

Review

Radar-Based Non-Contact Continuous Identity Authentication

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Received: 11 June 2020; Accepted: 11 July 2020; Published: 15 July 2020



Abstract: Non-contact vital signs monitoring using microwave Doppler radar has shown great promise in healthcare applications. Recently, this unobtrusive form of physiological sensing has also been gaining attention for its potential for continuous identity authentication, which can reduce the vulnerability of traditional one-pass validation authentication systems. Physiological Doppler radar is an attractive approach for continuous identity authentication as it requires neither contact nor line-of-sight and does not give rise to privacy concerns associated with video imaging. This paper presents a review of recent advances in radar-based identity authentication systems. It includes an evaluation of the applicability of different research efforts in authentication using respiratory patterns and heart-based dynamics. It also identifies aspects of future research required to address remaining challenges in applying unobtrusive respiration-based or heart-based identity authentication to practical systems. With the advancement of machine learning and artificial intelligence, radar-based continuous authentication can grow to serve a wide range of valuable functions in society.

Keywords: Doppler radar; non-contact measurement; respiration; heartbeat; sensor; authentication

1. Introduction

Doppler radar has been used in widespread applications, including weather forecasting, vehicle speed measurement, structural health monitoring, and the monitoring of air and sea traffic [1]. This technology has most recently been recognized for promise in healthcare applications though long term unobtrusive physiological monitoring [2–6]. The fundamental Doppler principle is illustrated in Figure 1a, where a reflected signal undergoes a phase shift due to the subtle movement of the chest surface caused by heartbeat and respiration [4–8]. Doppler radar remote life sensing of humans has been widely reported, with proof of concepts demonstrated for various applications [7,8]. This non-contact and non-invasive form of measurement has several potential advantages in medicine, especially for the monitoring of neonates or infants at risk of sudden infant death syndrome [9], adults with sleep disorders [10], and burn victims [11,12]. In addition, separation of respiratory signatures in a multi-subject environment has also been investigated [13–16]. Moreover, this form of respiration monitoring reduces patient discomfort and distress as electrodes need not be attached to the body. The inherent advantage of this unobtrusive non-contact measurement technique broadens potential applications beyond healthcare to include occupancy sensing [17] and related energy management in smart homes [18,19] and baby monitoring [20].

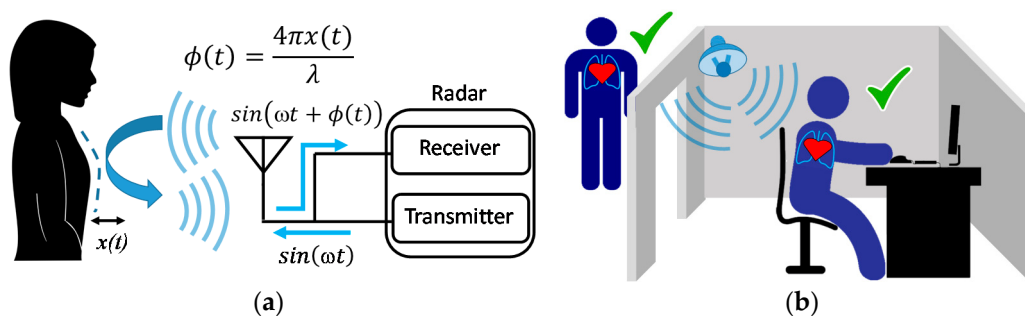


Figure 1. Basic principle of Doppler radar physiological sensing (a), and non-contact continuous identity authentication concept (b). A radar system typically consists of a transmitter and a receiver. When a transmitted signal of frequency ω is reflected its phase changes, $\phi(t)$, in direct proportion to the subtle motion.

Growing interest in physiological motion sensing through radar has led to the development of new front-end architectures [20,21], baseband signal processing methods [22], and system-level integration [21,23] to improve detection accuracy and robustness [24]. A review of recent advances in Doppler radar sensors has been reported by Li et al. [25]. One example is the application of this non-invasive technology to monitor infants for sudden infant death syndrome (SIDS) [26,27] which is one of the leading causes of infant mortality. Moreover, Doppler radar has also been implemented to monitor the health and behavior of terrestrial and aquatic animals [28–30]. Sleep monitoring is another emerging application where radar alleviates the measurement interference introduced by the conventional use of obtrusive devices such as torso straps and or spirometers [31]. A clinical study was performed to comparatively monitor patients suffering from sleep apnea using a radar sensor in conjunction with traditional intrusive sleep monitoring equipment, where the radar was found to provide stand-alone detection of most apnea events, as well as complementary detail to facilitate conventional diagnostics [31]. Furthermore, Food and Drug Administration (FDA) approval for the first commercial use of wireless, non-contact respiratory devices in the United States was granted in 2009 [32].

Beyond health sensing, Doppler radar also holds great promise to enhance system security and privacy, particularly in the area of user authentication as illustrated in Figure 1b. Existing system authentication methods predominately employ a one-off, interruptive approach, which authenticates only at the initial log-in of a session [33–36], with users actively engaging an input device or biometric reader. Such designs are vulnerable to open session exploitations and may interfere with user activity. There have been many studies focused on continuity in user authentication. Several have explored sensing technologies to acquire common physiological traits, including fingerprint [37], palm print [38], and iris [39], used to monitor and authenticate users throughout a session. Recent advancements in wearable sensors and pattern recognition further enable system architects to collect more subtle physiological patterns, such as those associated with electroencephalogram (EEG) [40], finger-vein [41], and gait [42], to verify users implicitly and continuously. Compared to these contact-based solutions, continuous authentication using non-contact, unobtrusive techniques, such as Doppler radar, can further improve system usability and expand the range of applications into domains with known privacy concerns [43,44]. For example, various visible and thermal-based cameras are employed to acquire face and gait features for user verification [45–47]. However, image-based approaches suffer from several irreconcilable dilemmas, including a lack of privacy and degraded performance under a low light ambient conditions [48,49]. Alternatively, a solution leveraging unobtrusive radar measurement of cardiopulmonary motion can be immune to such deficiencies and achieve consistent and reliable recognition under privacy-sensitive conditions [49–54].

This paper reviews recently reported research efforts in identity authentication based on the use of dedicated microwave Doppler radar or WiFi devices in a bi-static radar configuration for recognition of cardiopulmonary signatures, heart activity patterns, and respiratory features. This paper also critically evaluates the practical adoption of the proposed solutions and discusses future requirements for solving some of the remaining challenges needed for practical application.

The remainder of this paper is organized as follows: Section 2 describes cardiopulmonary diversity and physiological motion measurement. Section 3 describes research publications on the identification of people from dedicated radar and WiFi-based bi-static radar measured cardiopulmonary patterns and evaluates the applicability and limitations. Section 4 provides concluding remarks.

2. Cardiopulmonary Diversity and Physiological Motion Measurement

Doppler radar detects motion that occurs due to physiological events, including heartbeat, arterial pulsation, and breathing [55]. This physiological motion is concentrated in the thorax, where the heart and lung lie, but also includes the abdomen, which moves with respiration, and superficial pulses, which are present at any points in the body [55–58]. Torso deformation, due to respiratory effort, is a complex, three-dimensional pattern and it varies greatly with subject parameters and activity context [59,60]. Respiratory effort motion can come from one of the two primary regions: chest or abdomen, known as thoracic and diaphragmatic breathing, respectively [61]. When the heart contracts to generate the pressure that drives blood flow, it moves within the chest cavity, hitting the chest wall, and creating a measurable displacement at the skin surface that can be detected with Doppler radar [54–57]. Non-contact Doppler radar can operate at frequencies where primarily skin-surface motion is detected [54]. Changes in the volume and shape of the heart during systole move the ribs and soft tissue near the heart, causing the chest to pulse with each heartbeat [54–57]. Thus, Doppler radar systems can sense respiratory-related information as well as cardiac patterns.

