Biometric Authentication and Stationary Detection of Human Subjects by Deep Learning of Passive Infrared (PIR) Sensor Data

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Abstract— Deep learning has shown to be capable of learning features from complex datasets such as in the case of biometric authentication. Biometric authentication relies on unique biological qualities to verify a user's identity against a group of potential adversaries for security purposes. In this paper, a deep learning dependent biometric authentication system based on chest motion data captured by a passive infrared (PIR) sensor, CM-PIR, is proposed. PIR sensors are cheap, commercial-off-the-shelf (COTS) components that are dependent on motion across its field of view (FoV) for accurate detection of human subjects. Thus, CM-PIR utilizes deep learning for the accurate detection of stationary human subjects, as well as for biometric authentication. CM-PIR collects chest motion data from sixteen human subjects in nine different home locations. Coefficients of Fourier transform (FFT), discrete wavelet transform (DWT), and the absolute value of an acceleration filter calculated from the raw voltage PIR values were selected as the optimal features for input to the deep learning models for biometric authentication. Pre-processing of these features included a threshold voltage range, normalization, and finally principal component analysis (PCA). CM-PIR is 94% accurate in stationary human presence detection and 75% accurate for biometric authentication using a RNN with a 90 second window size. This work provides a promising solution for stationary human detection and biometric authentication using a PIR sensor in a real-world setting.

I. INTRODUCTION

Biometric authentication is a key field of study for the application of user authentication and security. Authentication of individuals via biometrics is inherently less prone to forgery than with conventional authentication systems. PIN numbers or fingerprints for example can be copied or replicated. In the instance of biometrics (iris, fingerprint, face recognition, heart rate, etc.), these unique qualities are less prone to adversarial concerns. Biometric authentication systems generally rely on the comparison of a stored biometric in a database to a newly collected biometric. Comparison techniques often utilize deep learning to automatically learn the intrinsic features found in biometric measurements. Deep learning has shown to be an accurate method for authentication and identification of individuals based on biometrics.

Biometric authentication and identification systems have used a variety of methods for many different applications. In [1], subjects were authenticated for wearable devices based on hybrid biometrics consisting of calorie burn and metabolic equivalent of task (MET) in both sedentary and non-sedentary periods. In [2], deep learning of finger knuckles and fingernail plates accurately authenticated human subjects.

ECG signal data is a common biometric for authentication and identification. ECG signal data measures the electrical activity of the heart and is collected using electrodes connected to the skin. ECG signals are able to authenticate and identify individuals based on the unique QRS complex identified in the wave pattern. In [3], ECG signal data from the MIT-BIH database identified individuals with 99.0% accuracy with the use of a convolutional neural network (CNN). In another instance, a QRS-resampling strategy was proposed for identification purposes in [4] to handle changes in heart rate. Although ECG signal data has shown high accuracy, the reliance of contact methods for extraction of ECG signal data is a major drawback. A heart-related biometric authentication system based on non-contact measurements would be more applicable to a real-world security setting. In [5], the researchers proposed *Cardiac Scan*, a system that continuously authenticates individuals based on a heart-related biometric that was captured with a Doppler radar sensor. This system provides a non-contact method for biometric authentication; however, a Doppler radar sensor is an active sensor causing energy and health-related concerns. A non-contact, passive sensor for user authentication would address these concerns.

Passive infrared (PIR) sensors are cheap, commercial-off-the-shelf (COTS) components that are commonly deployed as motion detectors in security applications. PIR sensors detect human subjects in its field of view (FoV) through a change in infrared radiation detected across the internal pyroelectric elements. PIR sensors have the major known drawback of being unable to reliably and accurately detect stationary human subjects, as there exists no change in infrared radiation in a stationary state. Thus, false negatives result from human detection using PIR sensors. A few novel designs have been published to address this problem. In our previous work, MI-PIR was proposed to address the stationary human detection problem. MI-PIR is a PIR sensor that rotates on a motor platform to artificially induce the motion required for human detection. MI-PIR was able to achieve 99% accuracy for the occupancy classification of an office-sized room using an artificial neural network

(ANN) [6]. Furthermore, related works have published PIR sensor designs that use an optical shutter to periodically chop the FoV of the PIR sensor, which allows for detection of stationary subjects with high accuracy [7-9].

