Continuous Authentication of Wearable Device Users from Heart Rate, Gait, and Breathing Data

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Abstract—The security of private information is becoming the bedrock of an increasingly digitized society. While the users are flooded with passwords and PINs, these gold-standard explicit authentications are becoming less popular and valuable. Recent biometric-based authentication methods, such as facial or finger recognition, are gaining popularity due to their higher accuracy. However, these hard-biometric-based systems require dedicated devices with powerful sensors and authentication models, which are often limited to most of the market wearables. Still, market wearables are collecting various private information of a user and are becoming an integral part of life: accessing cars, bank accounts, etc. Therefore, time demands a burden-free implicit authentication mechanism for wearables using the less-informative soft-biometric data that are easily obtainable from modern market wearables. In this work, we present a context-dependent soft-biometric-based authentication system for wearables devices using heart rate, gait, and breathing audio signals. From our detailed analysis using the “leave-one-out” validation, we find that a lighter $k$-Nearest Neighbor ($k$-NN) model with $k = 2$ can obtain an average accuracy of $0.93 \pm 0.06$, $F_1$ score $0.93 \pm 0.03$, and false positive rate (FPR) below $0.08$ at $50\%$ level of confidence, which shows the promise of this work.

I. INTRODUCTION

A. Motivation

Internet of Things (IoT) have increasing access to a multitude of devices with advanced capabilities that allow us to remotely collect information or control physical objects. Along with the growth of IoT, smartphones and wearables have advanced in their sensing and computational capabilities to a point which enable many new applications and usage scenarios to emerge [1], [2], [3], [4], [5]. Some include the ability to identify a user to third party services [6], store sensitive user information (i.e., passwords, credit card information) [7], manage financial payments [8], access phones and other paired devices [9], unlock vehicles [7], monitor or track individuals (e.g., child monitoring or fall detection), and assess an individual’s health and fitness. According to a recent market report, a 72.7% increase in wearable shipments and an associated increase in sales revenue of 78.1% are predicted from 2016 to 2022 [10].

Therefore, wearables also raise new challenges, especially in terms of security. Unauthorized access to a wearable can enable imposters to steal information from other sensitive IoT objects, which poses a significant risk [11]. Illustrations include, the stealing of sensitive personal information or delivering faulty dosage of a drug to a remote patient. Therefore, there is an imperative need for a robust and accurateauthentication mechanism specifically for wearable device users. Existing wearable devices either have no authentication systems or authentication mechanisms that are often knowledge-based regular PIN locks or pattern locks [7], which suffer from scalability issues [12]. Many times, users opt to completely disable security mechanisms out of convenience, as the design hinders the implementation of security itself. However, an implicit and continuous authentication system does not require any explicit user input, and thereby, such an authentication can work seamlessly without imposing any user burden.

B. Related Work

1) Wearable Constraints: Wearable device user authentication is a relatively new field of research compared to mobile authentication [6], [13], [14], [12]. The limited display sizes of wearables add another constraint that limits the choices of authentication mechanisms [6], [15]. But as technology advances, companies such as Samsung, Fitbit, Apple, Garmin, and Embrace can provide lower level granularity in data. In addition to this, increasingly more biometrics are available as more sensors are being added such as microphone, electrocardiograms (ECG), and GPS. However, some of the newer sensors, such as ECG are not yet accurate enough. For example, researchers have found that, although for people over the age of 85 Apple accurately detects atrial fibrillation at a rate of 96%, for people under 55, it only correctly diagnoses atrial fibrillation 19.6% of the time [16]. Another group of researchers designed wrist strapped ECG reader and developed an authentication system with an accuracy of 93.5%, which is limited by the ease of use and placement issues [17]. Therefore, an authentication scheme that can utilize data from different sensors, such as photo-plethysmography (PPG), accelerometer, gyroscope, and microphone, which are readily available on market wearables, could be more realistic to develop a stop implicit wearable authentication system.

2) Multi-modal Biometric Authentication: In previous work, combinations of biometrics were used to form multi-modal biometric authentication systems for increased reliability compared to unimodal systems, which often suffer from noisy data, intra-class variations, inter-class similarities, and spoof attacks [18]. For multi-modal authentication systems, researchers have utilized different hard- and soft-
biometrics. However, due to accuracy concerns in sensing capabilities and relatively low computational power of wearables, these multi-modal approaches are typically not implemented for implicit and continuous authentication on state-of-the-art wearables.

