (ICSCST). IEEE, 2015, pp. 235–239.

J. G. Casanova, C. S. Ávila, A. de Santos Sierra, G. B. del Pozo, and V. J. Vera, “A real-time in-air signature biometric technique using a mobile device embedding an accelerometer,” in International Conference on Networked Digital Technologies. Springer, 2010, pp. 497–503.

M. Haring, D. Reinhardt, and Y. Omlor, “Pick me up and i will tell you who you are: Analyzing pick-up motions to authenticate users,” in 2018 IEEE International Conference on Pervasive Computing and Communications Workshops (PerCom Workshops). IEEE, 2018, pp. 472–475.

J. Maghsoudi and C. C. Tappert, “A behavioral biometrics user authentication study using motion data from android smartphones,” in 2016 European Intelligence and Security Informatics Conference (ESISIC). IEEE, 2016, pp. 184–187.

A. Eremin, K. Kogos, and Y. Valatskayte, “Touch and move: Incoming call user authentication,” in International Conference on Information Systems Security and Privacy. Springer, 2018, pp. 26–39.

W. Lee and R. B. Lee, “Multi-sensor authentication to improve smartphone security,” in Proceedings of the 1st International Conference on Information Systems Security and Privacy, ICISPP, 2015, pp. 270–280.

Y. Li, H. Hu, and G. Zhou, “Using data augmentation in continuous authentication on smartphones,” IEEE Internet of Things Journal, vol. 6, no. 1, pp. 628–640, Feb 2019.

C. Song, A. Wang, K. Ren, and W. Xu, “Eyeveri: A secure and usable approach for smartphone user authentication,” in 35th Annual IEEE International Conference on Computer Communications, INFOCOM, 2016, pp. 1–9.

R. Ferrero, F. Gandino, B. Montrucchio, M. Rebaudengo, A. Velasco, and V. L. Benkhelifa, “On gait recognition with smartphone accelerometer,” in 2015 4th Mediterranean Conference on Embedded Computing (MECO). IEEE, 2015, pp. 368–373.

A. K. Jain, A. Ross, S. Prabhakar et al., “An introduction to biometric recognition,” IEEE Transactions on circuits and systems for video technology, vol. 14, no. 1, 2004.

P. N. Nagy, S. Maas, and H. Ailisto, “Using a mobile device recording sensors,” in EURASIP Journal on Advances in Signal Processing, vol. 2009, p. 7, 2009.

G. Qian, J. Zhang, and A. Kidane, “People identification using gait via floor pressure sensing and analysis,” in European Conference on Smart Sensing and Context. Springer, 2008, pp. 83–98.

H. M. Thang, V. Q. Viet, N. D. Thuc, and D. Choi, “Gait identification using accelerometer on mobile phone,” in 2012 International Conference on Control, Automation and Information Sciences (ICCAIS). IEEE, 2012, pp. 344–348.

T. Hoang, T. D. Nguyen, C. Luong, S. Do, and D. Choi, “Adaptive cross-device gait recognition using a mobile accelerometer,” JIPS, vol. 9, no. 2, p. 333, 2013.

J. Mantyjarvi, M. Lindholm, E. Vildjouani, S.-M. Makela, and H. Ailisto, “Identifying users of portable devices from gait pattern with accelerometers,” in Proceedings. (ICASSP’05). IEEE International Conference on Acoustics, Speech, and Signal Processing, 2005., vol. 2. IEEE, 2005, pp. ii–973.

M. Muaza and R. Mayrhofer, “An analysis of different approaches to gait recognition using cell phone based accelerometers,” in Proceedings of International Conference on Advances in Mobile Computing & Multimedia. ACM, 2013, p. 293.

B. Nick, M. O. Derawi, P. Bours, and C. Busch, “Scenario test of accelerometer-based biometric gait recognition,” in 2011 Third International Workshop on Security and Communication Networks (IWSCN). IEEE, 2011, pp. 15–21.

C. Nickel, T. Wirtl, and C. Busch, “Authentication of smartphone users based on the way they walk using k-nn algorithm,” in 2012 Eighth International Conference on Intelligent Information Hiding and Multimedia Signal Processing. IEEE, 2012, pp. 16–20.