PIR sensors have also been deployed for health and security-related purposes. In [10], a 2D Convolutional Neural Network (2D-ConvNet) was 98.98% accurate in classifying simulated epileptic seizure movements from ordinary motion and absence of motion. In our previous study, MI-PIR was 93% accurate at differentiating human targets in the closed office space. [6]. Further, PIR sensors have also been shown to accurately capture the chest motion of human subjects. In [11], the resting heart rate of multiple human test subjects was estimated by applying an acceleration filter to the chest motion data captured by a PIR sensor. This work propelled an interest in using a PIR sensor for stationary human presence detection and biometric authentication.

Towards a non-contact, passive method for biometric authentication, chest motion data is captured with a PIR sensor in this work. We propose a novel biometric authentication system based on collected chest motion data from a PIR sensor, CM-PIR. CM-PIR is dependent on deep learning to learn the intrinsic features present in the complex dataset. CM-PIR is shown to be most accurate in stationary human presence detection and biometric authentication while using a recurrent neural network (RNN) with long short-term memory (LSTM) units. CM-PIR authenticates one verified individual against twelve adversaries and an unoccupied scenario in this work. Data is collected from sixteen different subjects overall, with four of the individuals being removed from analysis with a threshold voltage range applied during pre-processing. The threshold voltage ensures data collection is from chest motion and not random motion by the subjects. Further, normalization and principal component analysis (PCA) is applied to deal with overfitting of the RNN model. CM-PIR is a novel approach to biometric authentication based on the passive, non-contact methods for data collection.

The rest of this paper is organized as follows. Section II describes the methods for data collection, pre-processing, and deep learning. Section III presents the results of the work and Section IV provides a discussion for the results. Section V concludes the study.

II. Chest Motion Monitoring via PIR

Chest data motion was captured using a PIR sensor in [11]. Thus, their methods for data collection and heart rate extraction in this paper was followed in our work. In their work, a PIR sensor is placed at chest height, one meter away from the test subject. The test subject is instructed to remain motionless throughout the data collection process. The chest motion captured involves two physiological processes, respiration and heart rate. To capture solely the heart rate data, an acceleration filter with a simple Lagrange low-pass filter was applied to the raw data, accurately quantifying the resting heart rate (RHR) of an individual. The absolute value of this acceleration filter was used as a feature for deep learning in our work. The filter presented in [12] is presented below.

$$g'_2 = [1\ 4\ 4\ {-4}\ {-10}\ {-4}\ 4\ 4\ 1] \quad (1)$$

The proposed solution for chest motion monitoring with a PIR sensor includes three steps: data collection, pre-processing, and deep learning. The entire process for CM-PIR is included in Figure 1. The green steps in the flowchart are for both stationary human presence and biometric authentication, whereas the biometric authentication systems includes the additional three orange steps (concatenation, normalization, and PCA).

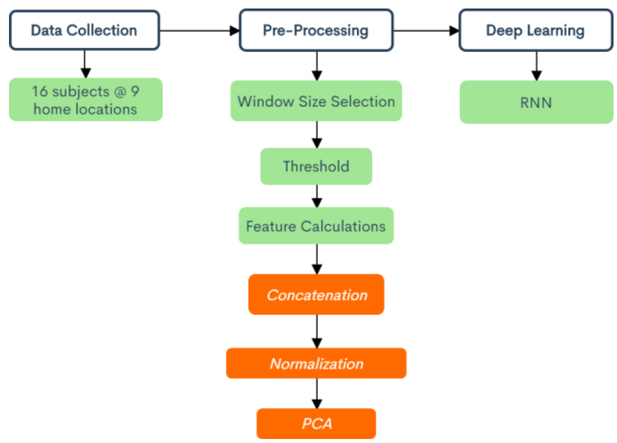

Figure 1. CM-PIR flowchart for stationary human presence detection and biometric authentication (orange).

