Improving Dynamic Biometric Security & Path Prediction Using Health Monitoring Wearables in a Wireless Sensor Network

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Abstract

In recent years Internet of Things (IoT) enabled wearables have exploded in popularity, especially in the health monitoring field. These consumer devices can track various biometric functions such as heart rate (HR), heart rate variability (HRV), respiratory rate (RR), electrocardiogram signals (ECG), and blood oxygen levels (B02). Currently, the primary goal of these devices is to give users insight into their health metrics. However, various potential secondary functions are left unutilized, including biometric security, and when paired within a Wireless Sensor Network (WSN) to aid in user path prediction. The following paper shows how incorporating these various features into a machine learning classifier can improve user identification, achieve the accuracy needed for biometric authentication, and aid in path prediction throughout a WSN. The experimental results show that adding in all the sensor information improves user authentication accuracy by up to 42% over our baseline HRV data. Overall, the best performing model gave us an average precision-recall score of 98% using only health metrics. Furthermore, adding simulated WSN location data to the health tracking information further increased overall authentication performance up to 45% over baseline and a max F1 score of 99%. While improvements in path prediction within a WSN are moderate, we see an overall average of 7% increase to classifier performance in this application. Thus, we conclude that adding additional health tracking information in combination with location information can achieve the accuracy needed for secure user authentication, and a nominal increase to user path prediction.

I. Introduction

A. Biometric Authentication

BIOMETRIC security adoption has become commonplace in modern times. With the increased need for multi-factor authentication and widespread smartphone adoption with biometric features, users have become accustomed to being biometrically authenticated regularly. The most commonly used methods include recognizing the face, iris, fingerprint, hand, and voice, each with varying intrusiveness and accuracy levels. The massive use increase for these methods means research into this area is at an all-time high. However, a research area in its infancy among consumer products is in a person's dynamic biometric patterns.

1) Static Authentication:

All the authentication methods listed above are static, meaning that the system will utilize unchanging biometric properties. For security, this works well enough in that it combines two of the three main factors for multi-factor authentication, something the user has (E.g., their smartphone) and something the user is (E.g., their fingerprint). However, these static methods demand the user must stop what they are doing, input their one-time biometric information, and receive verification from the system, disrupting their current workflow. Due to the data's static nature, once an adversarial attacker can replicate the input data, they have defeated that security method for the victim indefinitely.

2) Dynamic Authentication:

Naturally, the next possible phase of biometrics includes dynamic authentications. Dynamic biometrics look at behavioral data patterns over time to verify the current behavior matches the expected. Typically, this can include user interactions with the device (E.g., Captchas tracking cursor movement to verify legitimacy) to more human general behavior (E.g., arm movement while walking). Tracking dynamic features is a method of continuous authentication. If the user deviates from the pattern expected, authentication will fail and may require further verification. Dynamic biometrics can incorporate multiple features from multiple inputs to determine a pattern for a user in a way that a single static source cannot. In theory, a system could require a user to verify through facial, fingerprint, and voice recognition, resulting in a poor user experience. On the other hand, the system could dynamically track a user's hand, eye, and head movement without them ever needing to stop their task and interact with the authenticator.

B. WSN Path Prediction

Path prediction within a wireless sensor network utilizes information about a user's proximity to nearby sensor nodes and the user's location history and predicts where they are going. We can then take this data in combination with user's health metrics retrieved from IoT health tracking devices worn within a WSN to predict the user's path more accurately. Path prediction can have various potential applications, such as estimating the future load of sensors within a WSN to save energy and load balance network traffic intelligently. Alternatively, it could determine user location and activity to aid in health-based recommendations or automatically detect health emergencies and provide location data.

C. Health Tracking Wearables

Over the past decade IoT enabled wearables with health tracking capabilities have had a massive adoption rate. According to a 2019 survey twenty-one, percent of Americans say they own a smartwatch or fitness tracker [1]. Of the top health-tracking wearable manufactures (*Apple, Huawei, Xiaomi, Samsung, Fitbit* [2]), all of their top products contain the ability to track a wearer's heart rate. By extension, even if not currently supported, this would also enable all the devices to track other heart rate features such as heart rate variability through software updates [3]. Becoming more common is the ability to track blood oxygen levels, devices such as the *Fitbit Charge 4* and the *Apple Watch Series 6* have this capability. Many devices can also calculate the maximum volume of blood oxygen and respiratory rate using these sensors. In the following sections, we will show how to utilize the data for biometric authentication.

