Radar-Based Non-Contact Continuous Identity Authentication

Subjects: Computer Science, Artificial Intelligence

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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.

Radar Identity authentication Non-contact sensing

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][3][4][5][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][5][6][7][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][14][15][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].

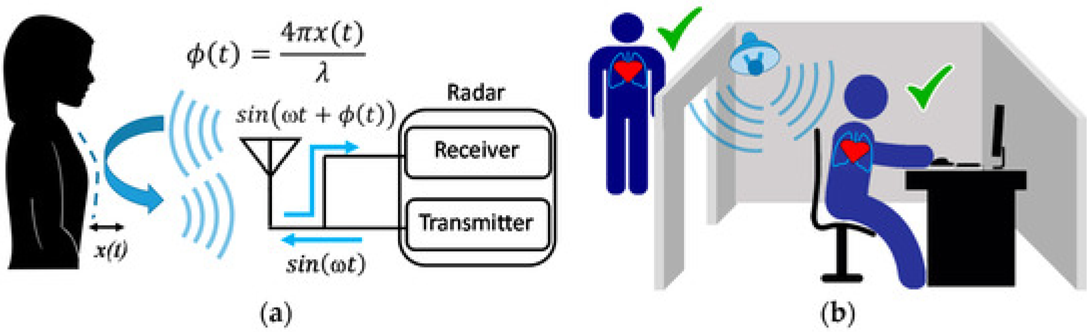

Figure 1. Basic principle of Doppler radar physiological sensing (**a**), and non-contact continuous identity authentication concept (**b**). A radar system typically consists of a transmitter and a receiver. When a transmitted signal of frequency ω is reflected its phase changes, φ (t), in direct proportion 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][29][30]. Sleep monitoring is another emerging application where radar alleviates the measurement interference introduced by the conventional use of obtrusive devices such 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 Unites 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][34][35][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][46][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][50][51][52][53][54].

2. 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][65][66][67][68][69][70][71][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][5][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 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

Reference Year of Publication	Hardware (RF Frequency)	Identification Features	Outcome
			• 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
[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	• Accuracy: 98.5% • Convolutional Neural Network

Reference Year of Publication	Hardware (RF Frequency)	Identification Features	Outcome
		• Short-time Fourier Transform ○ Heartbeat ○ Energy ○ Bandwidth	• 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
[52] [78] J. Liu et al., 2020	WiFi router & Laptop	• Respiration-based Morphological pattern • Fuzzy Wavelet based	• Accuracy: 95% • Deep learning • Participants: 20

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research al human ity, linear 2.4 GHz n coaxial MATLAB 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–Marquadrt 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.