3) Wearable Authentication: Researchers recently proposed authentication techniques that are more suitable for wearables, focusing more on approaches based on behavioral biometrics, such as gait [19], [20], [21], activity types [6], [11], gesture [22], keystroke dynamics [23] and physiological biometrics, such as PPG signals [24]. Almost all of these studies are based on project specific generated datasets. All of these user authentication techniques are limited in the scope of use, e.g., gait-based behavioral authentication approaches [20], [21] only work during walking. While other projects have addressed some of the limitations of gait-based approaches by considering different types of gestures [22] or activities [6], [11]. All of these models are based on movement and thereby, fail to work in the very common human state of being sedentary [23], [15]. Authentication approaches using physiological biometric data, such as ECG and bioimpedance [14] require very fine-grained samples and sensor readings are easily affected by noise, motion, etc., but these biometrics are always available. Focusing on one or a particular set of biometrics restricts the usability of a continuous authentication model, but with a collection of various combinations it is possible to build a more robust authentication system.

C. Contributions

The main contribution of this paper is an exploration of implicit and non-stop user authentication schemes utilizing multiple biometrics. In this approach, we use three different types of soft-biometrics: heart rate, gait, and breathing all of which are easily obtainable on most of the market wearables. While minute-level coarse-grained heart rate samples can be less informative, they are available almost all the time when a user wears the device. Adding another biometric, such as gait, can improve the performance. However, unlike the heart rate data, gait is available only when a user walks. Compared to gait, breathing audio signal can have a better availability, but it also suffers from various issues, such as a user’s distance from the microphone, presence of other sounds. Therefore, it is important to develop an authentication approach that can combine multiple biometrics based on contexts or scenarios, e.g., availability of biometrics, and can be easy to implement on wearables. In this work, we present a multi-biometric-based context-driven approach that works both in sedentary and non-sedentary periods (Section II-D). From our detailed feature computation and selection, hyper-parameter optimization, and finally, modeling with different classifiers, we are able to authenticate a user with an average accuracy of 0.93 ± 0.06, $F_1$ score 0.93 ± 0.03 (Section III-D), and FPR below 0.08 at 50% level of confidence while classifying (Section III-E).

II. Approach

In this paper, we intend to demonstrate the importance and effectiveness of different biometrics to identify wearable users using machine learning modeling. Before we describe the details of the analysis, we first introduce the datasets, pre-processing steps, feature engineering, and methods used in this work.

A. Datasets

We use three different datasets in our analysis.

- Fitbit dataset: We use the heart rate data collected at a rate of one sample per minute using the Fitbit Charge HR device from three subjects similar to our previous work [25], [26], [27], [15], [28], [29], [30], [31], [32], [33], [34], [35], [36], [37], [38]. Data was collected during various activity levels ranging from sedentary to high activity.
- Gait dataset: We use the WISDM dataset [39], where three (i.e., x, y, z directions) linear and angular acceleration readings were collected from accelerometer and gyroscope, respectively, at a rate of one sample in 50 ms from the LG G Watch with Wear 1.5 operating system. Data was collected under normal walking condition.
- Audio dataset: In this work, we use the breathing audio clips obtained from the ESC-50 dataset [40], where audio clips were, sampled at 22.05 kHz, around 5 seconds long. Data was collected, holding a device close to a subject during an idle state.

B. Data Pre-Processing

Since we are using real-world datasets, we need to process the dataset before using it. First, we need to segment the continuous stream of biometrics, such as heart rate, gait information, and desired audio events (i.e., breathing). Then, we perform data augmentation to simulate more physiological states from the collected data to increase robustness of experiment. Finally, we compute and select influential features before constructing authentication models.

1) Data Segmentation: Since heart rate and gait data were sampled at different frequencies, we segment the heart rate and gait samples into 10-sample windows to obtain stable and rich information. Unlike the heart rate or gait data, the audio data comes with other types of sounds in addition to desired breathing sounds. Additionally, some clips come with multiple breathing events separated by silence or noisy parts. Therefore, we segment the ESC-50 audio clips to fetch single inhalation breathing events. Thereby, we obtain around six inhalation breathing events per subject.