TABLE I. Comparison of Popular Health Tracking Wearables

Device	HR	HRV	RR	B02	ECG
Apple Watch 6	*	*	*	*	*
FitBit Charge 4	*	*	*	*	
Huawei Watch Fit	*	**		*	
Move ECG					*
Whoop Strap	*	*	*		
Xiaomi Mi Band 4	*	**			

** Indicates the product natively supports this feature.*
*** Indicates the product could support this feature via software updates.*

II. Overview of Health Metrics

A. Heart Rate Variability (HRV)

Heart rate variability is a measure of the variation in time between each heartbeat. The autonomic nervous system (ANS) controls this variation. It is interesting to track because as the body responds to stress and stimulus, this affects the ANS, which modifies the body's HRV [4]. In general, a higher HRV indicates a person is under less strain. HRV also works well for potential biometric authentication because while it is useful to compare an individual's historical HRV patterns, it is unique to an individual and not comparable to other people. For example, person A having an HRV higher than person B does not necessarily indicate person A is under less strain than B. The only way to determine person A's strain is by checking it against their historical baseline HRV level, which can vary in range and value from person B by a significant margin.

B. Respiratory Rate (RR) & Blood Oxygen Level (BO2)

Respiratory rate is the breathing rate or the number of breaths taken in a given timeframe. For the average person, their RR falls between ten and twenty breaths per minute. Due to the recent COVID-19 pandemic, much research into RR and a person's health is being conducted [5]. Devices such as the *Whoop* strap calculate RR through a phenomenon called Respiratory Sinus Arrhythmia, which is the function that as the lungs inhale, heart rate (HR) increases then during exhale heart rate decreases. From a data science perspective, this is simply another feature of HR data that may limit how much it adds to training our models. However, devices such as pulse oximeters measure RR through changes in blood oxygen levels, and it is conceivable that more and more consumer wearables will incorporate these sensors in the future [6].

C. Electrocardiogram Signals (ECG)

A promising new feature of wearable technology is incorporating ECG monitoring. Upcoming devices such as the *Move ECG* is a smartwatch containing a real-time ECG [7], and the Apple Watch 4 and beyond are also equiped with an electrical heart sensor to track ECG signals. An ECG records the electrical signal from the heart. Typically, an ECG is used to detect abnormalities, but if non-intrusive methods become available in wearables, we can unlock more features from this data.

III. Related Works

A. Dynamic Biometric Authentication

Dynamic biometrics as a subject contains many promising new ideas, yet we can see it is still in the early stages of development by the relatively low number of consumer products utilizing it. Considerable research is currently studying every aspect of human behavior and biological systems to give people an insight into their biology. Biological functions such as

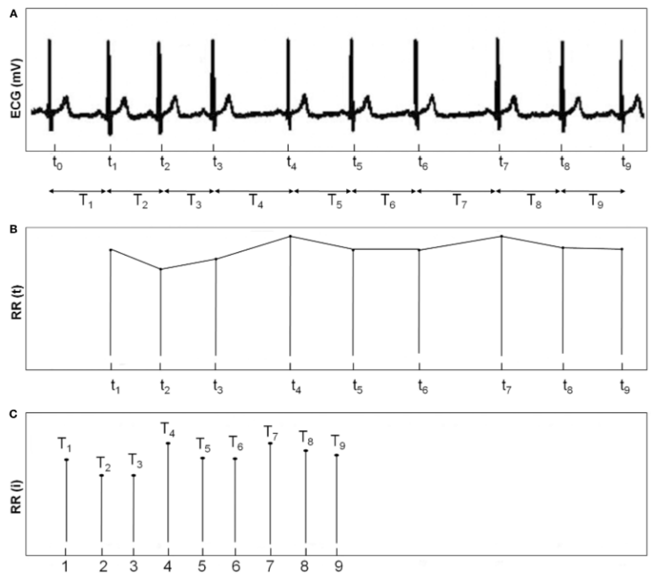

Fig. 1. (A) An ECG with an event series of R-peaks. (B) Interpolated RRi time series. (C) RRi time series [15].

