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

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Passive Infrared (PIR) Sensors

- COTS component commonly deployed in security and energy management applications
- PIR sensors detect the change in IR in its FoV
- Voltage output affected by ambient conditions
- Existing drawbacks include the inability to detect stationary occupants

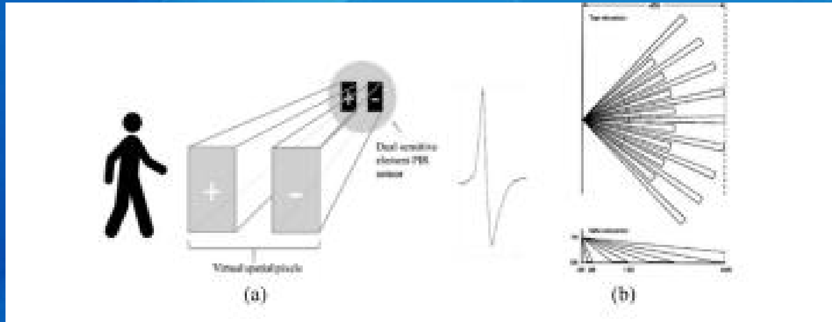


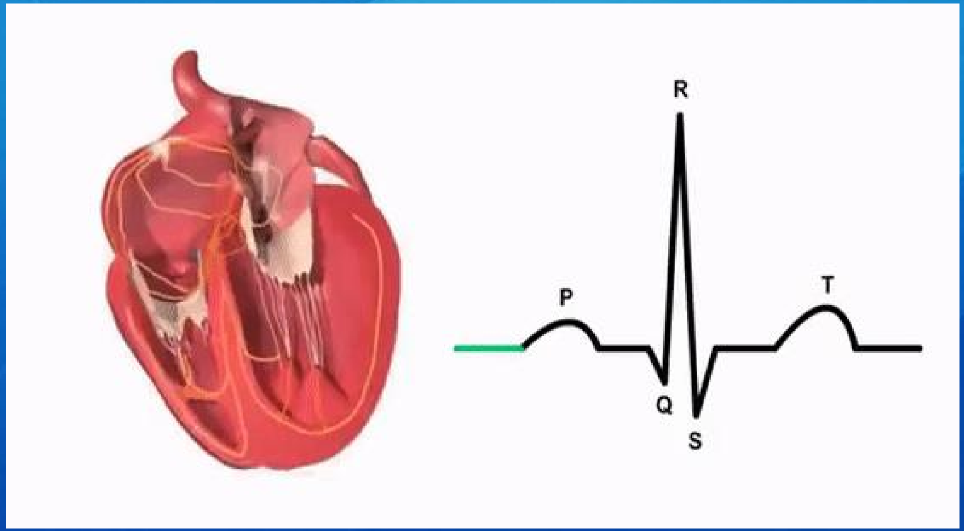
Fig. 1. (a). Human movement and the sensor output. (b). Multilayer Fresnel curtain lens its geometric coverage pattern.

H. Gami. (2017).

Panasonic AMN24112 Analog PIR Sensor

Heart Based Authentication & Identification

- Numerous techniques for authentication and identification based on heart signals
- Every individual has a unique heartbeat
- Based on size and shape of heart, opening and closing of valves
- QRS complex of ECG provides uniqueness in identification methods