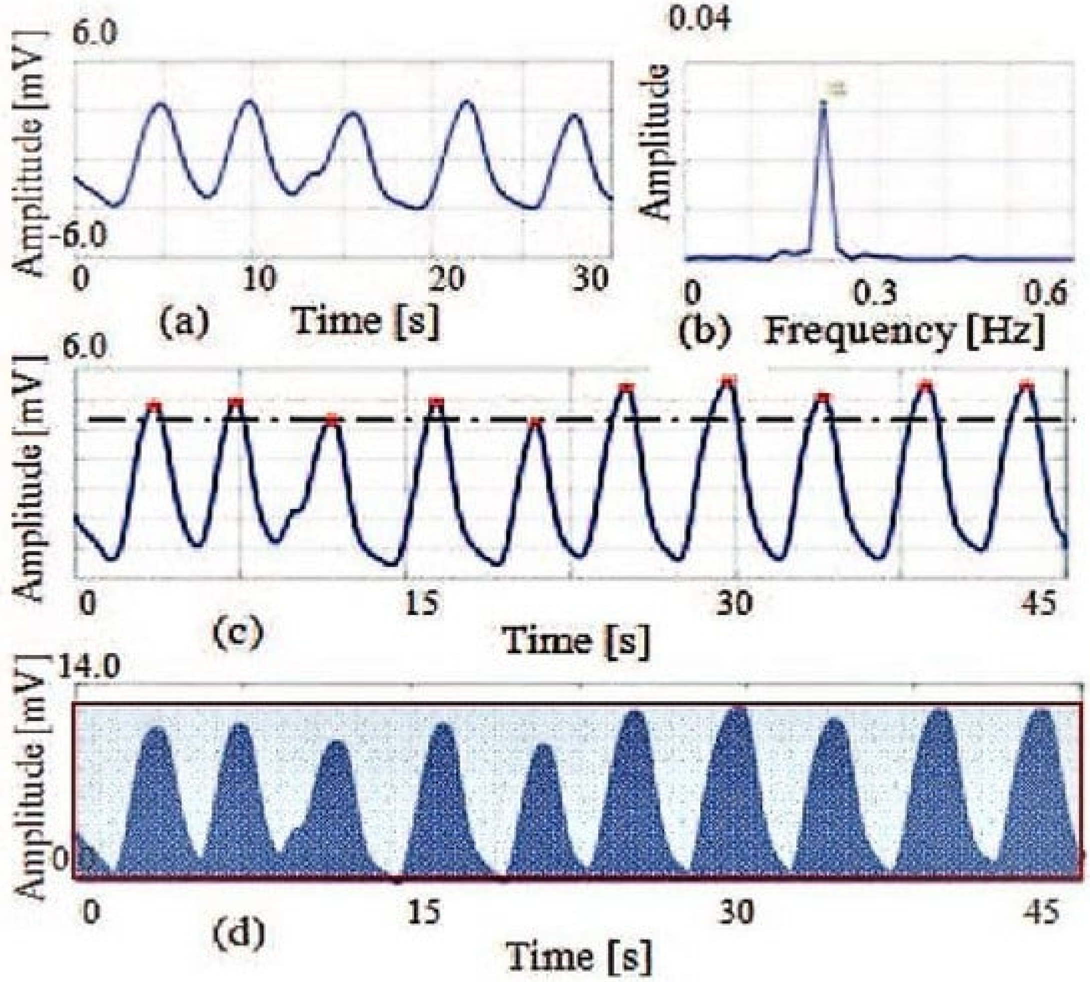

Figure 3. Radar-measured respiratory features from 30 second epochs. Pioneering efforts at recognizing subject identity from radar measured respiratory signals (**a**) involved extraction of three different features: breathing rate (**b**), linear envelop error (**c**), and packing density (**d**). Linear 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.

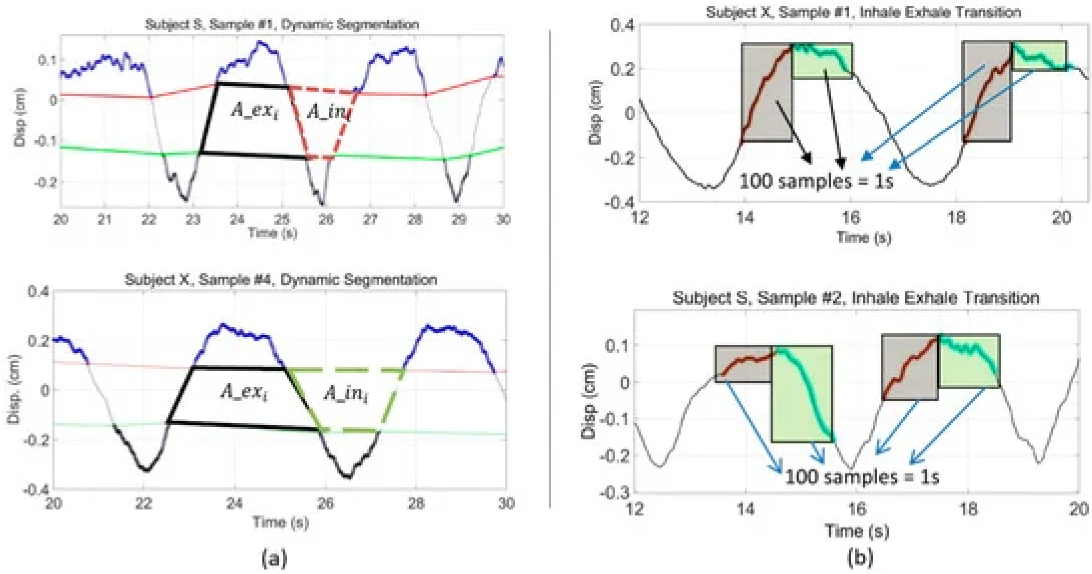

Figure 5. Respiratory pattern classifiers used for subject recognition. Dynamically segmented inhale/exhale area ratios of two subjects significantly differs, (**a**), as do signal patterns relating to the dynamics of breathing near the points where the inhale and exhale transition occurs, (**b**). From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