HRV, RR, and O2 levels are heavily studded with machine learning techniques to analyze health markers and predict future human wellness issues [8 – 10]. At the same time, biometric security as a whole has been studied for decades and will only keep growing as research filed as security becomes a larger issue, and consumer devices incorporate more biometric features. [11].

Merging dynamic biometric security and heath wearables data is a relatively undeveloped area creating an opportunity for advancement. Initial research proposed using HRV as a sole marker for authentication. In "*Heart-Based Biometrics and use of Heart Rate Variability in Human Identification Systems* [12]" Akhter et al. delve deep into the biological aspects of HRV and propose a user authentication classifier using various HRV features and analysis techniques. The paper's main sections involve the hardware developed to monitor HRV while not utilizing existing consumer smart devices to track this. The authors produced an initial accuracy of 82% using a KNN classifier in their testing set [12]. While they do an admirable job analyzing the HRV dataset, the testing results leave room for further exploration and validation. Our paper's main contributions show how we can incorporate more biometric function data while still using data conceivably derived from popular consumer products and improving the type of classifier proposed by the authors.

B. Path Prediction Within a WSN

There are multiple challenges faced which attempting to predict traffic load or mobile user paths throughout a WSN. First, we need to be able to estimate the location of the user, in "*Location Tracking in a Wireless Sensor Network by Mobile Agents and Its Data Fusion Strategies* [16]" Tseng et al. propose a method of determining user location within a WSN by detecting when a user falls within the range of a sensor. This sensor will then notify nearby sensors to start looking for the mobile agent. Once three or more sensors can detect the user, we now have a triangulated area that the user must be within, and as the user passes outside of one of the sides of this area, sensors will then know which other sensor to notify to start tracking forming a new triangular area. Our model will simulate this implementation as the user moves around the WSN area. The user will always be within range of four sensors in a grid layout to track the area the user must fall within.

In "*Object Tracking Based on the Prediction of Trajectory in Wireless Sensor Networks*" Shen et al. take a concept similar to this one step further and utilize trajectory to predict the path of the user beyond the location of the agent at any given time. Our implementation will be similar to this idea as we are utilizing information about where the user has been to help determine where they are going.

IV. Implementation

A. Health Metrics

Our model's proposed implementation will take time-series data from HRV, RR, B02, and ECG datasets. Since few consumer devices currently support all the sensors necessary to read these biological systems, we merged multiple datasets into a single dataset containing all four desired inputs. This method gives us the ability to generate data without sacrificing testability as no such dataset exists that contains all four core features that we need.

TABLE II. Training Dataset Header With All Health Based Sensor Features

USER_ID	TIME_S	HR	PULSE	MEAN_HRV	MEDIAN_HRV	RR	RR_SIGNAL	SP_02	MEAN_ECG	MEDIAN_ECG
1	1	94	93	0.8818922	0.885369	25	0.36852	97	0.812489	0.87647

1) Heart Rate Variability:

HRV is the variance in time between the beats of the heart. For example, if the heartbeats 60 beats per minute, it is not beating exactly once per second. Within that minute, there will be a variance in time between each beat. These periods between each beat are called R-R intervals (RRi), named from the heartbeat's R-phase measured in spikes when reading an ECG (Figure 1). However, most consumer wearables use light-sensitive photodiodes to detect the amount of blood flow to measure RRi and calculate HRV.

Our HRV simulation takes RRi data from the SWELL knowledge work data set [13]. The original intention of this dataset was to measure stress responses for office workers throughout their workday. These measurements work well for a standard biometric authentication required situation as it has a good selection of participants going through daily activates without any extreme variations in heart rate. The SWELL-KW dataset includes each participates RRi peak four times a second over three hours.

Now we can take this data and calculate an RRi mean and median peaks that determine an average variability among the readings. This period can vary based on how HRV is measured. For this experiment's purposes, it makes sense to measure across a single second as this matches the other sensor data nicely.

2) Respiratory Rate, ECG, & Blood Oxygen:

The rest of the data comes from the MIMIC II waveform medical database [12], specifically a subset of the data that contains ECG, Pulse O2, and Respiratory Signal data. This dataset is from an extensive study of 46 individual's physiological signals and contains some of the most representative data from all the sensors proposed in a future health tracking wearable that combines all these features.