It has been demonstrated in various clinical investigations that sedentary adult human subjects exhibit a diversity in respiratory pattern while awake, not only in terms of tidal volume and inspiratory and expiratory duration, but also in terms of air flow profile [52,55]. Every individual selects to exhibit one pattern among the infinite number of possible ventilatory variables and air flow profiles [55–57]. These variabilities are non-random and may be explained by either central neural mechanisms or chemical feedback loops [54,55]. In addition, each individual has a different physical size and shape of lungs, as well as different rib cage and abdominal muscle strength that contributes to the variations in breathing patterns [56].

In addition to variations in respiratory features, there is also significant variation in heart-based geometry [54–57]. In general, the human heart contains two upper cavities (atria) and two bottom chambers (ventricles) [62,63]. The successive contraction (systole) and relaxation (diastole) of both atria and ventricles circulate the oxygen-rich blood throughout the whole human body [62,63]. A diagrammatic section of the heart is shown in Figure 2a. The heart drives blood through the lungs and to tissues throughout the body [54]. Cardiac motion consists of contraction and relaxation of both atria and ventricles [58]. In one cardiac cycle, ventricles relax and passively fill with blood to 70% of the total volume from atria through the open mitral valve [58]. At the same time, the atria contract with heart muscles and pump blood. Figure 2b shows the motion of the heart through the phases of the cardiac cycle [57]. The cardiac motion cycle consists of five distinct stages including: (1) ventricular filling (VF), (2) atrial systole (AS), (3) isovolumetric ventricular contraction (IC), (4) ventricular ejection (VE), and (5) isovolumetric ventricular relaxation (IR) [62,63]. These cycles are significantly unique because of the different volumes, surface shape, and moving dynamics (speed, acceleration, etc.), and also deformation of the heart [58,62,63]. These stages or cycles are different for each person because of variations in size, position, anatomy of the heart and chest configuration, and various other factors [63,64]. It has also been demonstrated in various clinical investigations that no two persons have the same cardiac blood circulation [62,63].

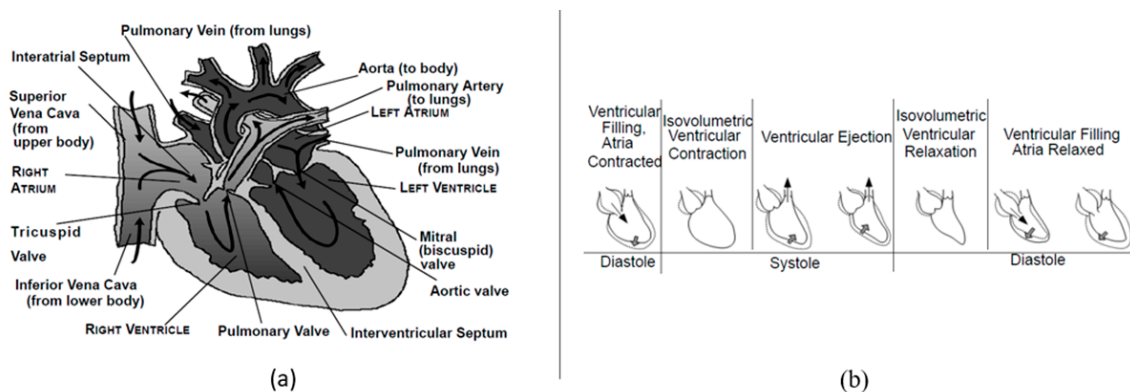


Figure 2. Diagrammatic section of the heart, (a), [55] and motion of the heart through the phases of the cardiac cycle, (b) [56]. The arrows indicate direction of blood flow.

Thus, cardiopulmonary motion is a unique identity marker for everyone, due to differences in physical organ size and shape, and muscle strength [62]. In addition, cardiopulmonary motion is controlled by central neural mechanisms or chemical feedback, which makes it extremely difficult to counterfeit or hide a living individual's motion signature [52].

3. Radar-based Continuous Identity Authentication Research

Identity authentication using microwave Doppler radar is gaining attention as it can add an extra layer of security to the vulnerable traditional one-pass validation approach (e.g., fingerprint, password, and facial/iris) [58]. Pattern recognition and unique identification are always challenging for this non-contact technology because of variations in human breathing patterns due to physical activity and emotional stress [55]. As future big data analyses emerge and machine learning algorithms improve, Doppler radar-measured physiological signals can be turned into increasingly useful data and knowledge [58]. In particular, diverse respiratory motion patterns have good potential to be used as biometric identifiers [58,64–72].

Identity theft continues to pose everyday challenges for consumers and the associated threat is increased as traditional identity authentication systems are targeted [58,69]. Traditional identity authentication methods, such as fingerprint, password, and facial recognition, all require an initial spot check at the start of user session, which potentially conveys personal information like bank account, social security number, and credit card and social networking account details [72]. In 2018, over 14 million people were victims of identity fraud in the United States [69]. Identity fraud can be significantly reduced by implementing multi-factor authentication systems, which can be further enhanced through integration of unobtrusive continuous radar-based identity authentication [58].

In this section, radar-based sensing authentication is categorized in two different ways, based either on breathing-related features, or heart-based features. Breathing motion is generally periodic, and respiratory-related features can be extracted from the time domain signature of the reflected phase signal and rate information extracted by performing an FFT [4–6]. Heartbeat motion is modulated on top of respiratory motion and the larger resulting breathing signal is dominant over the heartbeat signal [4]. This leads to a classical problem in FFT, where the stronger signal at given frequency leaks into other frequencies and can mask a weaker signal at nearby frequencies [4,5]. Generally, the radar captured signal is filtered outside the 0.005–0.5-Hz frequency band for extracting respiration information and 0.8–2 Hz for extracting heartbeat-related information. All the radar authentication research cited in this paper is focused on extracting two separate distinguishable features, based on either respiration or heartbeat. Extracting both simultaneously has the potential for stronger authentication; however, such a process may increase computational complexity. Table 1 provides a summary of published work on radar-based non-contact continuous identity authentication considered in this paper. In the next two subsections, details are provided on these two different unique features (breathing and heart,

respectively), including related identification demonstrations along with associated challenges for further development. There have also been attempts to use Doppler modulation of WiFi signals to authenticate people and this research is described in the third subsection.

Table 1. Systematic review on radar-based non-contact continuous identity authentication.

Reference Year of Publication	Hardware (RF Frequency)	Identification Features	Outcome
[52] A. Rahman et al., 2016	2.4 GHz Doppler Radar	• Respiration-based ○ Power ○ spectral density ○ Packing density ○ Inspiratory time	• Accuracy: 90% • Neural network classifier • Participants: 3
[58] F. Lin et al., 2017	2.4 GHz Doppler Radar	• Heart-based dynamics ○ Cardiac-motion cycle ○ Five points	• Accuracy: 98.61% • Support Vector Machine • Participants: 78
[68] A. Rahman et al., 2018	2.4 GHz Doppler Radar	• Respiration-based ○ Inhale-exhale area ratio ○ Minor component	• Accuracy: 95% • K-nearest neighbor • Participants: 6
[70] S. M. M. Islam et al., 2019	2.4 GHz Doppler Radar	• Respiration-based ○ FFT-based feature	• Accuracy: 100% • Support Vector Machine • Participants: 10 • Only sedentary breathing
[71] S. M. M. Islam et al., 2020	2.4 GHz Doppler Radar	• Respiration-based ○ Exhale Area: Air flow ○ Breathing depth	• Accuracy: 98.8% (normal) • Accuracy: 92% (combined) • Support vector machine • Mixture of sedentary and after short exertion breathing • Participants: 10
[72] S. M. M. Islam et al., 2020	2.4 GHz and 24-GHz Doppler Radar	• Respiration-based OSA patient ○ Peak power spectral density ○ Linear envelop error ○ Inspiratory duration	• Accuracy: 93% • OSA patient recognition • Support Vector Machine • Participants: 6
[73] D. Rissacher et al., 2015	2.4 GHz Doppler Radar	• Heart-based dynamics ○ Cardiac motion ○ Wavelet based time and frequency feature	• Accuracy: 82% • K-nearest neighbor • Participants: 20
[74] K. Shi et al., 2018	24 GHz Doppler Radar	• Heart based dynamic ○ Heartbeat signal complexity	• Accuracy: 94.6% • Support Vector Machine • Participants: 4

Table 1. Cont.