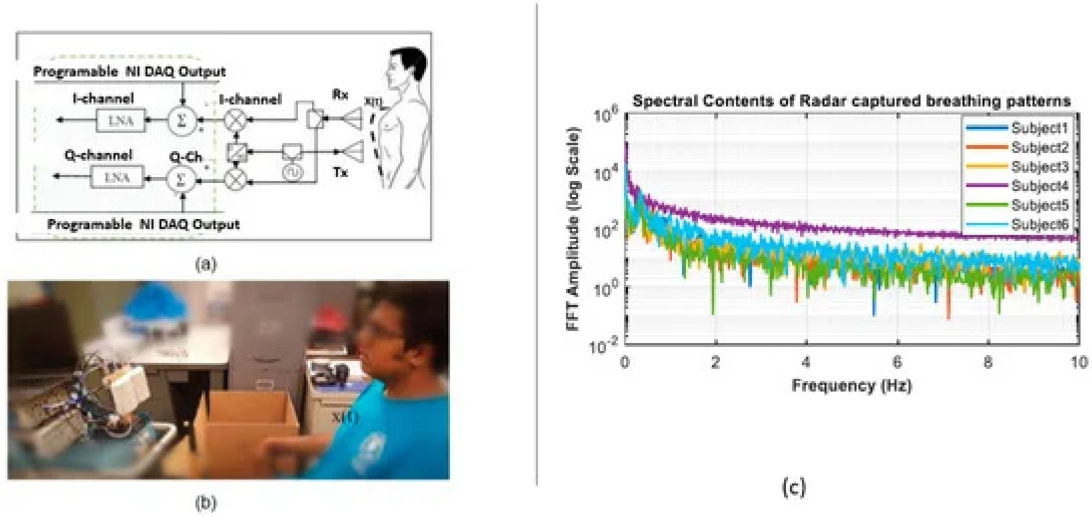

Figure 6. FFT/SVM based subject recognition study. A 2.4-GHz radar system (**a**) was used to measure subjects in seated position (**b**) and FFT-based extracted features up to 10 Hz were used to identify six different participants (**c**). From [70].

2.2. 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.

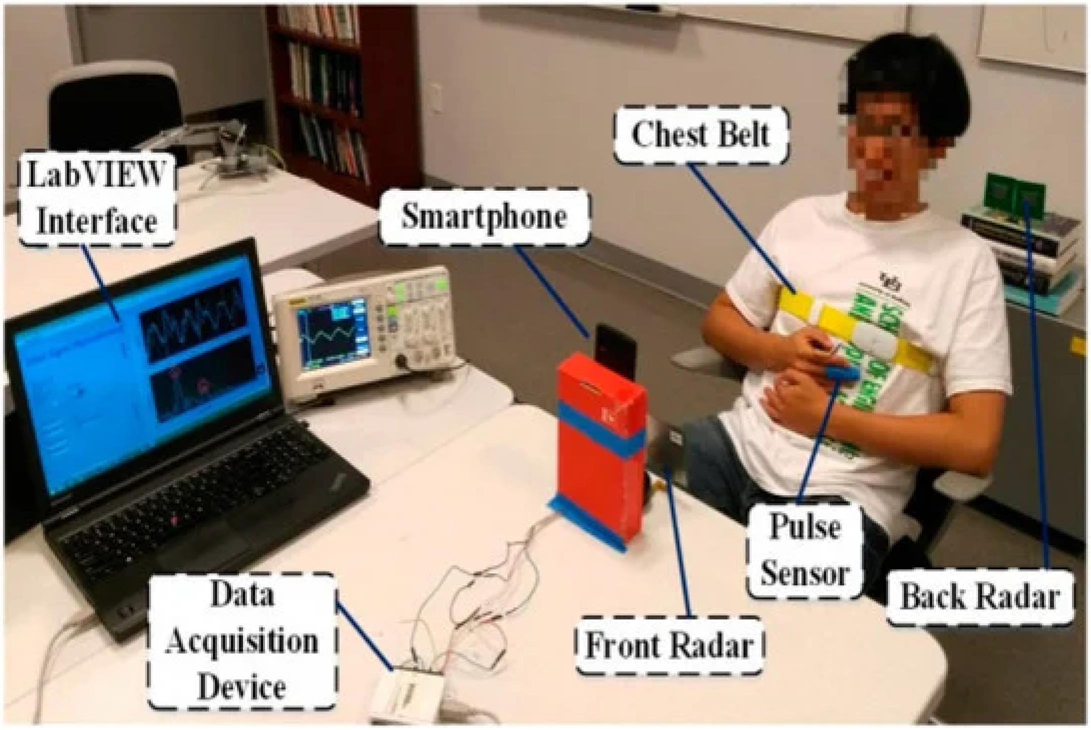

Figure 7. Experimental setup for cardiac scan continuous authentication system using microwave Doppler radar. A data acquisition device and LABVIEW interfaces were used to capture signals. A pulse sensor and chest belt were used for reference measurements. From [58].