Each individual has sensor data split up among two datasets. The Numeric dataset contains pulse, RR, and 02 levels recorded each second. Where the Signals dataset contains ECG signal data recorded at 125 Hz. Like the HRV data, we took the Signals dataset and compressed the signals into the recordings' average and median over a second.

We have a good representation of 46 individuals' HRV, RR, B02, and ECG data with these datasets. Using this, we created a scrubbed, merged, and normalized dataset for each user, and combined them into one. Table II shows the health features available in our final dataset. We can now take this data and pair it with out movment simulation for each user.

B. Path Prediction

TABLE III. Training Dataset Header With All Location Based Features

USER_ID	TIME_S	X	Y	X_PREV_1	Y_PREV_1	...	X_PREV_5	Y_PREV_5	FUTURE_LOCTION
22	180	113.034	62.398	111.786	64.234	...	80.981	70.301	24,33

To simulate movement through a WSN, we utilized the BonnMotion mobility scenario generation tool [18]. In the scenario configuration, the boundaries of our WSN are set to a 2D square grid 200 meters wide. We generated the motion of 46 individual users using the Random Waypoint mobility model. This model enables unique characteristics of the movement, destination, speed, and direction for each user. We then exported the movement data from the tool and loaded it into our dataset, matching movement for each user to individual health metrics at every given second in our total timeframe.

To utilize information about the user's path to help indicate where the user is going, we will store the user's current location and their previous location at one-minute intervals for the past five minutes in every row of the data frame. Using this data, we have the estimated (X,Y) coordinates in the WSN at every second, and we can utilize this to predict where the user is going.

We break up our WSN area in a square grid layout of 64 by 64 WSN nodes to achieve this. Each arrangement of four WSN nodes will form an set regions $(A1, A2, A3, ...An)$. Each area is then assigned a label based upon the row and column regarding the physical location in the network. In Figure 2, we have created a visualization of our simulated network. Each dot represents a mobile agent in the network, and the red labels represent an area and location formed by the range of four nodes in the network.

Finally, to create our training dataset, we can take the user's location five minutes into the future from our current location and see which area they fall into can set the label as our classification target. Ultimately we are left with a location dataset containing all the features shown in Table III, and finally, we can combine this with our health metrics dataset to create a complete dataset of 46 users' health metrics and location over 480 minutes.

V. Findings

Using our health metrics and location datasets, we created a final aggregated dataset and tested the effects of adding the various feature data. Utilizing the sklearn python library, we ran the following classifiers with optimized hyper-parameters, random

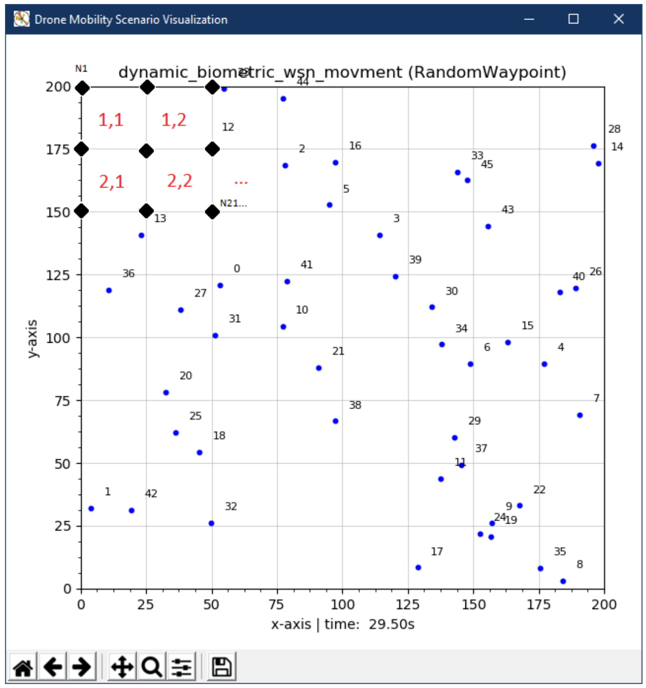

Fig. 2. A vizualization of the mobile agents movement through network. Black triangles represt a WSN node. Blue dots represt a user's current position. Red labels represent the label assigned to the area formed by four nodes.

forest, support vector (SVC), k-nearest neighbors (KNN), decision tree, multi-layer perceptron (MLP), Gaussian Naive Bayes, and quadratic discriminant analysis. For biometric authentication we targeted the USER_ID feature and for path prediction our target was FUTURE_LOCTION.