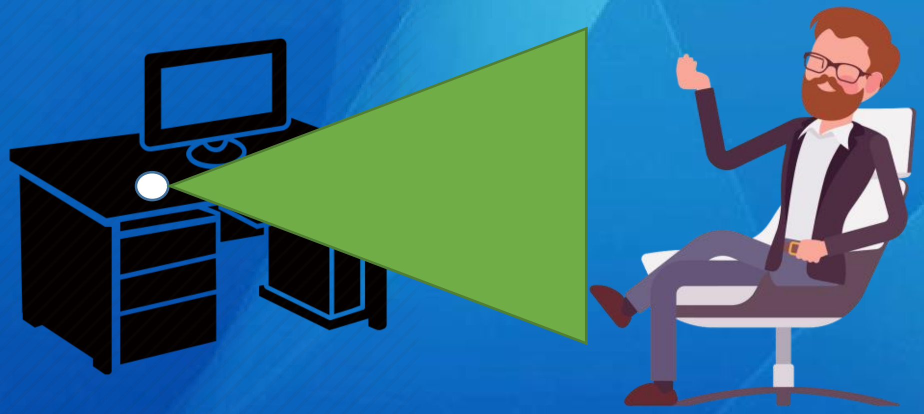


gyfcat.com

Research Motivation

Stationary Human Detection

- Detecting subjects at desk location



Biometric Authentication

- Authenticating one individual for computer security

Google Images

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Related Work

- Stationary Human Detection with PIR Sensors
  - Optical shutter
  - *MI-PIR*
- Biometric Authentication
  - Wearable device authentication based on activity
  - Finger nail plate authentication
  - ECG authentication and identification
  - *Cardiac Scan*

J. Andrews, M. Kowsika, A. Vakil, and J.Li. (2020).

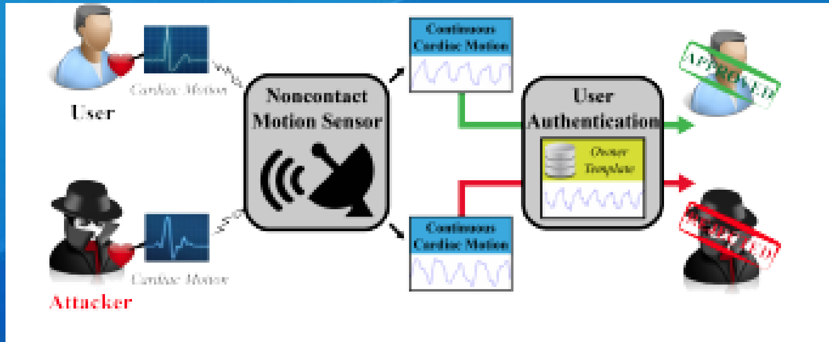

Figure 1: A novel continuous authentication method using cardiac motion captured by a non-contact radar.

F. Lin, C. Song, Y. Zhuang, W. Xu, C. Li, and K. Ren. (2017).

Proposed Solution

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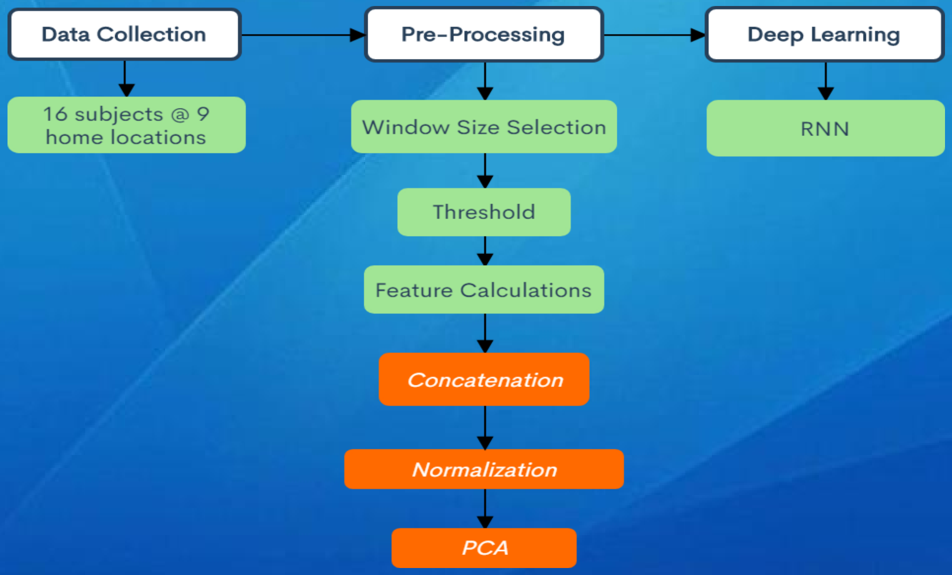
- CM-PIR
  - A stationary detection and biometric authentication system based off of chest motion collected with a PIR sensor
  - Deep learning to learn the differences between human presence and background and between verified user and all other adversaries



CM-PIR flowchart for stationary presence and biometric authentication (orange).