Reference Year of Publication	Hardware (RF Frequency)	Identification Features	Outcome
[75] T. Okano et al., 2017	24 GHz Doppler Radar	• Heart based dynamics ○ Power spectral density	• Accuracy: 92.8% • Autoregressive analysis • Participants: 11
[76] P. Cao et al., 2020	24 GHz Doppler Radar	• Heart based dynamics • Short-time Fourier Transform ○ Heartbeat ○ Energy ○ Bandwidth	• Accuracy: 98.5% • Convolutional Neural Network • Participants: 10 • Mixture of normal and abnormal breathing
[77] J. Zhang et al., 2016	WiFi router & Laptop	• Channel state Information ○ Gait Pattern	• Accuracy: 93% • K-nearest neighbor • Participants: 16
[78] J. Liu et al., 2020	WiFi router & Laptop	• Respiration-based Morphological pattern • Fuzzy Wavelet based	• Accuracy: 95% • Deep learning • Participants: 20

3.1. Radar-Based Identity Authentication through Respiration Related Features

One of the first attempts at radar-based identity authentication using breathing pattern was reported by a research group at the University of Hawaii, where they integrated a neural network classifier to recognize individual human beings [52]. In this work they extracted three different respiratory features (peak power spectral density, linear envelop error, and packing density) from respiratory motion measurements, as illustrated in Figure 3. A 2.4 GHz quadrature direct conversion Doppler radar system was used for this experiment, assembled from coaxial components. A data acquisition system recorded the data and post processing was performed in MATLAB (MathWorks, Natick, MA, USA). Three subjects with similar breathing rates were selected and various features were investigated, such as power spectral density, linear envelop error, and packing density, which convey the breathing energy and air flow profile related phenomena. The research concentrated on using the Levenberg–Marquardt back propagation algorithm to perform classification [52]. Figure 4 illustrates the experimental setup and reported results for training and applying a neural network classifier to recognition of the Doppler radar physiological measurements [52]. The overall classification accuracy was above 90%, which clearly illustrates that the proposed technique can be effective for this application. However, this work was limited to identifying only three participants. Another issue is that the experiment was entirely focused on measuring a single subject at a time.

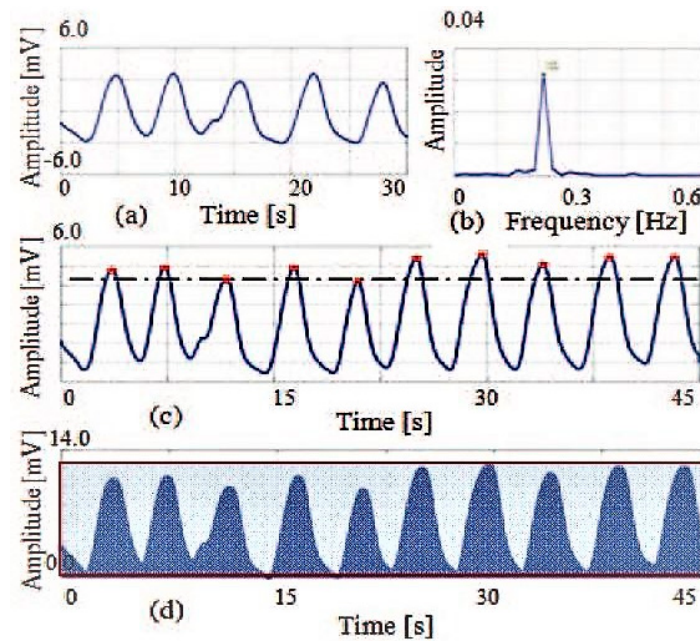
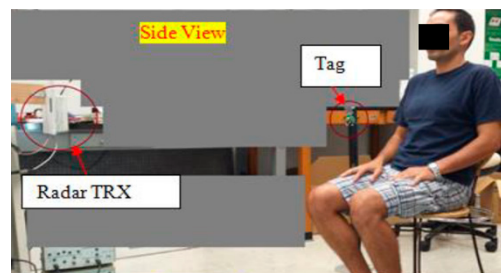


Figure 3. Radar-measured respiratory features from 30 second epochs. Pioneering efforts at recognizing subject identity from radar measured respiratory signals (a) involved extraction of three different features: breathing rate (b), linear envelop error (c), and packing density (d). Linear envelop error shows the peak distribution differences and packing density illustrates the differences in air flow profile with the inhale and exhale area episodes. Taken from [52].



(a)

TABLE II
TESTING RESULTS CONFUSION MATRIX

	Person 1	Person 2	Person 3	Success
Person 1	7	0	0	100 %
Person 2	0	13	4	76.4%
Person 3	0	0	17	100%

(b)

Figure 4. Human identification experiment using a radar system. The test set-up is shown, (a), along with the neural network recognition results, (b). From [52].

Subsequent research by the same group reported on continuous authentication based on dynamic segmentation where they used inhale and exhale area ratios of the captured respiratory pattern as unique features for six different participants [68]. Dynamic segmentation evaluates the displacement and identifying points in the range of 30–70% of both exhale and inhale episodes, which defines four boundary points of a trapezium [65]. The ratio of these two areas provides a useful feature which indicates how quickly the next cycle of inhalation begins [68]. Figure 5 illustrates the inhale/exhale area ratio features for two different subjects, which differ significantly. Based on extracted unique features,

a K-nearest algorithm was integrated to identify each person, which showed a classification accuracy of almost 90% [68]. In order to increase the accuracy of the proposed method, minor component analysis was performed on subject data sets which showed overlapping inhale/exhale area ratios. For minor-component analysis, a linear demodulation technique was employed [68]. The variation in minor component shows the radar cross section and high frequency component of respiration and heart signal modulation. Higuchi fractal dimension analysis was performed on minor components of the radar captured signals to identify overlapped inhale/exhale area ratios of subjects, which increased the classification accuracy to 95% [68]. The proposed method clearly shows efficacy. However, the number of subjects of tested was small and further investigation is required to establish larger data set functionality.