1) Dynamic Biometric Authentication Accuracy:

Looking at the results (Table 3), we can see clearly that basic HRV features alone may not be enough to determine biometric identification accurately. Adding RR and ECG data increases classifier precision by an average of 17.57%, while including 02 sensor data increases this advantage to 20.42%. Finally adding in all health features and our WSN location based data improves this by an average of 28.14%. The most improved classifier overall being the multilayer perceptron neural network, which improves by a massive 45% over standard HRV data. As expected, decision trees do not improve much when adding additional information as these perform best at making predictions rather than classifying existing data. In our scenario, false positives (authenticating an invalid user) would be more harmful than false negatives, making precision a crucial score.

It is no surprise that adding additional feature data to a machine learning model improves classification accuracy. The question becomes, can we predict that if a consumer device tracks these various features, will this be enough for biometric authentication? Using our highest performing model, the random forest classifier using all sensor data can achieve a respectable 99% user identification precision and recall. Before anything is determined, we need to keep in mind how an implementation of this might exist. Our test compiles feature data every second due to the limited period we have for each individual. In a real-world scenario, the user would wear their device most of the day and only need to run the prediction at the time of authentication. Tuning the data aggregation and model updates would be vital to implementation. Nevertheless, this would likely improve our overall accuracy. Another critical consideration is that a wearable would only need to predict a user is still the same user across time. Our example is a worst-case scenario when comparing a user to a large number of other users. With a relatively little amount of tuning, we can achieve a solid 0.98 precision-recall score. When accessing sensitive data such as financial or medical user information, this false positive rate may be too high. Though, as a backup factor in multi-factor authentication, this makes an attractive solution.

Initial results using only HRV data falls within the range of the expected of 82.22% as found in *Akhter et al.* [12]. Considering that their model was trained on 81 subjects and extracted ten HRV features for their KNN classifier, our HRV only model underperforms a bit by comparison. Our random forest HRV classifier is -3% from their KNN accuracy and our own KNN classifier trails by -9%. However, this is good news as it suggests that our HRV only model has room for improvement but using the additional sensor information sees improvements beyond that.

TABLE IV. Comparison of Sensor Data on Biometric Classification Accuracy

Dataset	Model	Precision	Recall	F1	Diff
HRV	Random Forest	0.79	0.79	0.79	-
+RR+ECG	Random Forest	0.94	0.94	0.94	0.15
+RR+ECG+B02	Random Forest	0.98	0.98	0.98	0.19
+WSN Loc	Random Forest	0.99	0.99	0.99	0.20
HRV	SVC	0.68	0.67	0.67	-
+RR+ECG	SVC	0.89	0.89	0.89	0.22
+RR+ECG+B02	SVC	0.97	0.97	0.97	0.30
+WSN Loc	SVC	0.99	0.99	0.99	0.32
HRV	KNN	0.74	0.73	0.73	-
+RR+ECG	KNN	0.85	0.85	0.84	0.11
+RR+ECG+B02	KNN	0.94	0.94	0.94	0.21
+WSN Loc	KNN	0.99	0.99	0.99	0.25
HRV	Decision Tree	0.2	0.27	0.19	-
+RR+ECG	Decision Tree	0.26	0.29	0.25	0.6
+RR+ECG+B02	Decision Tree	0.2	0.23	0.18	-0.1
+WSN Loc	Decision Tree	0.26	0.28	0.23	0.04
HRV	MLP	0.47	0.47	0.44	-
+RR+ECG	MLP	0.73	0.71	0.71	0.27
+RR+ECG+B02	MLP	0.87	0.86	0.86	0.42
+WSN Loc	MLP	0.91	0.91	0.91	0.45
HRV	Gaussian NB	0.54	0.56	0.54	-
+RR+ECG	Gaussian NB	0.77	0.77	0.76	0.22
+RR+ECG+B02	Gaussian NB	0.9	0.88	0.88	0.34
+WSN Loc	Gaussian NB	0.90	0.90	0.90	0.36
HRV	Quadratic	0.62	0.63	0.62	-
+RR+ECG	Quadratic	0.82	0.82	0.82	0.20
+RR+ECG+B02	Quadratic	0.87	0.82	0.80	0.18
+WSN Loc	Quadratic	0.97	0.97	0.97	0.35