Chest Motion Monitoring via PIR

- "Resting heart rate estimation using PIR sensors"
  - 10 Hz sampling rate, 1 m data collection
  - Subjects remain motionless during collection
  - Extracted heart rate signal from a PIR sensor with an acceleration filter
    - $g'_2 = [1\ \ 4\ \ 4\ \ -4\ \ -10\ -4\ \ 4\ \ 4\ \ 1]$

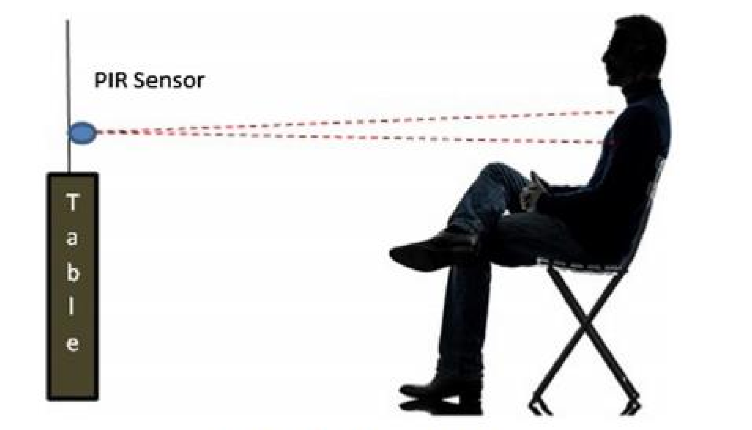


Fig. 1. Data collection experimental setup.

H. Kapu, K. Saraswat, Y. Ozturk, A. Cetin. (2017).

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CM-PIR: Data Collection

- Verified resting heart rate estimation with Apple Watch Series 3 heart rate sensor
- Followed previous paper in data collection methods
- Collected data from 16 subjects at nine different home locations
- Demographics:
    - 15 to 60 years old
    - 6 females, 10 males
    - Family relationships

Data collection setup.

Verification of acceleration filter with Apple Watch Series 3.

Data Pre-Processing

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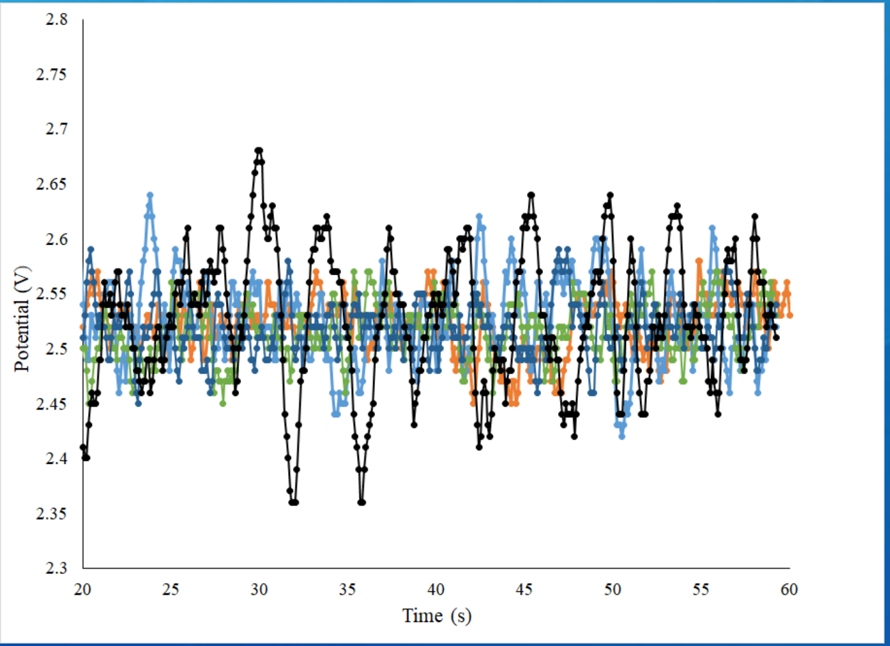
- Optimal window size selection of 90 seconds
- Threshold of 1.5 V to 3.5 V to ensure collected motion is due to chest motion only
- Feature calculations
  - FFT
  - DWT
  - Acceleration filter
- Biometric authentication
  - Concatenation of calculated features
  - min_max normalization of features
  - PCA to reduce dimensionality