T. Hoang, D. Choi, and T. Nguyen, “Gait authentication on mobile phone using biometric cryptosystem and fuzzy commitment scheme,” International Journal of Information Security, vol. 14, no. 6, pp. 549–560, 2015.

E. Vildjouani, S.-M. Makela, M. Lindholm, R. Rihimäki, V. Kyllönen, J. Mäntyjarvi, and H. Ailisto, “Unobtrusive multimodal biometrics for ensuring privacy and information security with personal devices,” in International Conference on Pervasive Computing, Springer, 2006, pp. 187–201.

C. Nickel and C. Busch, “Classifying accelerometer data via hidden markov models to authenticate people by the way they walk,” IEEE Aerospace and Electronic Systems Magazine, vol. 28, no. 10, pp. 29–35, 2013.

W. Xu, G. Lan, Q. Lin, S. Khalifa, M. Hassan, N. Bergmann, and W. Hu, “Keh-gait: Using kinetic energy harvesting for gait-based user authentication systems,” IEEE Transactions on Mobile Computing, vol. 18, no. 1, pp. 139–152, 2018.

N. Kolokas, S. Krinizis, A. Drosou, D. Ioannidis, and D. Tzovaras, “Gait matching by mapping wearable to camera privacy-preserving recordings: Experimental comparison of multiple settings,” in 2019 6th International Conference on Control, Decision and Information Technologies (CoDIT). IEEE, 2019, pp. 338–343.

A. Ferreira, G. Santos, A. Rocha, and S. Goldenstein, “User-centric based biometrics,” IEEE Transactions on Security and Privacy, vol. 14, no. 6, pp. 549–560, 2015.

F. Hong, S. You, M. Wei, Y. Zhang, and Z. Guo, “Mgra: Motion gesture recognition via accelerometer,” Sensors, vol. 16, no. 4, p. 530, 2016.

J. Yan, Y. Qi, Q. Rao, and S. Qi, “Towards a user-friendly and secure hand shaking authentication for smartphones,” in 2018 17th IEEE International Conference On Trust, Security And Privacy In Computing And Communications 12th IEEE International Conference On Big Data Science And Engineering (TrustCom/BigDataSE). IEEE, 2018, pp. 1170–1179.
F. Monrose and A. D. Rubin, “Keystroke dynamics as a biometric for authentication,” *Future Generation Computer Systems*, vol. 16, no. 4, pp. 351–359, 2000.

R. Joyce and G. Gupta, “Identity authentication based on keystroke latencies,” *Communications of the ACM*, vol. 33, no. 2, pp. 168–176, 1990.

I. V. McLaughlin et al., “Keypress biometrics for user validation in mobile consumer devices,” in *2009 IEEE 13th International Symposium on Consumer Electronics*. IEEE, 2009, pp. 280–284.

S. Zahid, M. Shahzad, S. A. Khayam, and M. Farooq, “Keystroke-based user identification on smart phones,” in *International Workshop on Recent advances in intrusion detection*. Springer, 2009, pp. 224–230.

E. V. C. Urtiga and E. D. Moreno, “Keystroke-based biometric authentication in mobile devices,” *IEEE Latin America Transactions*, vol. 9, no. 3, pp. 368–375, 2011.

S.-s. Hwang, S. Cho, and S. Park, “Keystroke dynamics-based authentication for mobile devices,” *Computers & Security*, vol. 28, no. 1-2, pp. 85–93, 2009.

J.-s. Wu, W.-C. Lin, C.-T. Lin, and T.-E. Wei, “Smartphone continuous authentication based on keystroke and gesture profiling,” in *2015 International Carnahan Conference on Security Technology (ICCAST)*. IEEE, 2015, pp. 191–197.

C. Giuffrida, K. Majdanik, M. Conti, and H. Bos, “I sensed it was you: authenticating mobile users with sensor-enhanced keystroke dynamics,” in *International Conference on Detection of Intrusions and Malware, and Vulnerability Assessment*. Springer, 2014, pp. 92–111.