2) Audio Data Augmentation: Breathing audio could be altered due to change of environments, physical state, or mood. To simulate this and capture the variations, we augment the original audio breathing events using various pitch shifts and speed changes.

- Pitch shift: We consider 15 different pitch shifts ranging from $-\frac{1}{2}$ to $\frac{1}{2}$ with $\frac{1}{2}$ increments
- Speed change: We consider seven speed changes ranging from .25x to 2x times the speed of an original
clips with an increment of .25x, skipping 1x since that would represent the original clip, which we have already included as a pitch shift with value 0. Thereby, each original breathing clip is augmented using a total of 22 modifications.

C. Feature Computation

We compute the following sets of candidate features.

- Heart rate features: From the windows of 10 samples we compute 21 statistical features: mean ($\mu$), median ($Mdn$), standard deviation ($\sigma$), variance ($\sigma^2$), coefficient of variance ($cov$), range ($ran$), coefficient of range ($coran$), first quartile or 25th percentile ($p25$), third quartile or 75th percentile ($p75$), max ($max$), inter quartile range ($iqr$), coefficient of inter quartile ($coi$), mean absolute deviation ($mad_Mdn$), median absolute deviation ($mad_\mu$), energy ($E$), power ($P$), root mean square ($rms$), root sum of squares ($rss$), signal to noise ratio ($snr$), skewness ($\gamma$), and kurtosis ($\kappa$), described in [37].
- Gait features: We compute mean ($\mu$), variance ($\sigma^2$), and kurtosis ($\kappa$) from each window of x-, y-, and z-axis readings obtained from gyroscope and accelerometer, separately.
- Audio features: From each inhalation breathing event we compute 40 Mel-frequency cepstral coefficients (MFCCs), where, $MFCC_i$ represents the $i^{th}$ coefficient.

Thereby, we obtain 21 features from a single heart rate window, 18 features (i.e., three from the six axes of accelerometer and gyroscope) from a gait window, and 40 features from every breathing clip.

D. Feature Selection

To select the most influential features, we use the Scikit learn feature selection package and apply the three techniques: Correlation approach, Select from a Model (SelectFromModel), and Select the K Best (SelectKBest). In each iteration of the leave-one-out training-testing, described in Section III-A, we select different sets features, which are very similar with changes in ordering.

- Correlation approach: We apply this approach to select the most influential heart rate and gait features. We find mean, variance, and skewness are the three uncorrelated features from both heart rate. Therefore, we remain with three heart rate features.
- Select from a Model (SelectFromModel): In this approach, we use the Random Forest Models. This feature selection approach provides a relative importance of features in percentages.
- Select the K Best (SelectKBest): This is our last feature selection approach that also provides an importance score for each feature and based on that score we rank the features. Then, we try with different numbers of features, i.e., $K$, to find the best model performance. In this work, we find $K = 10$ performs the best.

E. Methods

In Figure 1, we present an overview of our proposed implicit and continuous wearable-user authentication scheme utilizing various combinations of three biometrics (heart rate, gait, and breathing patterns) which are easily obtainable from most of the market wearables. The proposed system uses different collections of the three biometrics based on their availability and model confidence.

We first try to authenticate a user based on the heart rate obtained from the photo-plethysmogram (PPG) sensor. If the system can authenticate the user with enough confidence, it allows the user to access the device. Otherwise, it checks the next authentication module that relies on other biometrics.

The authentication system first tries to check whether the user is moving using the on-device accelerometer and gyroscope data. If the user is moving, the system tries to authenticate the user based on gait and heart rate biometrics. If the system can authenticate the user with enough confidence, it allows the user to access the device.

However, if the user does not move or the gait and heart rate-based module cannot authenticate the user, the system tries to combine breathing biometric collected from the on-device microphone. Based on the way the authentication system reaches the breathing module, it either combines breathing with only heart rate biometric or both heart rate and gait biometrics.