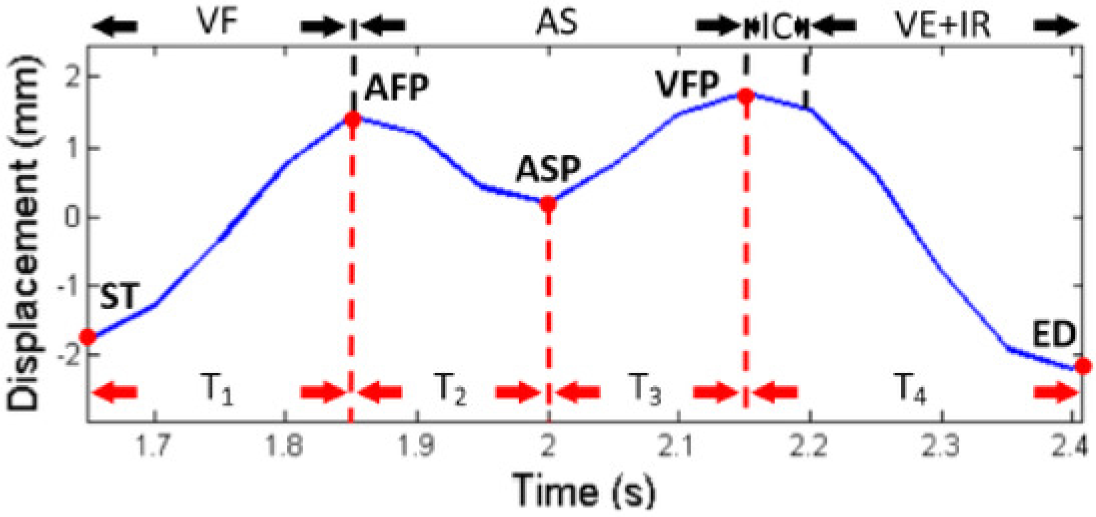

Figure 8. Cardiac motion marker. The cardiac motion cycle defined by five different points (red dots) within five different points of displacement and timing was calculated as a unique feature for recognizing people. From [58].

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.

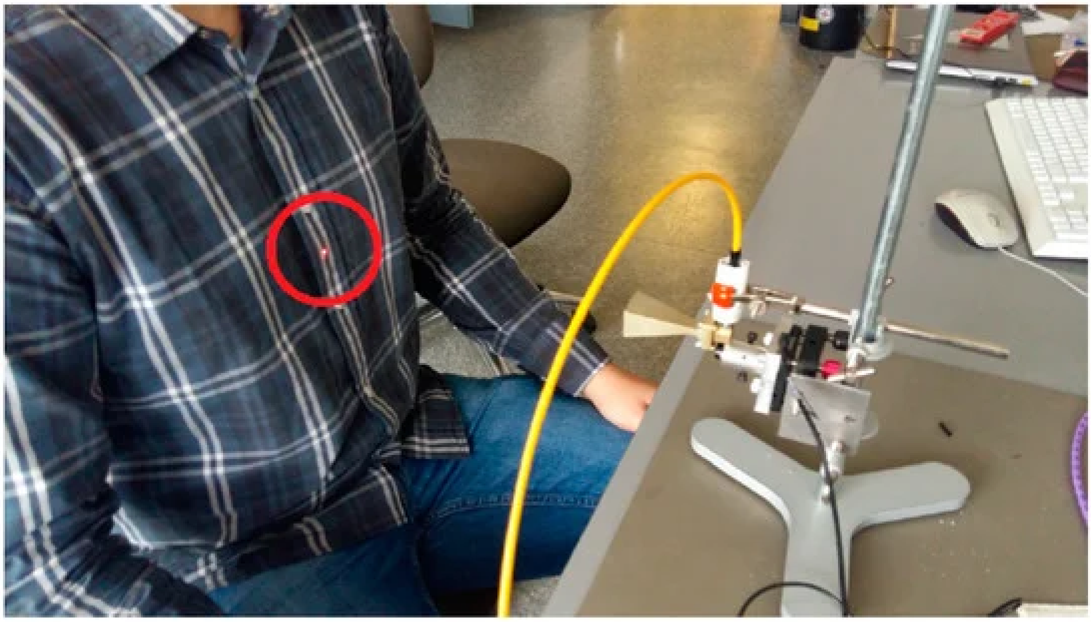

Figure 9. Experimental setup for unique identification of a human from radar captured respiration pattern which includes six-port technology. From [74].