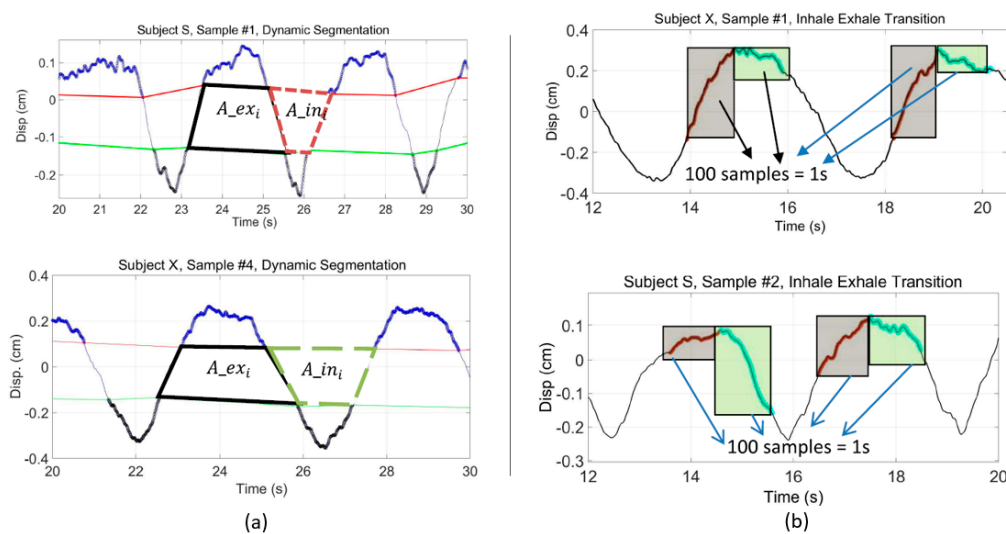


Figure 5. Respiratory pattern classifiers used for subject recognition. Dynamically segmented inhale/exhale area ratios of two subjects significantly differs, (a), as do signal patterns relating to the dynamics of breathing near the points where the inhale and exhale transition occurs, (b). From [68].

Another limitation of this approach is the reliance on two different parameters (inhale/exhale area ratio and minor component analysis). Further investigations also demonstrated that, as inhale/exhale ratio become more similar, false classification may occur [70]. To increase performance further, an FFT based feature extraction approach was applied with an integrated support-vector machines (SVM) classifier using a radial basis function [70]. The performance of the proposed system increased as the FFT based feature extraction approach contains all breathing dynamics related features (breathing rate, breathing depth, inhale rate, exhale rate and airflow profile). Figure 6 illustrates the FFT based feature extraction approach used for six different participants. As the data set and number of participants was small, continued experimentation remains needed to verify the efficacy of the FFT-based feature extraction approach. For further investigation, the feasibility of the FFT-based approach for extracting identifying features from radar respiratory traces for sedentary subjects was tested, along with measurements of the subjects just after performing physiological activities (walking upstairs) [69]. It was found that subject recognition still worked but was not as effective after performing short exertions as it was for sedentary subjects [71]. Experimental results demonstrated that, after short exertion, the dynamically segmented exhale area and breathing depth increased by more than 1.4 times for all participants, which made evident the uniqueness of the residual heart volume after expiration for recognizing each subject, even after short exertions [71]. They also integrated a machine learning classifier SVM, with a radial basis function kernel which resulted in an accuracy of 98.55% for subjects in a sedentary condition and almost 92% for a combined mixture of conditions (sedentary and after short exertions) [71]. Furthermore, they also investigated identity authentication of patients with obstructive sleep apnea (OSA) symptoms based on extracting respiratory features (peak power spectral

density, packing density, and linear envelop error) for radar captured paradoxical breathing patterns, in a small-scale clinical sleep study integrating three different machine learning classifiers (SVM, k-nearest neighbor (KNN), and random forest). Their proposed OSA-based authentication method was tested and validated for five OSA patients with 93.75% accuracy, using a KNN classifier which outperformed other classifiers [72]. This study was limited to only six supine subjects in the controlled environment of a sleep center.

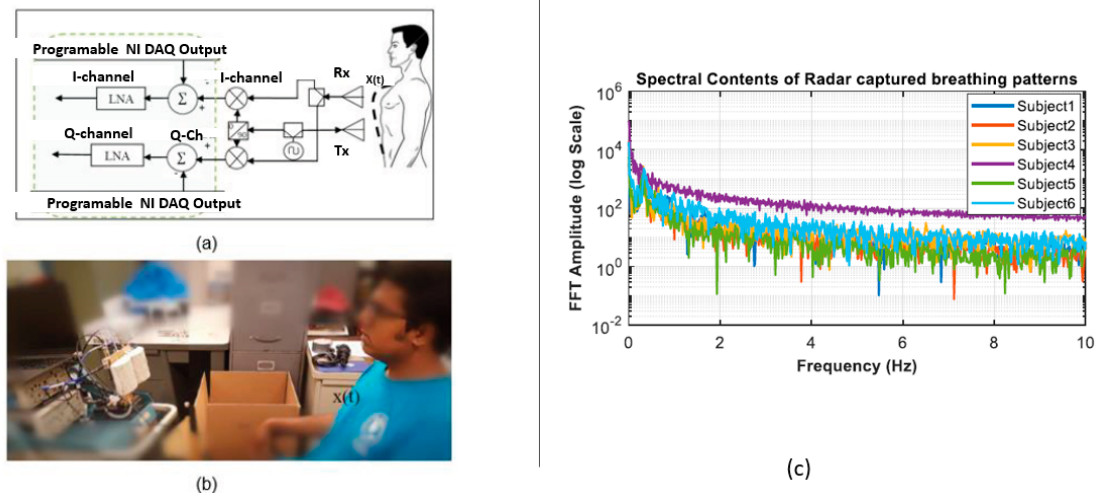


Figure 6. FFT/SVM based subject recognition study. A 2.4-GHz radar system (a) was used to measure subjects in seated position (b) and FFT-based extracted features up to 10 Hz were used to identify six different participants (c). From [70].

3.2. Radar-Based Identity Authentication through Heart-Based Features

One of the first attempts at recognizing people from their heart-based features (cardiac cycle) from Doppler radar was reported on by a research group at Clarkson University [73]. They used a 2.4-GHz heterodyne radar system from which cardiac data was extracted, and an ensemble average was computed using ECG as time reference [73]. A continuous wavelet transform was integrated to provide time-frequency analysis of the average radar-measured cardiac cycle and a k-nearest neighbor algorithm was used to recognize people with an accuracy of 82%. This was the first reported attempt for applying cardiac-based features using a cardiac-radar system as biometric identification tool [73]. The low classification accuracy occurred as there was overlap in the ensemble average of the cardiac cycle; therefore, further investigation and experimentation is required to demonstrate efficacy for more reliable recognition of subjects from radar captured signals.

A study conducted by a research group at the University of Buffalo [58] proposed a continuous identity authentication system named “Cardiac Scan”. This system used a 2.4-GHz Doppler radar transceiver with two antennas (one for transmit and another for receive functions) each having a beam width of 45° . The radar power consumption was 650 mW with a 5V-volt source and 130 mA of current [58]. The customized Doppler radar was placed in front of the subject at 1 meter [58]. Figure 7 shows the experimental set up of the proposed cardiac scan system, from which five different points were extracted from the radar captured respiration patterns which were hypothesized to fully represent cardiac motion. Based on the hypothesis the experiment illustrated that these heart-based geometry measures differ from person to person due to difference in size, position and anatomy of the heart, chest configuration, and various other factors [58]. From their experimental results, it was also clear that no two subjects had the same heart, tissue, and blood circulation system, as there were significant differences in their cardiac cycle points measured in the radar data set [58]. Figure 8 illustrates the cardiac motion marker for one segment captured from the radar respiration measurement. In this work, the user’s cardiac-motion related features were stored in the system. A SVM with a radial basis

function (RBF) kernel classifier was employed to uniquely identify different participants. A study of a 78 subject data set was reported, and the proposed system achieved an accuracy of 98.61% and a 4.42% equal error rate [58]. One of the limitations of the above proposed technique is that the complete study was performed with healthy sedentary persons and only for single-subject measurements. If subjects have cardiovascular diseases, unique identification may be problematic as the cardiac cycle would be affected. Further study is also required to verify that the proposed heart-based cardiac cycle points remain consistent after subjects perform varying degrees of physiological activity.

