Chapter 11

Short-distance radar sensing application

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11.1 Introduction AQ1

Human-related sensing plays a more and more important role because of the emerging applications that include search and rescue, security and surveillance, and other important operations. Radar offers a number of unique advantages compared with the other technologies (e.g., infrared cameras [1] and lidar systems [2]). For instance, the Doppler radar system is cost-effective and can sense the target unobtrusively by penetrating obstacles with lower propagation loss. Due to these characteristics, researchers usually employ the Doppler radar in the long-distance object detection (e.g., pedestrian detection [3] and human localization [4]). But recently, researchers start to find out that the use of the Doppler radar is also a natural choice for human micro-motion sensing. Because Doppler information represents the time rate of change of a range, the Doppler radar can suppress stationary clutters to highlight human-related micro-scale movements. The employment of the Doppler radar in short-range micro-motion sensing widely broadens the domain of human sensing network. In the following, we highlight the emerging radar sensing applications in the area of home-based smart-health and human biometrics. AQ2

11.1.1 Smart healthcare

In the healthcare domain, the quality of sleep has gained increasing attention because there is a growing recognition of the adverse effects from poor sleep quality and sleep disorders. Patients with sleep disorders are prone to suffer from chronic diseases such as obesity, diabetes, and hypertension. Vorona *et al.* [5] demonstrated the relationship between obesity and sleep time. Spiegel *et al.* [6] showed that sleep loss increases the risk for diabetes and obesity. Unfortunately, people are usually not aware of sleep disorders because they happen during sleep. Therefore, it has become a chronic, underexplored but critical health challenge in modern life.

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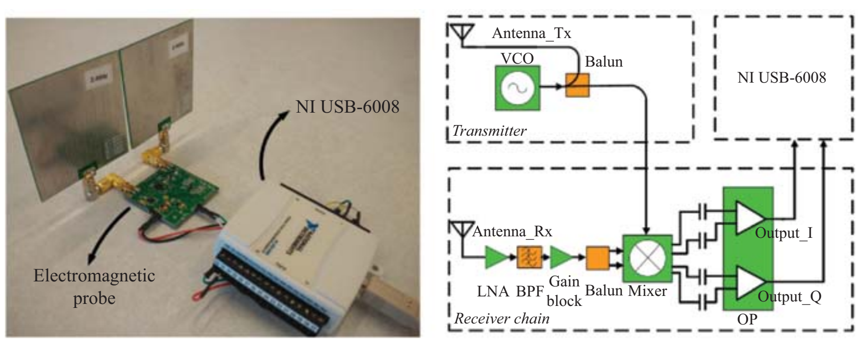
To date, there are several methods to perform sleep monitoring based on polysomnography devices or real-time infrared camera. However, the obtrusiveness [7,8] and lack of privacy [9,10] of these methods prevent people from using current sleep monitoring systems in daily life. Therefore, it is interesting to explore how to accurately detect the very small magnitude of human sleep activities without interrupting the user's sleep at night.

One research group successfully addressed this challenge by developing a Doppler radar-based sleep monitoring system, called SleepSense, which is non-contact and cost-effective [11,12]. Sleep is a period of inactivity and rejuvenation. During sleep, the breathing pattern and movement distribution pattern are particularly being interested, as they characterize the different sleep states and are closely associated the sleep quality. Based on the movement distribution pattern and breathing pattern, they defined three sleep events: on-bed movement event, bed-exit event, and breathing event. The on-bed movement event contains the movements such as turnover and arm trebling. In the breathing event, the subject keeps still on the bed without body movements. The bed-exit event refers to the event with bed-exit movement, which indicates the interruption of sleeping state. Successful recognition of these three interested sleep events is the basis for obtaining the breathing pattern and movement distribution pattern.