Similar to the previous cases, the system in breathing module tries to authenticate the user. If the system can authenticate the user with enough confidence, it allows the user to access the device. Otherwise, the user’s access to
the device is revoked and require some sort of external verification, such as pin locks or passwords. 

Based on the various combinations of the three biometrics that we use in our authentication approach, we define the following models:

- Heart rate data-driven model (HR model)
- Heart rate and gait data-driven model (HRG model)
- Heart rate and breathing data-driven model (HRB model)
- Heart rate, gait, and breathing data-driven model (HRGB model)

### III. USER AUTHENTICATION

Before presenting the detailed evaluation of our models, we first present training-testing set split and our modeling scheme, followed by list of performance measures and hyper-parameter optimization.

#### A. Training-Testing Set

In our binary modeling, we try to distinguish a valid user (class 0) from the two impostors (class 1). To avoid overfitting, we consider at least 10 times more data-points, i.e., instances than the number of features. While training-testing, we follow the “leave-one-out” strategy, where we keep one instance for testing and use the rest of the $N-1$ instances for training with $N$ be the number of total instances from each class. We balance our training dataset, by considering the same $N-1$ number of instances from each class. Since our impostor class (class 1) consists of two person data, we pick $(N-1)/2$ instances from each imposter. Similarly, we balance our test sets. While adding the augmented data into train and test sets, we follow the same split that we consider on original data. For example, if a user has $N=6$ breathing events and in our “leave-one-out” approach, we use the first five instances for training and the sixth instance for testing, then the breathing events that are generated from the first five events using different augmentation approaches are added to the training set. Similarly, events that are generated from the sixth breathing event are added to the test set. This way, we keep our training and testing instances mutually exclusive.

#### B. Performance Measures

To evaluate the performance of different models we consider Accuracy (ACC), Root Mean Square Error (RMSE), False Positive Rate (FPR), False Negative Rate (FNR), $F_1$ score, and Area Under the Curve - Receiver Operating Characteristic (AUC-ROC). Terminologies have their usual meaning in machine learning, when classifying a subject using a feature set [37], [41]. For an ideal system, it is desirable to have a lower RMSE, FPR and FNR, but a higher ACC, $F_1$ score, and AUC-ROC.

#### C. Hyper-Parameter Optimization

We use the grid search package in the Sci-kit learn to find the optimal hyper-parameter sets. For each “leave-one-out” modeling, we perform the hyper-parameter optimization using various ranges of values. From the different iterations of the “leave-one-out” approach with balanced mutually exclusive training-test sets, we obtain similar values for the hyper-parameters. In Tables III and IV we present the set of optimal values obtained from different modeling approaches.

#### D. Authentication Model Evaluation

In Table III we present the performance of the best models using various biometric combinations and different classifiers with their optimal parameter sets. From the table, we observe that the best HR model (i.e., model that only uses heart rate data) can provide an average accuracy of $0.61 \pm 0.18$ and an average AUC-ROC $0.54 \pm 0.07$. As discussed previously in the Section IIA if the HR model cannot authenticate a user with enough confidence or fails to authenticate, we use additional gait biometric (i.e., HRG model).

In Table III we observe that adding gait biometric (when available) with heart rate, all measures improve. In case of the best HRG model (i.e., model that uses heart rate and gait biometrics), ACC increased by 38%, $F_1$ score increased by 218%, and AUC-ROC increased by 56% compared to the best HR model. The FPR also improves (i.e., drops) from $0.70 \pm 0.20$ to $0.26 \pm 0.10$. While gait data is only available while a user is moving, its inclusion can significantly boost the authentication performance, compared to a model that uses only less accurate minute-level heart rate data.