**The first row in each section indicates the baseline performance of using only heart rate data. The next three rows show the improvments made by adding additional sensor data to the HRV data.*

2) *Predicted Path Classification Accuracy:*

Next, in Table V, we can see the results of running our classifiers targeting the FUTURE_LOCATION feature, which predicts an area of 4 WSN nodes the user will be within five minutes from their current position. The first row in each section indicates the model's accuracy using only WSN location-based data and no health tracking metrics. Then the next row shows the difference adding in the health tracking info makes to the accuracy.

The results for path prediction are less impactful than our previous look at user identification. We can see our highest performing model uses the random forest classifier with an F1 score of 0.91, which is a good result on its own however our theory that adding in health tracking metrics shows a marginal 1% improvement over the location only based model. Our most significant improvement came from the MLP model, which increased by 29%. However, this model was not a great performer using only location data, so the improvement does not mean much, especially considering the average improvement across all models is 7%.

Ultimately, adding in health metrics to location-based data does not significantly improve path prediction using our implemented methods. However, in this highly simulated data environment, some nuances of repeated patterns of real users reacting to their environment may be missed in the health metrics.

VI. Future Works

Although this paper's work has shown improvements over using a single feature in dynamic biometric authentication and small improvments in path prediction, we believe that this is still an area of research with much room to grow. Various IoT-enabled wearables exist with the sensors required to obtain the data proposed in this paper. In the future, as health monitoring wearables improve and add more functionality, taking another look at using real data would lead to further discovery. The practical software and user experience implementation of this idea has not been attempted in consumer devices yet. Work still needs to be done in the area of software implementation.

There will be a need to find the optimal rate of aggregating the sensor data. Another consideration is how well authentication will perform when the user is under particular stress, which affects all the data mentioned. Should data be combined with a centralized model or exist only locally? How will the initial validation period build the model for the user? How does this method compare to other types of biometric security? As we can see, there is an endless amount of work left on the subject, and this is all before we have any mainstream devices implementing features like the ones proposed here. Once more data of this type of use case exists, many more discoveries will be made.

TABLE V. Comparison of Sensor Data on Predicted Path Classification Accuracy

Dataset	Model	Precision	Recall	F1	Diff
Location	Random Forest	0.90	0.90	0.90	-
+Health	Random Forest	0.92	0.91	0.91	0.01
Location	SVC	0.67	0.69	0.67	-
+Health	SVC	0.73	0.74	0.73	0.06
Location	KNN	0.85	0.85	0.85	-
+Health	KNN	0.72	0.71	0.71	-0.06
Location	Decision Tree	0.26	0.36	0.27	-
+Health	Decision Tree	0.25	0.36	0.27	0.00
Location	MLP	0.34	0.45	0.36	-
+Health	MLP	0.66	0.68	0.65	0.29
Location	Gaussian NB	0.58	0.60	0.58	-
+Health	Gaussian NB	0.67	0.68	0.67	0.09
Location	Quadratic	0.65	0.27	0.28	-
+Health	Quadratic	0.71	0.34	0.38	0.10

**The first row in each section indicates the baseline performance of using only location based data. The next row shows the improvments made by adding in the health trcking data.*

VII. Conclusion

Considering the results shown in our models, dynamic biometric security using health monitoring wearables has a promising future. Our findings saw an up to 45% gain in precision and recall by adding RR, ECG, B02, and WSN location data to our baseline HRV features. Using our highest performing classifier with all features gave us a 99% total average precision-recall. While utilizing helth based metrics in combination with WSN location based date did not show substatial improvment over purely location tracking based methods the idea leaves room for further exploration. With minimal updates to our models, and as consumer wearable technology improves, we have confidence that secure authentication methods can soon include dynamic biometrics using health monitoring wearables within a WSN.

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