Raw voltage from PIR sensor.

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

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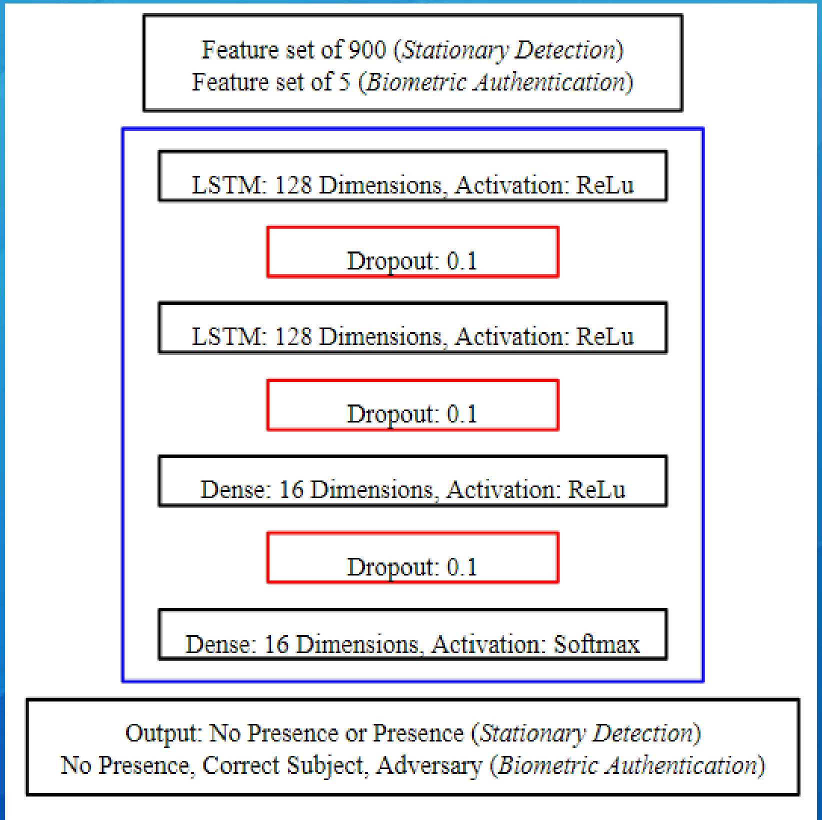
Deep Learning

- RNN deep learning model proposed
- LSTMs added for vanishing gradient issue
- Dropout layers to help with overfitting
- Built with Keras
- 125 epochs used
- 291 samples for training and 63 samples for testing



RNN architecture for stationary human presence detection and biometric authentication