In Table III we observe that the HRB model (i.e., model that uses heart rate and breathing biometrics) achieves a

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### TABLE I: Summary of features selected from different biometrics

| Biometrics          | Selector (parameters) | Selected features |
|---------------------|-----------------------|-------------------|
| Heart rate          | SelectKBest ($K = 10$) | $p_{25}, \mu, \sigma, \text{max}, Mdn, p_{15}, \kappa, \gamma, P$ |
| Heart rate and gait | SelectFromModel ($p = 0.90$) | $Z_{-gy}, Y_{-gy}, Y_{-acc}, \mu, Z_{-gy} \sigma^2, Z_{-acc} \kappa, X_{-acc} \kappa, Y_{-gy} \sigma^2, Y_{-acc} \sigma^2, X_{-acc} \sigma^2$ |
| Heart rate and breathing | SelectKBest ($K = 10$) | MFCC3, MFCC7, MFCC4, MFCC6, MFCC9, MFCC11, MFCC15, MFCC38, MFCC13, MFCC40 |

### TABLE II: Summary of features selected from heart rate, gait, and breathing biometrics together

| Selector (parameters) | Selected features |
|-----------------------|-------------------|
| SelectFromModel ($p = 0.90$) | MFCC3, MFCC4, MFCC7, MFCC1, MFCC6, Z_{-gy} \kappa, Y_{-gy} \kappa, Y_{-acc} \mu, MFCC13, Y_{-gy} \kappa, Z_{-gy} \sigma^2, MFCC10, MFCC15, X_{-acc} \kappa, MFCC11, MFCC18, MFCC36, MFCC38, MFCC26, MFCC17, MFCC12, MFCC14, Z_{-gy} \sigma^2, \mu |
| SelectKBest ($K = 10$) | MFCC5, MFCC7, MFCC4, MFCC6, MFCC1, Y_{-acc} \mu, MFCC9, MFCC38, MFCC2, MFCC11 |
TABLE III: The best HR, HRG, and HRG models with average and standard deviation of performance measures

| Model | Classifier (parameters) | Feature count | ACC       | RMSE      | FPR       | FNR       | $F_1$ score | AUC-ROC   |
|-------|-------------------------|---------------|-----------|-----------|-----------|-----------|-------------|-----------|
| HR    | SVM (poly. kernel, $d = 2$, $C = 1$) | 10            | 0.61 (0.18) | 0.62 (0.16) | 0.70 (0.20) | 0.08 (0.16) | 0.27 (0.09) | 0.54 (0.07) |
| HRG   | RF (number of estimators, $n = 500$) | 13            | 0.84 (0.09) | 0.40 (0.01) | 0.26 (0.10) | 0.05 (0.03) | 0.86 (0.03) | 0.84 (0.04) |
| HRB   | $k$-NN ($k = 6$, minkowski distance) | 10            | 0.91 (0.04) | 0.29 (0.04) | 0.17 (0.04) | 0.00 (0.00) | 0.92 (0.03) | 0.91 (0.02) |

TABLE IV: The best HRGB models with average and standard deviation of performance measures

| Classifier (parameters) | Feature count | ACC       | RMSE      | FPR       | FNR       | $F_1$ score | AUC-ROC   |
|-------------------------|---------------|-----------|-----------|-----------|-----------|-------------|-----------|
| RF (number of neighbors $= 450$) | 23            | 0.91 (0.04) | 0.27 (0.01) | 0.19 (0.04) | 0.00 (0.00) | 0.91 (0.03) | 0.91 (0.02) |
| $k$-NN ($k = 2$, minkowski distance) | 10            | 0.93 (0.06) | 0.27 (0.01) | 0.14 (0.07) | 0.00 (0.00) | 0.93 (0.03) | 0.93 (0.04) |
| NB                      | 10            | 0.91 (0.01) | 0.30 (0.00) | 0.18 (0.01) | 0.00 (0.00) | 0.92 (0.01) | 0.91 (0.01) |
| SVM (poly. kernel, $d = 1$, $C = 1$) | 10            | 0.92 (0.03) | 0.29 (0.01) | 0.17 (0.06) | 0.00 (0.00) | 0.92 (0.02) | 0.92 (0.03) |
| SVM (dtb kernel, $\gamma = 0.01$, $C = 1$) | 10            | 0.93 (0.03) | 0.27 (0.01) | 0.15 (0.06) | 0.00 (0.00) | 0.93 (0.03) | 0.93 (0.03) |

Better performance compared to the HRG model. We achieve a 35% drop in the FPR while comparing the HRB with the HRG model. Additionally, we observe ≈ 8% increases, while comparing the ACC, $F_1$ score, and AUC-ROC of the HRB model with the HRG model. While comparing the HRB model to the HR model, we observe a huge performance improvement. Compared to the HR model, the HRB model performs better with a $F_1$ score (an increase of 241%) and AUC-ROC (an increase of 68%) with a high accuracy of 0.91 ± 0.02.