A. Data Collection

CM-PIR consists of a PIR sensor, a microcontroller, and a PC. The PIR sensor used in CM-PIR is the Panasonic AMN 24112. This is an analog PIR sensor with four internal pyroelectric elements. The PIR sensor is connected to an Elegoo Uno R3 microcontroller and data is sent to the PC through the serial terminal of the Arduino IDE. Data is collected at a 10 Hz sampling rate, as in [11].

Sixteen individuals were recruited for data collection purposes. The age of the individuals in the study ranges from 15 to 60 years old. Three subjects are siblings and three other subjects are related to each other. Included in the dataset are six females and ten males, and data is collected at nine different home locations. With the change in ambient environments, range of demographics, and the family relation of some of the subjects in the dataset, the authentication system is hypothesized to be more robust. Table 1 provides the dataset used in this work.

Table 1. Data distribution and labels for each scenario with pre-processing and a 90 second window size.

Category	Data Collected (Samples)	Data Used (Samples)	Real Labels (Integer Labels)	Location
Stationary Detection	123	122	No Presence (0)	A-D
	443	295	Presence (1)	A-I
Biometric Authentication	123	122	No Presence (0)	A-D
	219	133	Subject A (1)	A-D
	224	162	Adversaries (2)	B, D-I
Individual Subject Distribution	123	122	No Presence (0)	A - D
	219	133	Subject A (1)	A - D
	40	34	Subject B (2)	A - C
	19	19	Subject C (3)	B
	35	32	Subject D (4)	B
	18	14	Subject E (5)	E
	9	7	Subject F (6)	E
	11	11	Subject G (7)	B
	6	0	Subject H (8)	F
	14	0	Subject I (9)	G
	13	11	Subject J (10)	G
	12	6	Subject K (11)	B
	7	0	Subject L (12)	H
	12	0	Subject M (13)	I
	13	11	Subject N (14)	F
	12	7	Subject O (15)	F
	13	10	Subject P (16)	D

B. Data Pre-Processing

Prior to input into the deep learning model, data is first pre-processed. For the purposes of implementing stationary human presence detection and biometric authentication, tests were split into selected window sizes to increase the data from the 65 continuous samples that were collected. A 90 second window size was found to be the optimal choice for both stationary human presence detection and biometric authentication. This window size is shown in the number of collected samples presented in Table 1.

To limit data captured by subtle movements from the subjects, the 90 second windows were then chopped to only include the values between 1.5 V and 3.5 V, as shown in Table 1. This process ensured that the deep learning models only learned from chest motion data, and not any other random motion captured in the data collection process. Typical motion data from the PIR sensor causes the output to generate a voltage change from 0 V to 5 V. From the initial results, chest motion data falls roughly in the 2.0 V to 3.0 V range.

Features were selected and compared for the optimal performance of the deep learning models. Based on the success of our previous work in [6], the absolute value of the Fourier transform (FFT) coefficients were calculated and used this in the model. This measures the signal power of the PIR raw voltage data in the frequency spectrum and proved to be a powerful indicator of stationary human presence. In addition, based on the work in [11], we found the absolute value of the acceleration filter to be a powerful feature for biometric authentication, as this feature is an extraction of the heart motion of the subjects. Finally, the discrete wavelet transform (DWT) of the raw voltage signal was found to increase the performance of biometric authentication and was applied as a feature. These three features were concatenated together and then normalized from zero to one with the min/max scaler provided in the sklearn import package.

Finally, PCA is utilized as a pre-processing tool to reduce the dimensionality of the input data. PCA applies an orthogonal linear transformation to transform the data to a new coordinate system that is optimized by the greatest variance [12]. Due to the complexity in the PIR chest motion dataset, and thus the normalized feature set, PCA was implemented to remove redundancies in the dataset and calculate values for the important characteristics of the feature set. Between multiple locations and a variety of individuals wearing clothing of different material items, the many potential variables in the training data are evident. These differences, coupled with a limited amount of training data, can lead to overfitting, for with a limited number of samples there can be large differences between the features learned from and the features tested on. As a result, PCA with five components was implemented on the concatenated features to calculate features representative of the entire feature set.