F. Inguañez and S. Ahmadi, “Securing smartphones via typing heat maps,” in *2016 IEEE 6th International Conference on Consumer Electronics-Berlin (ICCE-Berlin)*. IEEE, 2016, pp. 193–197.

T. Anusas-amornkul, “Keystroke-based biometric authentication in smartphones,” in *Proceedings of the 9th International Conference on Information Communication and Management*. ACM, 2019, pp. 70–74.

V. Shankar and K. Singh, “An intelligent scheme for continuous authentication of smartphone using deep auto encoder and softmax regression model easy for user brain,” *IEEE Access*, vol. 7, pp. 48 645–48 654, 2019.

M. Kaman, M. Akila, and N. Krishnaraj, “Biometric personal authentication using keystroke dynamics: A review,” *Applied soft computing*, vol. 11, no. 2, pp. 1565–1573, 2011.

P. S. Teh, A. B. J. Teoh, and S. Yue, “A survey of keystroke dynamics biometrics,” *The Scientific World Journal*, vol. 2013, 2013.

S. Bhattacharya and T. Santhanan, “Keystroke dynamics for biometric authentication—a survey,” in *2013 International Conference on Pattern Recognition, Informatics and Mobile Engineering*, Feb 2013, pp. 17–23.

V.-D. Stanciu, R. Spolaor, M. Conti, and C. Giuffrida, “On the effectiveness of sensor-enhanced keystroke dynamics against statistical attacks,” in *Proceedings of the Sixth ACM Conference on Data and Application Security and Privacy*. ACM, 2016, pp. 105–112.

Z. Sitova, J. Šeděnka, Q. Yang, G. Peng, G. Zhou, P. Gasti, and K. S. Balagani, “Hmog: New behavioral biometric features for continuous authentication of smartphone users,” *IEEE Transactions on Information Forensics and Security*, vol. 11, no. 5, pp. 877–892, 2015.

A. Burro, B. Crispo, S. Gupta, and F. Del Frari, “DIALERAUTH: A motion-assisted touch-based smartphone user authentication scheme,” in *Proceedings of the Eighth ACM Conference on Data and Application Security and Privacy*, 2018, pp. 267–276.

S. Mondal and P. Bours, “Swipe gesture based continuous authentication for mobile devices,” in *2015 International Conference on Biometrics (ICB)*. IEEE, 2015, pp. 458–465.

T. Nohara and R. Uda, “Personal identification by flick input using self-organizing maps with acceleration sensor and gyroscope,” in *Proceedings of the 10th International Conference on Ubiquitous Information Management and Communication*. ACM, 2016, p. 58.

C.-C. Lin, C.-C. Chang, D. Liang, and C.-H. Yang, “A new non-intrusive authentication method based on the orientation sensor for smartphone users,” in *2012 IEEE Sixth International Conference on Software Security and Reliability*. IEEE, 2012, pp. 245–252.

L. Lu and Y. Liu, “Safeguard: User reauthentication on smartphones via behavioral biometrics,” *IEEE Transactions on Computational Social Systems*, vol. 2, no. 3, pp. 53–64, 2015.

A. Jain and V. Kanhangad, “Exploring orientation and accelerometer sensor data for personal authentication in smartphones using touch-screen gestures,” *Pattern recognition letters*, vol. 68, pp. 351–360, 2015.

D.-H. Shih, C.-M. Lu, and M.-H. Shih, “A flick biometric authentication mechanism on mobile devices,” in *2015 International Conference on Informative and Cybernetics for Computational Social Systems (ICCSS)*. IEEE, 2015, pp. 312–317.

H. Sauevance and P. Bhattacharosod, “User authentication using combination of behavioral biometrics over the touchpad acting like touch screen of mobile device,” in *2008 International Conference on Computer and Electrical Engineering*. IEEE, 2008, pp. 82–86.

H. Xu, Y. Zhou, and M. R. Lyu, “Towards continuous and passive authentication via touch biometrics: An experimental study on smartphones,” in *10th Symposium On Usable Privacy and Security (SOUPS)*, 2014, pp. 184–197.