To perform sleep monitoring in a remote and cost-effective manner, they instrumented an electromagnetic probe as shown in Figure 11.1. In their case, the electromagnetic probe was developed based on the COTS components. Specifically, AQ4 the electromagnetic probe generates a single-tone carrier signal which is transmitted to the subject. When the microwave hits the subject, the body displacement (caused by the movement or the respiration) of the subject enables the microwave to generate a phase shift. This phase shift is proportional to the corresponding body displacement. By demodulating this phase information properly,



(a) (b)

Figure 11.1 (a) The electromagnetic probe and the DAQ NI-USB6008 device. (b) The block diagram of electromagnetic probe. The electromagnetic probe captures the sleep-related signal and outputs the baseband signal, which is digitized by a DAQ device [11] AQ5

they were able to obtain the displacement information. The electromagnetic probe adopted direct-conversion radar architecture to capture the subject movement and breathing signal. In the circuit implementation, the voltage-controlled oscillator (VCO) in the transmitter generates a carrier signal at 2.4-GHz space. The VCO also provides local oscillator to the mixer in the receiver chain. The output power of this transmitter is around 0 dBm. The system combined a low-noise amplifier (LNA), a AQ6
band-pass filter (BPF), a gain block, a balun, a mixer, and two baseband operational amplifiers (OPs) form the receiver chain. The LNA amplifies the received signal at 2.4 GHz. The interferences with frequencies outside the 2.4-GHz band are removed by the BPF. A gain block is adopted to further amplify the received signal. Two OPs with the same gain of 40 dB are used to amplify the downconverted $I(t)$ and $Q(t)$ baseband signals. Lastly, an NI data acquisition (DAQ) device, NI USB-6008, AQ7
digitizes the baseband $I(t)$ and $Q(t)$ signal.

Overall, their system can monitor and classify the sleep-related events by detecting the on-bed movement activities during sleep based on the radar signal. The Doppler effect [13] has been employed in various motion detection applications, such as gait assessment, vital signal detection, and hand gesture recognition. In SleepSense, a specialized Doppler radar was developed to measure subject's chest displacement remotely. The sampled baseband radar signal went through a demodulation module that uses the extended differentiate and cross multiple (DACM) algorithm to obtain the body movement information from sleep status. Afterward, the sleep status recognition framework processed the displacement signal and accurately recognized three sleep stages, i.e., on-bed movement, bed exit, and breathing section. By deploying such a sleep monitoring system at home, SleepSense can help people to assess sleep quality, even diagnose the sleep disorders at the earliest stages (Figure 11.2). AQ8

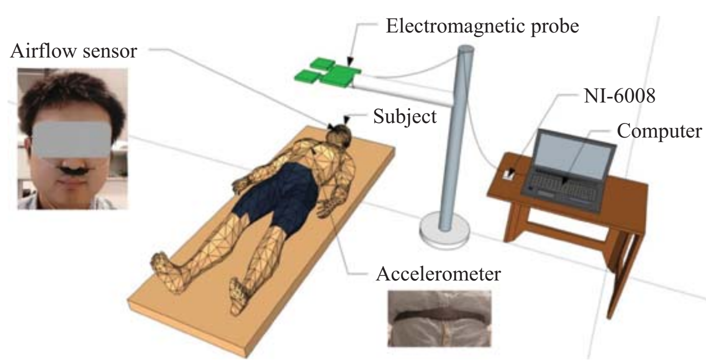


Figure 11.2 The experimental setup: the subject lies his back on a mattress. The electromagnetic probe locates on the top of the chest with the distance of one meter. In the meanwhile, an airflow sensor and an accelerometer sensor are attached to serve as the ground truth measurements [11]

Another work also proposed a routine long-term home monitoring solution based on radar sensing technology [14]. With the growth of aging population, innovative technology approaches have been increasingly investigated for the last two decades aiming at human-being long-term monitoring. However, current solutions suffer from critical limitations as they are based on devices attached to the patient's body, involving pressing a button, e.g., worn as a necklace, in emergency situations [15,16]. However, persons in such situation may already be unconscious or no longer sufficiently reflexive to do so. The ideal solution is therefore a contactless health monitoring system, avoiding the need for actions by the elderly person.