C. Deep Learning

In order to automatically learn the intrinsic features found in chest motion data captured by a PIR sensor, deep learning is proposed. For CM-PIR in this work, an RNN model was developed for both stationary human presence detection and biometric authentication classifications.

RNN is a type of ANN that has an internal memory and is particularly useful for the learning of temporal information. While normal ANNs learn in a feedforward approach, RNNs is trained in a recursive approach. Particularly, RNNs are useful for this purpose as they take time and sequence into account while learning from time-series data i.e. RNNs learn not just from the current input at hand but the input that has been previously learned. This is accomplished by the use of their internal state memory, which allows the models to process variable length sequences of inputs, thereby making them applicable to tasks that are not segmented in nature. Long short term memory (LSTM) units are applied to RNNs to deal with the vanishing gradient issue that decreases the performance of a RNN [13].

To develop the RNN for the CM-PIR system, we used the Keras deep learning framework, which is a simplified, high level framework built atop of TensorFlow. The complete architecture of the RNN used in this work is presented below in Figure 2.

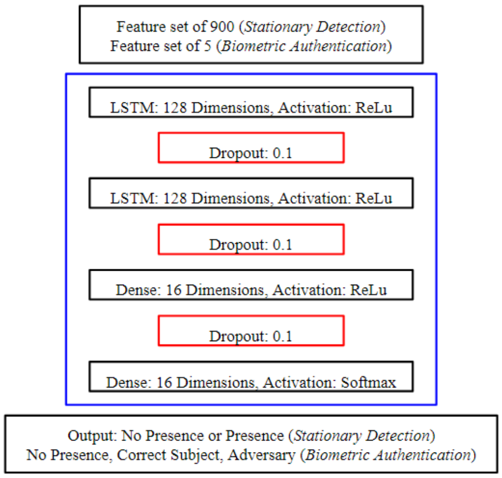

Figure 2. RNN architecture for stationary human presence detection and biometric authentication.

The RNN input tensor is composed of five features for the PCA feature set and fed into the 128 dimension LSTM unit. The feature set is then fed into a dropout layer with weight of 0.1. Every layer of the neural network except for the last is followed by a dropout layer to reduce overfitting. An additional LSTM unit of 128 dimensions, and two dense layers of 16 dimensions completes the neural network. All the layers implement the rectified linear unit (ReLu) activation function, expect for the last which uses the softmax activation function. Sparse categorical cross-entropy is used for loss and Adam is used for optimization. 125 epochs are used for both classifications.

III. Results

At a 90 second window size, there are 291 samples available for training and 63 samples available for testing, as the data was split into 70% for training, 15% for testing, and 15% for validation.

For stationary human presence detection, CM-PIR has shown 94% accuracy with the RNN model using the absolute value of the FFT as the feature inputted into the model. Table 2 presents the accuracy, precision, recall, and F1 score for the classification for the RNN result. Precision is the value of the True Positive (TP) over the summation of TP and False Positive (FP). Recall is the value of the TP over the summation of TP and False Negative (FN). Finally, F1 score is the harmonic mean of the precision and recall [14]. Figure 3 presents the confusion matrix for the RNN model, which helps to visually identify the performance of the model.

For biometric authentication, CM-PIR 75% accuracy with the RNN model. The RNN model used the PCA result of the normalized feature set containing the absolute value of FFT, the absolute value of the acceleration filter, and the absolute value of the DWT for learning. Table 3 presents the accuracy, precision, recall, and F1 score for biometric authentication using the RNN model. Figure 4 presents the confusion matrix.

Table 2. Precision, Recall, F1 Score, and Accuracy for stationary human presence.