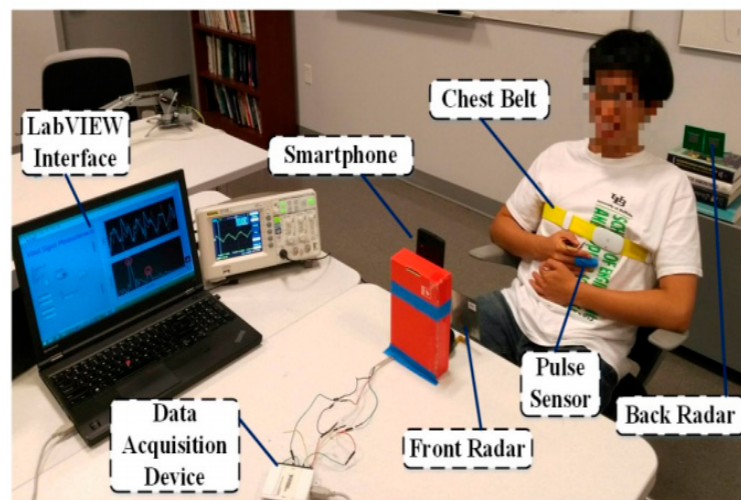


Figure 7. Experimental setup for cardiac scan continuous authentication system using microwave Doppler radar. A data acquisition device and LABVIEW interfaces were used to capture signals. A pulse sensor and chest belt were used for reference measurements. From [58].

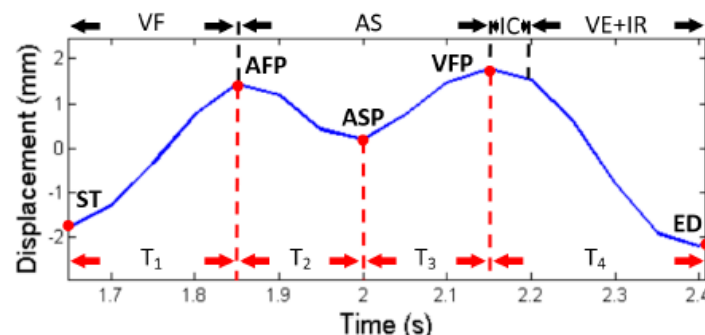


Figure 8. Cardiac motion marker. The cardiac motion cycle defined by five different points (red dots) within five different points of displacement and timing was calculated as a unique feature for recognizing people. From [58].

In another reported study, cardiac measurement of different persons was used to uniquely identify each using a 24-GHz continuous wave radar system employing six-port measurement technology [71]. Figure 9 represents the hardware setup used for this experiment. A six-port measurement system consists of two input ports and four output ports. The two input signals are superimposed to extract phase shift information due to chest displacement. This particular work focused on extracting heartbeat signal information for each participant, as the exact position and angle of the heart in the thorax, as well as the anatomy of the thorax itself, is a little different for every person due to varying tissue and muscle/fat components [74]. Due to these differences, the radar-captured heartbeat signal involved different propagation and attenuation characteristics. As each person has a different heart position and dimensions, dominant features exist in the heartbeat signal which form a complex and unique pattern. Figure 10 illustrates the heartbeat signal variation for each participant. Initially a 5-second heartbeat signal was used for identifying unique features for each participant. Integrated machine learning

classifiers were also used to recognize people. A quadratic SVM outperformed other classifiers, with an accuracy of 74.2%. To increase the accuracy, a 7-second heartbeat segment was used, which increased the classification accuracy to 94.6%. The study provides a clear indication that heart-based geometry can be used as a unique feature to identify people. However, validation for this study only included four different participants. Thus, further investigation is required for larger data sets having varying conditions, especially those involving measurements made after physical activities.

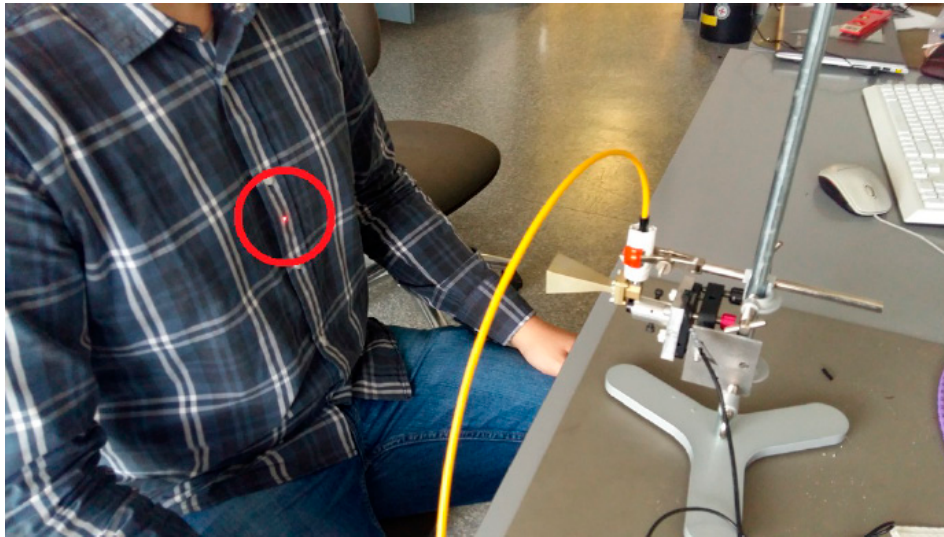


Figure 9. Experimental setup for unique identification of a human from radar captured respiration pattern which includes six-port technology. From [74].

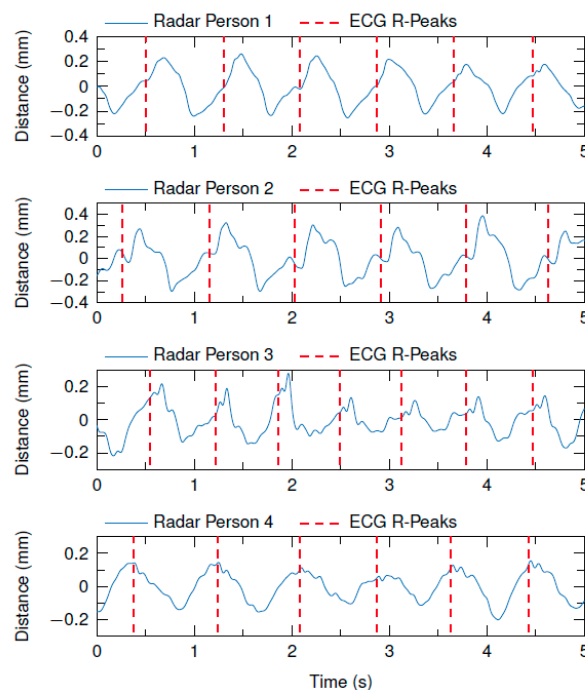


Figure 10. Heartbeat curves recorded by a 24-GHz radar for four subjects. Each signal is periodic but for each subject the pattern is a bit different which serves as a unique feature for recognition of identity. From [74].

Another study used a 24-GHz radar system to extract heartbeat related unique features to recognize eleven different participants [75]. An autoregressive (AR) model-based frequency analysis was introduced, which is superior to FFT, having a window length of 100 milliseconds, from which power spectral density could be calculated [75]. Each peak in this analysis represents the contraction and extraction of the heart. The first peak was used as a reference and then a period of 0.2 s before and after, 0.4 s, was used as a template. Template matching was used to detect all heartbeats. The average of the power spectral density was used as a unique identification number for each participant. Figure 11 illustrates the power spectral density features extracted from the radar respiration signal and PSD profile for eleven different participants. The success rate was 92.8%. The proposed method clearly demonstrates heart-based PSD feature extraction efficacy for recognizing people. However, if the position between the radar and human subject changes or the heart rate fluctuates greatly then the proposed method produces false classification. Motion artifacts and multi-subject scenarios were not considered and remain a significant challenge for this approach.