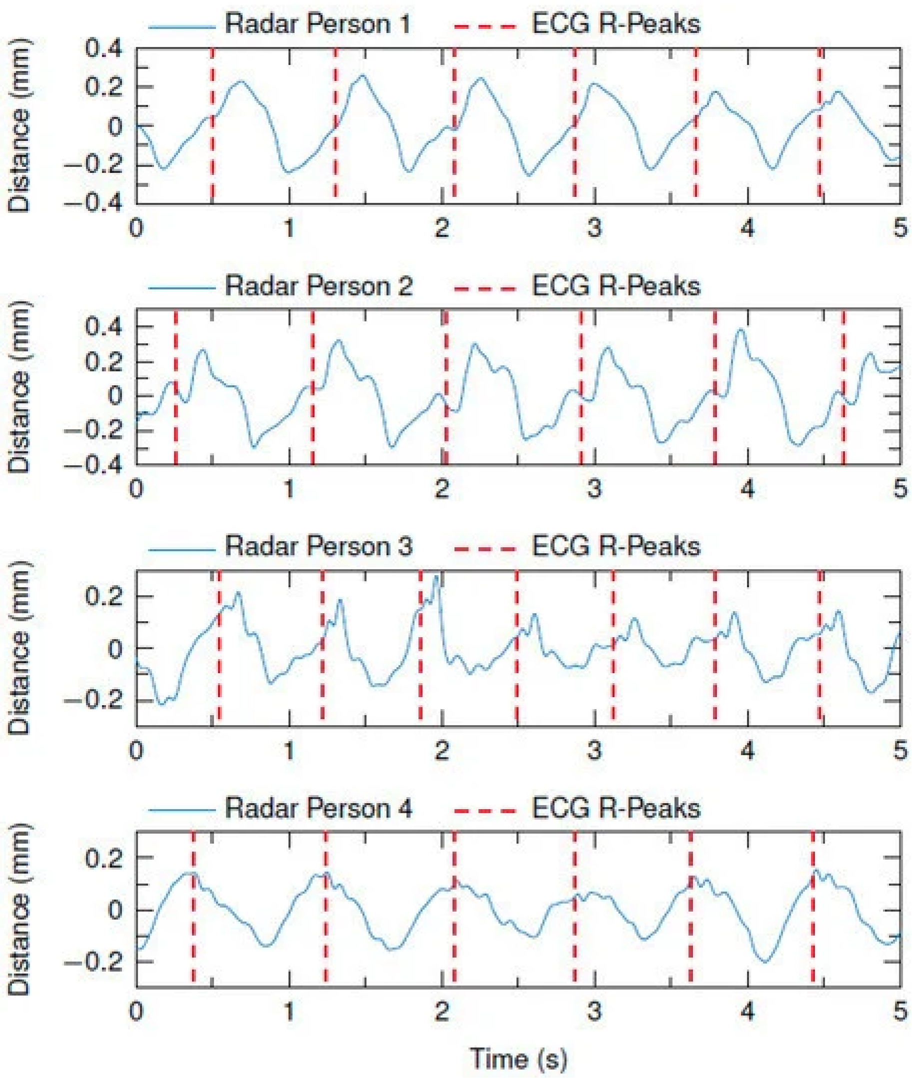

Figure 10. Heartbeat curves recorded by a 24-GHz radar for four subjects. Each signal is periodic but for each subject the pattern is a bit different which serves as a unique feature for recognition of identity. From [74].

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.