	Precision	Recall	F1 Score	Support
0	0.86	0.95	0.90	19
1	0.98	0.93	0.95	44
Accuracy			0.94	63
Macro Avg.	0.92	0.94	0.93	63
Weighted Avg.	0.94	0.94	0.94	63

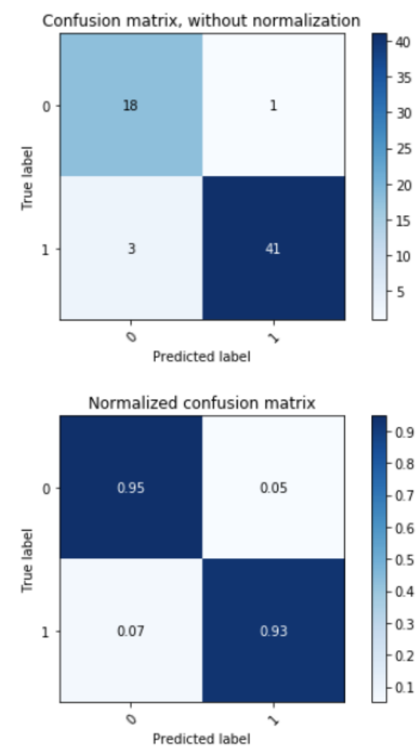

Figure 3. Confusion matrix for stationary human presence detection using an RNN.

Table 3. Precision, Recall, F1 Score, and Accuracy for biometric authentication.

	Precision	Recall	F1 Score	Support
0	0.76	0.87	0.81	15
1	0.71	0.75	0.73	20
2	0.76	0.68	0.72	28
Accuracy			0.75	63
Macro Avg.	0.75	0.77	0.75	63
Weighted Avg.	0.75	0.75	0.74	63

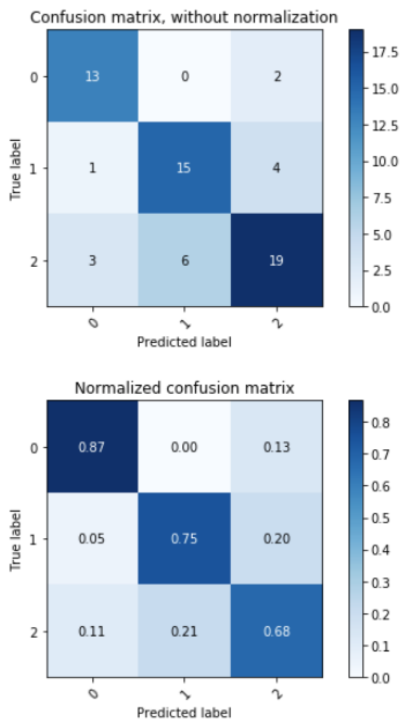

Figure 4. Confusion matrix for biometric authentication using an RNN.

IV. Discussion

PIR chest motion data has shown to be accurate in detecting perfectly still human subjects and has provided promise as an accurate method for biometric authentication. The optimal accuracy for both classifications was obtained using an RNN model. This indicates that biometric authentication using PIR sensor data has a strong dependence on temporal information; however, biometric authentication results could be improved with various proposed solutions including increased data collection, systematic data collection, and optimization of parameters.

Due to the fact that deep learning requires abundant training data to be most accurate, more data collected is hypothesized to improve the results of both stationary human presence detection and biometric authentication. In addition, although the results are more robust, a central location for data collection would theoretically improve the accuracy as there would be less ambient environments to learn from. Finally, optimization of different parameters in pre-processing and learning would help increase the accuracy for both classifications

To understand the accuracy obtained from the RNN models better, data visualization and comparison tables will be presented. Understanding the accuracy obtained via the RNN will help alleviate the black box stigma surrounding deep learning models.

A. *Stationary Human Presence Detection*

In comparison of existing stationary human detection approaches with a PIR sensor, our solution provides an alternative method. CM-PIR detects stationary humans with a traditional PIR sensor, whereas other solutions include an optical shutter [7-9] or require the rotation of the sensor for accurate results [6]. Proposed solutions in [6-9] provide a larger sensing distance, but the independence from additional architecture makes CM-PIR a promising solution for PIR stationary human presence detection.