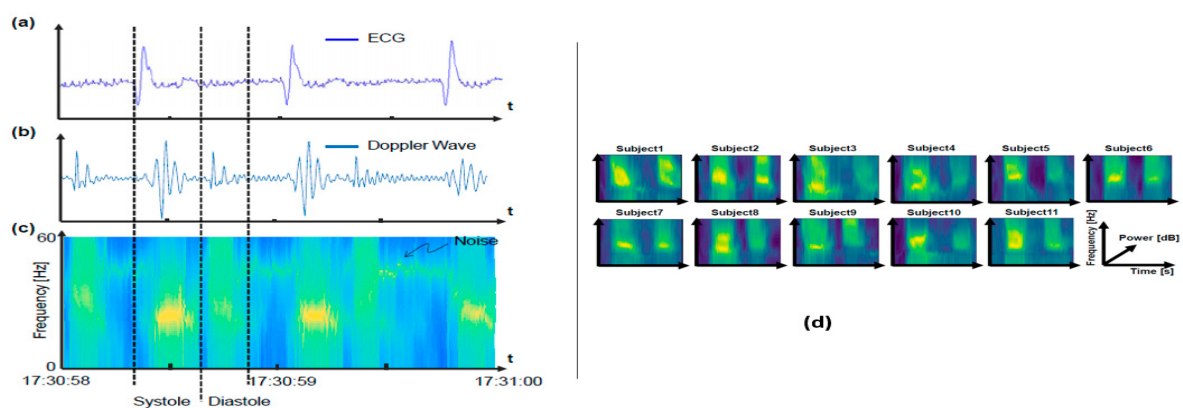


Figure 11. Measured 24-GHz heartbeat patterns for autoregressive PSD analysis based subject recognition. Measurement of heartbeats are shown for electrocardiogram (reference) (a), Doppler radar (b), PSD of Doppler sensor output (c), and (d) PSD for 15-s Doppler radar for eleven participants [75].

Recently, another study demonstrated the efficacy of radar-based identity authentication using a short-time Fourier Transform (STFT) [76]. Each person sat a 1.5 m distance and physiological signatures were recorded for about 6 seconds of the breathing pattern, using a 24-GHz continuous wave radar. An STFT was used to characterize the micro-Doppler signature of ten different participants, followed by basic image transformation methods like translation, rotation, zoom, mirror, and cropping. The STFT image was used to represent heart-based features for each different subject. A deep convolutional neural network (DCNN) was used to classify subjects based on their radar captured micro-Doppler signatures. Figure 12 illustrates the STFT images for four participants which are significantly different for each subject and include unique features for identification. From the spectrogram, three different heart-based features were extracted, such as the period of the heartbeat, the energy of the heartbeat, and the bandwidth of the signal. A deep convolutional neural network was then trained, and the resulting classification accuracy was almost 98.5%.

To extract heart-based or respiratory information, data segmentation generally plays an important role. Segments correspond to the FFT window size and should contain at least one full respiration cycle and multiple cardiac cycles [58,70]. The number of segments used for a data set also plays an important role for authentication time and accuracy [58]. Increasing the FFT window size will bring a benefit in resolution as a higher number of samples are included in the operation, but this will also increase the time delay and complexity of authentication and is not generally justified for real-time operation.

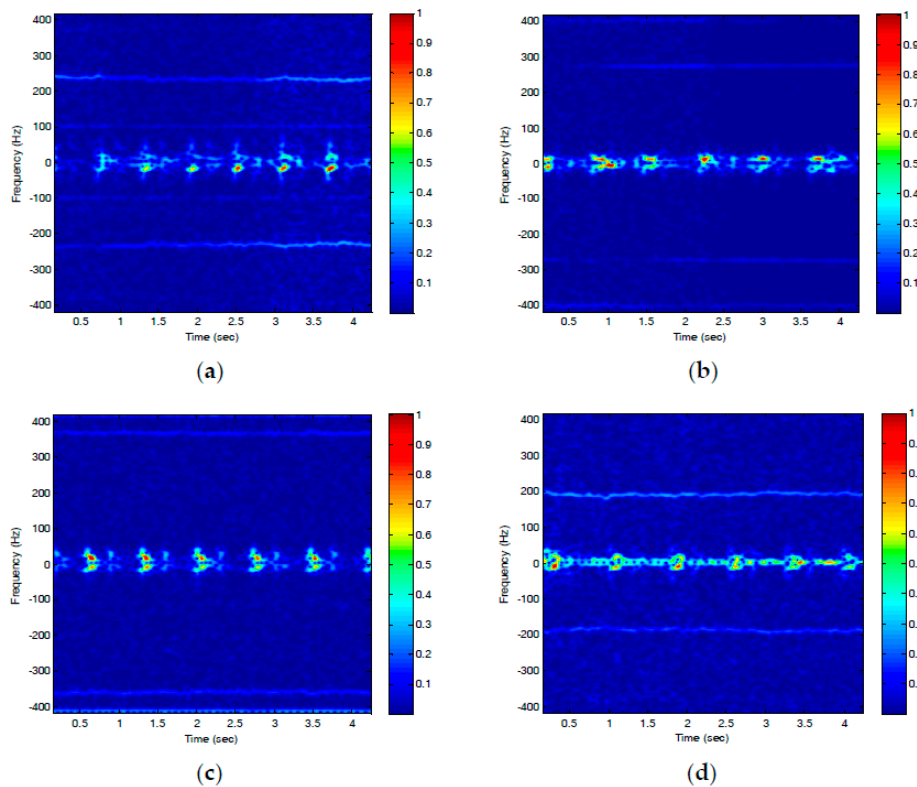


Figure 12. (a–d) Short time Fourier transform (STFT) of four different participants for extracting micro-Doppler signatures. The images for four different participants clearly have significantly different spectral content. From [76].

3.3. WiFi-ID: Non-Contact Human Identification Using WiFi Signals

Several studies in parallel seek to achieve non-intrusive continuous identity verification using off-the-shelf WiFi devices [77–81] (Figure 13). These methods leverage the fact that the majority of IEEE 802.11 WiFi protocols have the access point (AP) explicitly sending out known pilot symbols, shown in Figure 13b, prior to the data communication, which allows the receiver(s) to measure the wireless channel effect in terms of signal attenuation, e.g., receive signal strength (RSS), plus phase offset, e.g., channel state information (CSI), and cancel the channel effect for better reception. Since the wireless channel effect is the combined result of scattering, fading, and power decay with distance, it is also correlated to body movement if human subjects are present within the environment [82,83]. These studies on WiFi sensing aim to distill the physiological patterns from the channel measurements via various signal processing algorithms and utilize the patterns for continuous identification and authentication, which are briefly surveyed below.

In [79], Abdelnasser et al. proposed a non-invasive RSS based WiFi breathing estimator (Figure 14). The design leverages the fact that inhalation and exhalation can cause a perceivable periodic pattern in the RSS observed by a device positioned on the chest surface [77]. The pattern can be analyzed to characterize various breathing-related physical factors [77]. For instance, the authors examine the RSS with bandpass filtering and fast Fourier transform (FFT) to obtain the subject's breathing rate and heart rate. This effect extends to scenarios when the subject obstructs the line-of-sight (LOS) between the transmitter and the device.