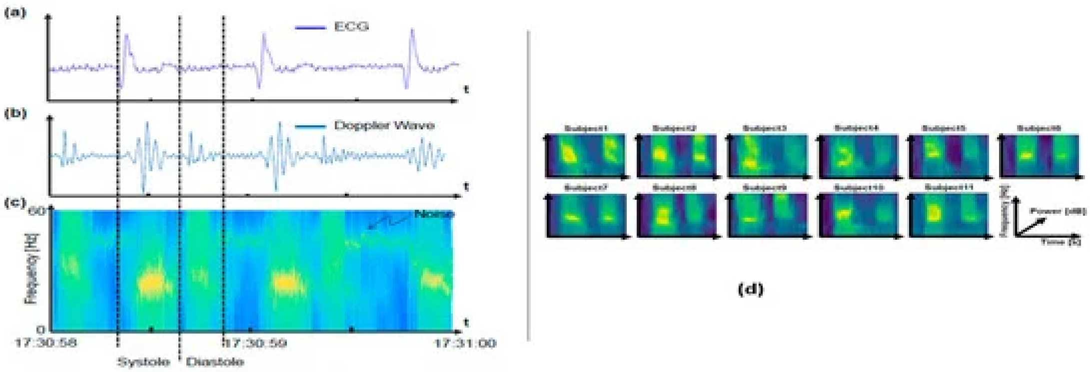

Figure 11. Measured 24-GHz heartbeat patterns for autoregressive PSD analysis based subject recognition. Measurement of heartbeats are shown for electrocardiogram (reference) (**a**), Doppler radar (**b**), PSD of Doppler sensor output (**c**), and (**d**) PSD for 15-s Doppler radar for eleven participants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

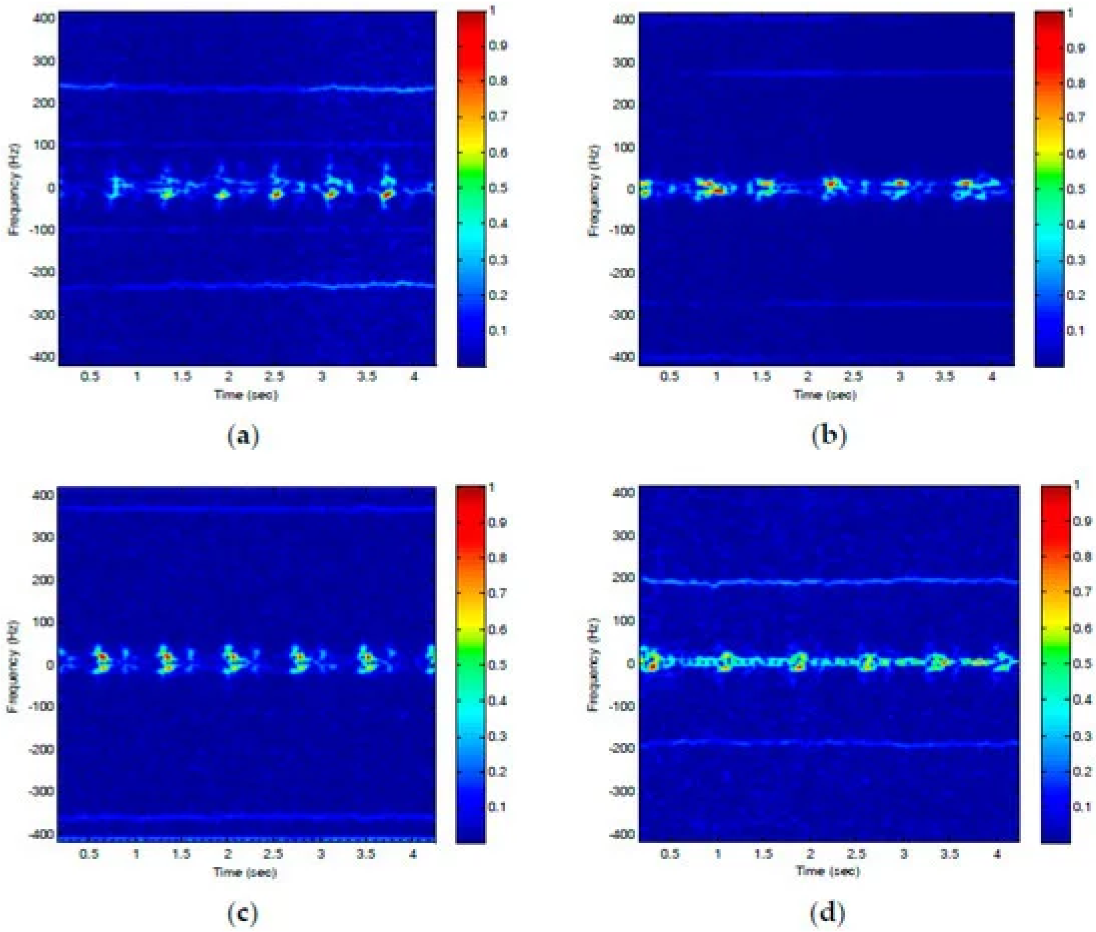

Figure 12. (**a**–**d**) Short time Fourier transform (STFT) of four different participants for extracting micro-Doppler signatures. The images for four different participants clearly have significantly different spectral content. From [76].

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.

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