Finally, in Table IV we present the performance comparison among different classification models and their optimal parameter sets using the heart rate, gait, and breathing biometrics together. In the table, we observe a modest performance improvement, i.e., an accuracy increase of accuracy by 2% (0.91 to 0.93), while comparing the HRGB model with the HRB model. Similar improvements are observed in case of other performance metrics. However, in case of the HRGB model we obtain a simpler and faster classifier, i.e., the $k$-NN with $k = 2$ (number of neighbors needed for a classification), compared to the HRB model that uses the $k$-NN model with $k = 6$. Therefore, considering the implementation endowment, i.e., a wearable, that has energy constraints, an authentication model that uses heart rate, gait, and breathing biometrics and the $k$-NN classifier with $k = 2$ can be a better choice.

Fig. 2: The change of FPR and FNR with varying confidence thresholds (HRB model with the $k$-NN classifier)

E. Error Analysis

As discussed previously in Section II-E, the authentication system allows a user to access the device only when it can validate the user with enough confidence. In this section, we present an analysis on how our system performs with the change of confidence level, i.e., threshold. In case of an ideal system, it is desired to have a lower FPR and FNR. In Figures 2 and 3, we present our analysis of error rates (FPR and FNR) with varying confidence thresholds. In Figure 2, we observe that FPR sharply drops with the increase of thresholds from 0.1 to 0.9 and the FPR drops below 0.05 at confidence threshold 0.9. However, in Figure 3 we observe a sharp drop between threshold values of 0.4 and 0.5. The FPR drops from 0.14 to 0.08 during this increase of threshold and FPR remains steady before and after that change in threshold. Though the FPR in case of HRGB model remains a little bit high compared to the HRB model, but the HRGB model needs a smaller confidence threshold of 0.5 to achieve this FPR and at this 0.5 confidence threshold HRGB model can drop the FPR ≈ 54% compared to the HRB model (i.e., FPR of 0.08 versus 0.175). Therefore, it is desirable to use an authentication model that uses heart rate, gait, and breathing biometrics with a low confidence threshold of 0.5.

IV. LIMITATIONS, DISCUSSION, AND CONCLUSIONS

Our work tested the feasibility of authenticating users implicitly and continuously based on the three separate biometrics, i.e., heart rate, gait, and breathing, that are easily obtainable in most of the market wearables, which are usually not equipped with powerful sensors, such as cameras or fingerprint scanners. To the best of our knowledge, this is the first work that attempts to authenticate a wearable device user...
without any explicit user burden using three different soft-biometrics in a more case-based approach, i.e., availability of data. Through our detailed analysis we show that we can authenticate a user with an average accuracy of 0.93 ± 0.06, \( F_1 \) score of 0.93 ± 0.03, and AUC-ROC of 0.93 ± 0.04, with a less than 0.08 FPR at 50% confidence threshold using three biometrics together. This shows the promise for developing an implicit and continuous authentication system for the market wearables to secure our valuable information as well as to create a safe gateway to access various services and devices.

This work has some limitations, which we plan to address in the future. First, we have limited number of audio breathing clips. However, we increase the data volume using standard audio augmentation approaches. Second, in this feasibility work, we use a set of three subjects. We perform a leave-one-out validation approach to deal with this limitation and our achieved performance measures show a promise to further investigate this with a large-scale extended period study. Third, we use different datasets, which could affect the performance. However, we use three independent biometrics and perform correlation analysis to select uncorrelated features; thereby, our results potentially shows a baseline performance, which could further be improved by using the three biometrics from the same subject since that could more uniquely identify a user compared to our case. Before mass deployment, there needs a study for an extended period with several subjects to incorporate user variability and behavior changes over time. Finally, more advanced modeling techniques such as deep learning models (recurrent neural networks or convolutional neural networks) may further improve the accuracy of the models, but that will require to off load data from the wearable to server, which can lead to additional locations to secure; therefore, our approach of using lighter machine learning models, such as the k-NN with \( k = 2 \), have a higher scope to implement on the wearables.

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