Table 4. Stationary human presence detection comparison with existing proposed solutions.

Reference	Proposed Solution	Classification	Accuracy
[6]	Motion-Induced	Occupancy – ANN	99%
[7]	Optical Shutter	Presence - Voltage	100%
[9]	Optical Shutter	Presence - Voltage	100%
CM-PIR	Chest Motion	Presence - RNN	94%

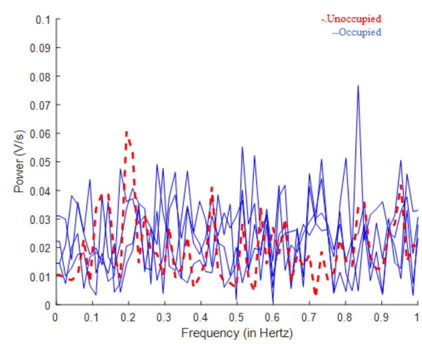

Figure 5. FFT of an unoccupied scenario (red) versus four different occupied scenarios (blue).

The absolute value of FFT, calculated from the raw PIR sensor data, proved to be an accurate feature for stationary human presence detection. This was also the case in our past work [6]. Figure 5 compares an unoccupied scenario with the first four subjects in the study in the frequency spectrum to gain better insight into the performance of the RNN model. Figure 5 provides evidence that the signal power in the frequency spectrum is greater for the occupied scenarios in comparison to the unoccupied scenario.

B. *Biometric Authentication*

There exists a variety of proposed methods for biometric authentication. The majority of authentication systems collect data at one general location, whereas in the case of CM-PIR data is collected at nine different home locations. In terms of PIR, this involves much more ambient environments to learn from, making the dataset more robust. The most comparable solution to the CM-

PIR authentication approach is *Cardiac Scan* presented in [5]. This method for authentication relies on a Doppler radar for continuous authentication, whereas CM-PIR uses a passive sensor to authenticate individuals based on a heart-related biometric. A comparison of the current solutions for biometric authentication are included in Table 5.

Table 5. Biometric authentication comparison between existing literature and CM-PIR.

Reference	Proposed Solution	Subjects - Locations	Accuracy
[5]	Doppler Scanner	78 - 1	98.61%
CM-PIR	PIR	16 - 9	75%

For biometric authentication, each of the waveforms in the normalized feature set are unique. In addition to the FFT values, the absolute value of the acceleration filter developed in [11] was inputted as a feature. To identify the impact of the heart rate on the model's performance, the absolute value of the heart rate signal for three different scenarios is plotted in Figure 6. The distinct waveform in each category provides evidence that there exists a difference in cardiac motion between the labels.

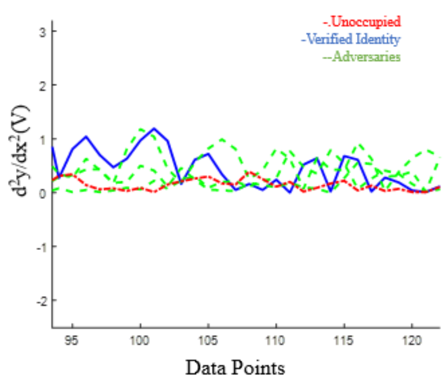

Figure 6. Modeled heartbeat of an unoccupied scenario (red), the verified user (blue), and the adversaries (green).

V. Conclusions

In this work, we have proposed a PIR sensor for stationary human presence detection and biometric authentication based on the chest motion of human subjects. CM-PIR proved to be 94% accurate in stationary presence detection and 75% accurate in biometric authentication of one subject against twelve adversaries. The results of this work show promise for a highly accurate and continuous authentication system based on chest motion biometrics. This proposed work would be ideally implemented as an authentication system at a desk location, where the PIR sensor would be at the chest height of a user. Passively capturing chest motion data for biometric authentication purposes is the novelty of this proposed system.

Acknowledgments

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