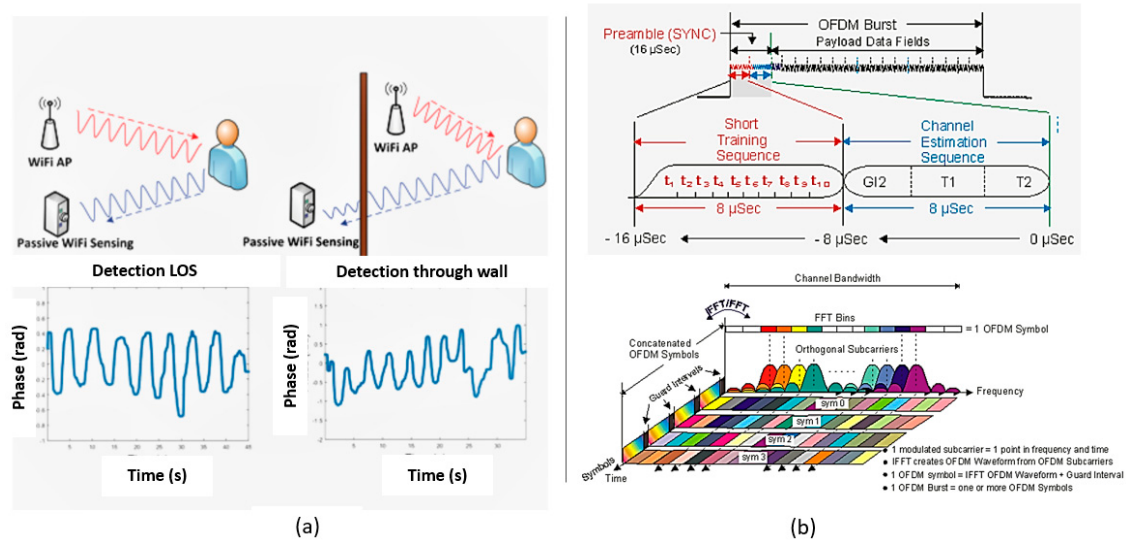


Figure 13. Vital signs sensing with WiFi signals. Passive WiFi sensing for through wall respiration detection using URSP (a) [80], exploiting the wireless channel measurements through orthogonal frequency division multiplexing (OFDM) pilot symbols (b) [82].

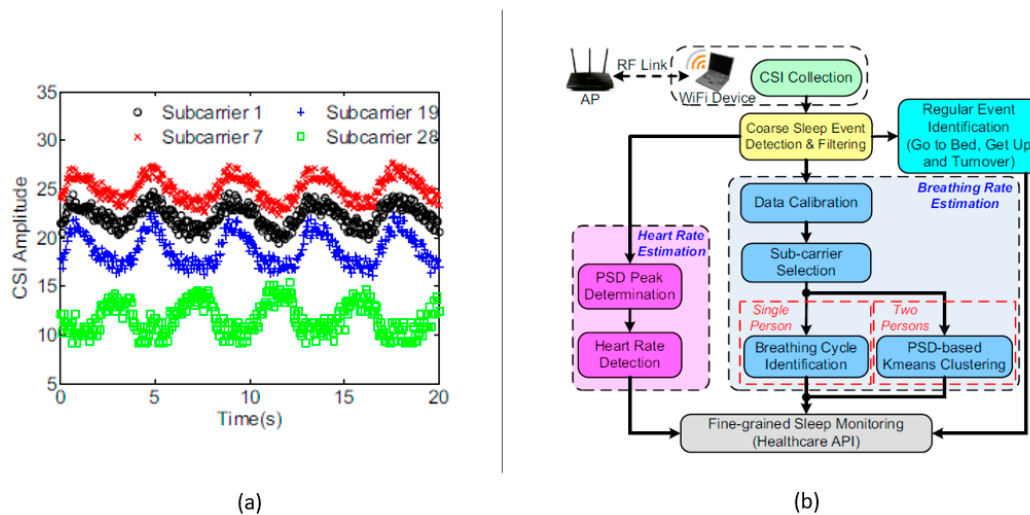


Figure 14. Wi-Fi sensing of cardiopulmonary motion. Channel state information of four different subcarriers over time during sleep study are shown (a), along with an overview of the system design used to capture respiratory biometrics (b) [79].

In [77], Zhang et al. analyzed the channel state information (CSI) to identify people within the environment. In their experiments, the orthogonal frequency division multiplexing (OFDM) pilot signal exchanged between a WiFi router and a receiver node (e.g., laptop) are exploited to extract the CSI, which can be regarded as the aggregated result of the multipath fading. A person walking within the environment would affect the multipath reflections with the particular gait pattern, thus creating unique perturbations in the CSI, allowing the system to differentiate individuals via the received WiFi signal [79].

Similarly, in [78], Liu et al. extracted fine-grained CSI of individual OFDM subcarriers from off-the-shelf WiFi devices to detect minute movements and provide accurate breathing (inhalation and exhalation) and heartbeat (diastole and systole) estimation, concurrently. The system, shown in Figure 14, utilizes multiple CSIs captured at different OFDM subcarriers to differentiate the small body movement of breathing and heartbeat. Their experiment shows that the CSI granularity in

commercial devices is sufficient to track the cardiopulmonary vital signs of one isolated person, as well as two-people in a bed, which covers typical in-home scenarios.

In [78], Liu et al. combined the CSI-based approach with a deep neural network to achieve continuous, non-intrusive, user verification, as illustrated in Figures 15 and 16. The design collects respiratory-related patterns in CSI by applying an empirical mode decomposition (EMD)-based adaptive filter, which mitigates immanent radio interference and other irrelevant body movement [81]. The resulting patterns are further processed through waveform morphology analysis and fuzzy wavelet packet transforms (FWPT) to construct unique respiratory biometrics, which are input to a two-hidden-layer neural network for user classification.

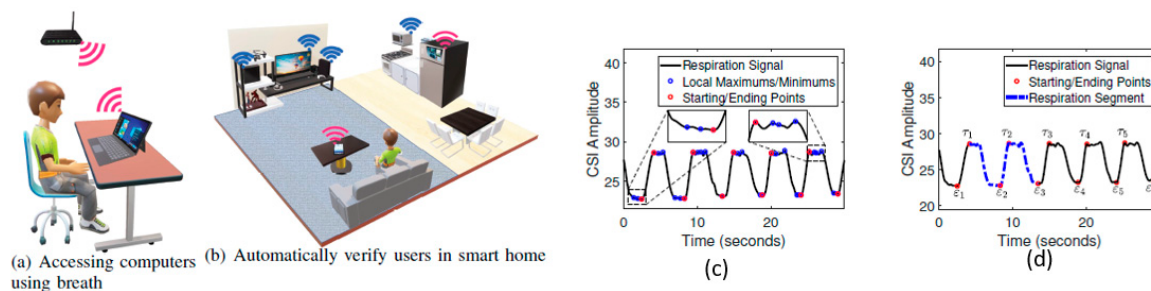


Figure 15. Example of continuous user verification using WiFi signals leveraging respiratory pattern. The concept is illustrated, (a,b), along with morphological respiratory features of captured waveforms using WiFi signals, (c,d). From [78].