Results: Stationary Detection

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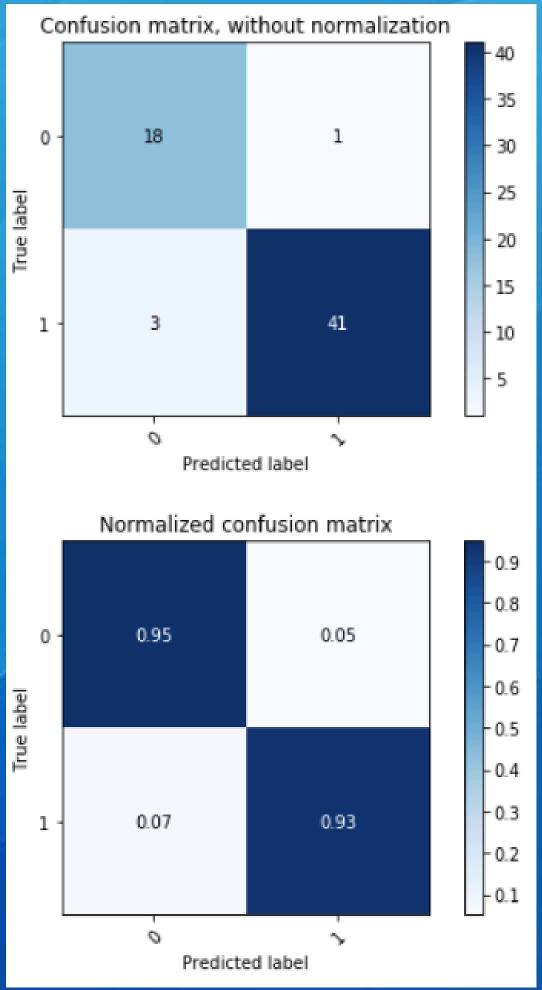
- Absolute value of FFT (signal power) as input
- 94% accuracy

	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

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



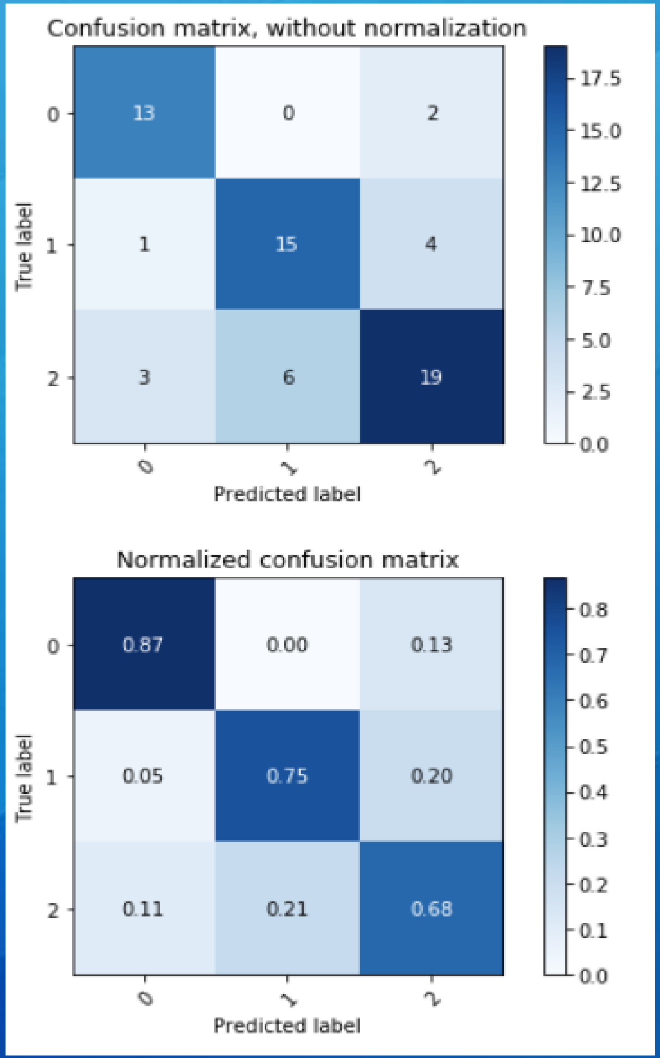
Confusion matrix for stationary human presence classification.

Results: Biometric Authentication

- Concatenated PCA feature input
- 75% accuracy

	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

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



Confusion matrix for biometric authentication classification.