K. W. Nixon, X. Chen, Z.-H. Yao, and Y. Chen, “Slowmo-enhancing mobile gesture-based authentication schemes via sampling rate optimization,” in *2016 21st Asia and South Pacific Design Automation Conference (ASP-DAC)*. IEEE, 2016, pp. 462–467.

J. Nader, A. Aalsdaon, P. Prasad, A. Singh, and A. Elchouemi, “Designing touch-based hybrid authentication method for smartphones,” *Procedia Computer Science*, vol. 70, pp. 198–204, 2015.

M. Antal and L. Z. Szab ó, “Biometric authentication based on touchscreen swipe patterns,” *Procedia Technology*, vol. 22, pp. 862–869, 2016.

A. Primo and V. V. Phoha, “Music and images as contexts in a context-aware touch-based authentication system,” in *2015 IEEE 7th International Conference on Biometrics Theory, Applications and Systems (BTAS)*. IEEE, 2015, pp. 1–7.

T. Feng, J. Yang, Z. Yan, E. M. Tapia, and W. Shi, “Tips: Context-aware implicit user identification using touch screen in uncontrolled environments,” in *Proceedings of the 15th Workshop on Mobile Computing Systems and Applications*. ACM, 2014, p. 9.

C. Shen, Y. Zhang, X. Guan, and R. A. Maxion, “Performance analysis of touch-interaction behavior for active smartphone authentication,” *IEEE Transactions on Information Forensics and Security*, vol. 11, no. 3, pp. 498–513, 2015.

Z. Syed, J. Helwick, N. Banerjee, and B. Cukic, “Touch gesture-based authentication on mobile devices: The effects of user posture, device size, configuration, and inter-session variability,” *Journal of Systems and Software*, vol. 149, pp. 158–173, 2019.

Z. I. Rauen, F. Anjomshoa, and B. Kantarci, “Gesture and sociability-based continuous authentication on smart mobile devices,” in *Proceedings of the 16th ACM International Symposium on Mobility Management and Wireless Access*. ACM, 2018, pp. 51–58.

R. Rocha, D. Carneiro, R. Costa, and C. Analide, “Continuous authentication in mobile devices using behavioral biometrics,” in *International Symposium on Ambient Intelligence*. Springer, 2019, pp. 191–198.

S. Mondal and P. Bours, “Continuous authentication and identification for mobile devices: Combining security and forensics,” in *2015 IEEE International Workshop on Information Forensics and Security (WIFS)*. IEEE, 2015, pp. 1–6.

F. A. Alsulaiman, J. Cha, and A. El Saddik, “User identification based on handwritten signatures with haptic information,” in *International Conference on Human Haptic Sensing and Touch Enabled Computer Applications*. Springer, 2008, pp. 114–121.

L. Cai and H. Chen, “Touchlogger: Inferring keystrokes on touch screen from smartphone motion,” *HotSec*, vol. 11, no. 2011, p. 9, 2011.

O. Miguel-Hurtado, S. V. Stevenage, C. Bevan, and R. Guest, “Predicting sex as a soft-biometrics from device interaction swipe gestures,” *Pattern Recognition Letters*, vol. 79, pp. 44–51, 2016.

C. Bevan and D. S. Fraser, “Different strokes for different folks? revealing the physical characteristics of smartphone users from their swipe gestures,” *International Journal of Human-Computer Studies*, vol. 88, pp. 51–61, 2016.

S. Azenkot, K. Rector, R. Ladner, and J. Wobbrock, “Passchords: Secure multi-touch authentication for blind people,” in *Proceedings of the 14th international ACM SIGACCESS conference on Computers and accessibility*. ACM, 2012, pp. 159–166.

H. Khan, A. Atwater, and U. Hengartner, “Itus: an implicit authentication framework for android,” in *Proceedings of the 20th annual international conference on Mobile computing and networking*. ACM, 2014, pp. 507–518.

O. Miguel-Hurtado, R. Blanco-Gonzalo, R. Guest, and C. Lunert, “Password evaluation of a mobile whole authentication system,” in *2016 IEEE International Carnahan Conference on Security Technology (ICCSS)*. IEEE, 2016, pp. 1–8.