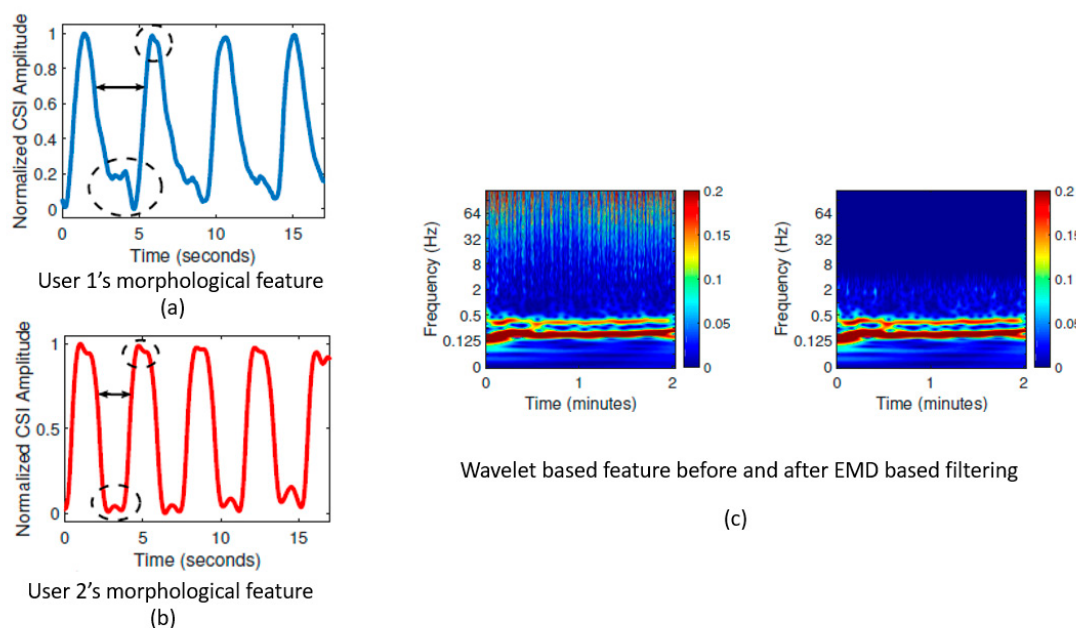


Figure 16. Waveform morphology analysis with EMD. Morphological features representing the respiratory pattern of two different participants in an experiment are shown, (a,b), along with fuzzy wavelet-based features which represent the frequency domain components of the respiratory pattern (c). After EMD filtering much of the noise and interference is removed. From [78].

Fundamentally, WiFi setups for human identification can be regarded as bistatic or multistatic radar systems, in which the transmitter(s) and receiver(s) are separated. Comparing to monostatic radar systems, such as CW radar, the transmitter(s) and receiver(s) in these configurations operate independently and lack coherency, which limits radar sensitivity and resolution. The issue is partially compensated by the packet synchronization mechanism of the WiFi protocol, which, however, introduces latency in target detection. Methods using RSS are generally less sensitive to subtle body

movement, compared to CSI-based approaches, due to the lack of phase information. In contrast, the latter exhibits less tolerance to background noise and synchronization errors. Current research to improve the reliability of WiFi-based identity verification engages the problem using a two-pronged approach. The data analytic approach aims to extract more distinguishable and consistent features from the WiFi signals using state-of-the-art machine learning or statistical learning algorithms. The device-and-spectrum approach aims to suppress the irrelevant signal and directly capture the physiological signatures by exploiting the frequency and bandwidth advantages of new 802.11 protocol family members, such as 802.11ad.

3.4. Discussion

Non-contact radar-based continuous authentication systems may ultimately resolve the trade-off between security and utility that plague existing authentication systems, provided that current reliability limitations can be overcome. Current implementations in this category are mostly experimental, with their performance unsatisfactory for practical use. Fundamentally, the difficulty is due to the narrow margin of tolerances toward false/missed detection during system authentication. Unlike other non-critical applications, false/missed detections in authentication could result in irreversible credential revocation and permanent loss of access privilege. This risk is amplified by unpredictable events and noise within a casual sensing environment. For instance, when multiple subjects present close to the sensor, identification might be challenging due to the mixture of signal reflection. Existing studies mostly focus on identification of isolated single subjects without random movement. However, if the system cannot isolate respiratory signatures reliably for multiple subjects, the identity authentication system performance will deteriorate in practice. Furthermore, methods intended to separate subjects [13] may detrimentally discard information that is relied upon for identification. Another potential limitation is that the sample sizes of existing experimental efforts are often limited. Some respiratory or heart-related features need to be validated for a large population to show their uniqueness. So far, results based on small scale studies reported by different researchers appear promising, but further exploration is required. Finally, authentication measurements are subject not only to natural environmental interference, but also to intentional subversion which poses further difficulty.

One of the major challenges in radar-based non-contact continuous identity authentication results from the motion noise produced by random body movement during respiration sensing and by the presence of multiple subjects [25]. While much research relies on the recognition and exploitation of common opportunities for analyzing time periods of sedentary physiological motion [84,85], successful Doppler radar respiration sensing during random body movement has also been demonstrated in the literature [86–88]. Prior research has demonstrated the efficacy of a Doppler radar sensor with a camera aided random body movement cancellation technique. In the associated methodology, random body movement can be mitigated by utilizing three different strategies, such as using (1) phase compensation at the Doppler RF front-end [88], (2) phase compensation for baseband complex signals [87], and (3) cancellation during demodulation techniques [86]. It has also been demonstrated that using multiple transceivers (bio-radar technique), different body movement can be cancelled [86,89]. Additionally, blind source separation (BSS), or independent component analysis (ICA), has been utilized to extract breathing rate and heart rate with the presence of two subjects [90] and to cancel random body movement [91]. Phased array radar systems with beamforming techniques have also been investigated to isolate the respiratory signature based on estimation of the direction of arrival of the subject [13,92,93]. In addition to that, frequency modulated continuous wave (FMCW) radar integrated with beam steering technique has been investigated to isolate the respiratory signatures in multiple subject scenarios [94]. In addition, a portable handheld radar-based cardiopulmonary monitoring system has also been investigated, where motion compensation was performed by integrating the EMD technique to reliably extract the respiratory information [22,95,96]. These proposed solutions have demonstrated the efficacy of radar-based respiration sensing techniques under random body movement or in the presence of multiple subjects. Future non-contact radar authentication research will likely involve

the integration of these and other motion-noise suppression techniques to create a robust real-world continuous authentication solution.

4. Conclusions

This paper reviews principles and research relating to the identification of people from radar captured cardiopulmonary patterns. Over four decades, there have been significant advancements in theory and engineering directed to enable biomedical Doppler radar for healthcare monitoring. However, achieving persistent and reliable measurements and recognition of multiple targets remains the primary obstacle toward a practical implementation. On this front, there are several promising results attained under controlled laboratory environments. However, large-scale studies for varying physiological conditions are yet to be conducted, and solution spaces yet to be explored. With recent advances in machine learning and artificial intelligence, human identification based on breathing patterns and heart-based dynamics demand further investigation for the potential to form a sound alternative to traditional biometric systems. By overcoming this fundamental challenge, microwave Doppler radar sensors can become common devices for daily activities monitoring. Continued experimentation and further exploration are required to bring this unobtrusive form of identity authentication system into real-world application.

Author Contributions: Conceptualization, S.M.M.I.; original draft preparation and writing, S.M.M.I.; review, editing, supervision, and fund acquisition, O.B.-L., Y.Z., and V.M.L. All authors have read and agreed to the published version of the manuscript.

Funding: This work is supported in part by the National Science Foundation (NSF) under Grants IIP-1831303, Grant IIS-1915738, and CNS-1948568.

Acknowledgments: The authors would like to acknowledge the assistance of graduate students in the Biosensing Laboratory at the Electrical Engineering Department at the University of Hawaii.

Conflicts of Interest: Boric-Lubecke and Lubecke founded Adnoviv, Inc., a company that is the prime awardee of an NSF STTR grant that partly supported this work. The University of Hawaii has granted a license to Adnoviv, Inc., to commercialize Doppler radar technology for occupancy sensing purposes, and owns equity in Adnoviv, Inc.

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