Discussion: Stationary Detection

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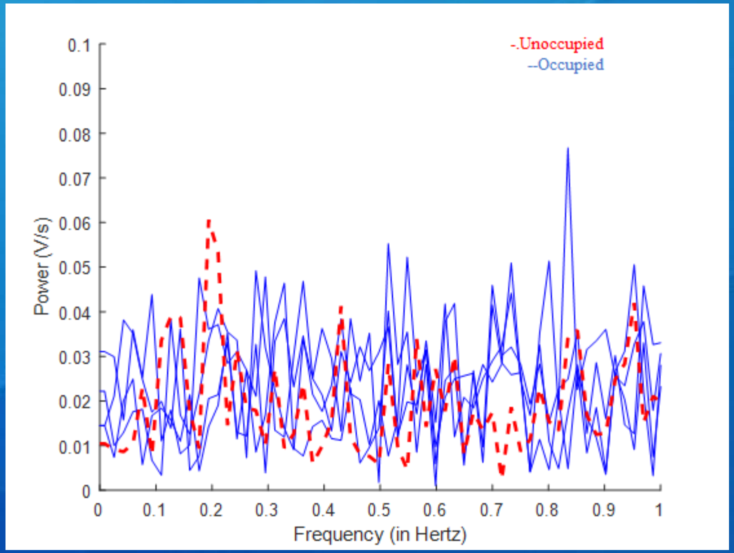
- Signal power of the chest motion proved an accurate indicator of human presence
- Multiple locations in dataset provided various ambient environments to learn from
- Simple design for stationary human presence detection
- Centralized location would increase accuracy
  - Current dataset is more robust

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%

Stationary human presence detection comparison with existing proposed solutions.



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

Discussion: Biometric Authentication

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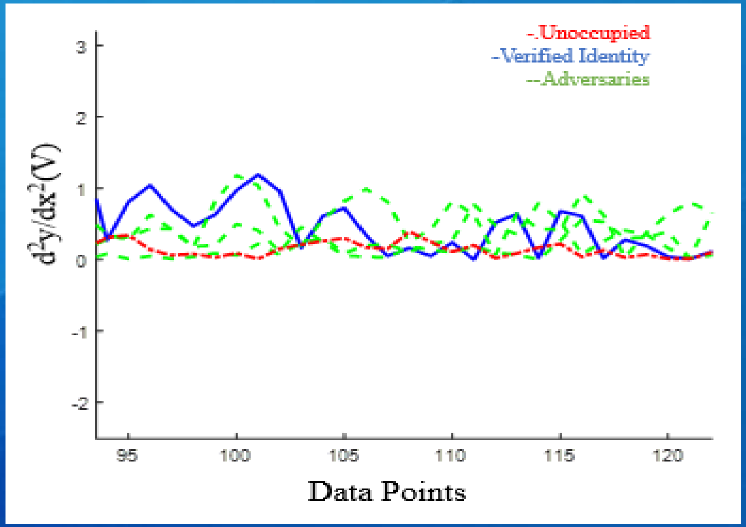
- Simple, passive, unobtrusive method for biometric authentication
- PCA helped with overfitting due to limited dataset
- Learning between individuals and various ambient conditions
- Increasing data collection would initially enhance accuracy

Reference	Proposed Solution	Subjects - Locations	Accuracy
[5]	Doppler Scanner	78 - 1	98.61%
CM-PIR	PIR	12 - 7	75%

Biometric authentication comparison between existing literature and CM-PIR.



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

Summary

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- Novel technique for stationary human presence detection
- Novel technique to authenticate individuals based on cardiac motion
- Both classifications based on data collected passively and unobtrusively with a PIR sensor
- Both classifications using RNN deep learning model with LSTM units
- 94% accuracy for stationary human presence detection
- 75% accuracy for biometric authentication

Future Work

- Increase accuracy results of biometric authentication
  - Systematic data collection and validation
  - Greater data collection
  - Segmentation of heartbeats
  - Sensor fusion with RF/WiFi modalities

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