In the last two decades, attention has been focused mainly on contactless vital sign monitoring for remote fall which is also in connection with health monitoring in home environments. Many relevant academic developments are based on radar techniques implemented as a single device sensor, e.g., continuous-wave (CW) Doppler radar or ultra-wideband impulse-radio (UWB-IR) radar in the controlled condition. Other investigations are systems based on video cameras [17], floor vibration [18], and acoustic sensors [19]. Besides privacy concerns, the use of video camera systems is still troubled by issues related to low light environments, field of view, and image processing, resulting in a success rate of 90% using two cameras [17]. Successes in floor vibration and acoustic sensors are similarly limited due to environmental interference and background noise. Moreover, they are also less effective in detecting cases of soft human falls, defined as a fall after the individual collides with an object (e.g., table, chair, or carpet).

As a result, the authors in [14] proposed a full system which enables indoor, noninvasive fall detection, and tagless localization. The system combined radar, wireless communications, and data-processing techniques. Moreover, it has been designed to satisfy the European and Federal Communications Commission (FCC) UWB spectrum masks, and it can also be potentially connected to medical monitoring personnel to provide a prompt alert in the event of emergencies. Figure 11.3 shows a simplified block diagram of the proposed health monitoring system. It consists of a sensor, combining both radar and wireless communications features, and a base station for data processing. A radar waveform is generated and sent to the target, and then its reflected echo, containing speed and absolute distance information, is collected by the receiver. The resulting baseband signals are digitized and transmitted wirelessly to a base station that consists of a Zigbee module, a laptop, and a microcontroller. The latter collects and transfers the data received from the Zigbee module to the laptop to determine remotely the target's absolute distance and to distinguish a fall event from normal movements (e.g., walking or sitting down).

The data processing is not performed by the sensor in order to avoid complex processor on board, reducing costs, size, and energy consumption. Moreover, this represents a flexible solution if multiple sensors will be used in the future. In fact, the base station should combine and process multiple pieces of information simultaneously. The radar waveform was designed based on a previous hybrid approach [20]. It consisted of a single tone, at 5.8 GHz in the ISM band, alternated AQ9

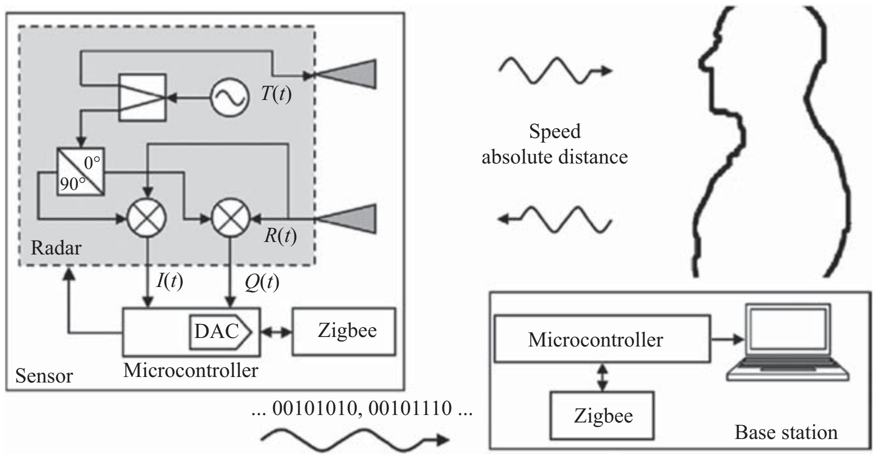


Figure 11.3 The simplified block diagram of the proposed health monitoring system [14]

with a stepped frequency CW (SFCW) waveform working in the UWB band. Each tone lasts 1 s and was used to continuously detect the speed of a person using the Doppler concept. The SFCW waveform was used to detect the target's absolute distance. It consisted of $N = 40$ coherent CW pulses (called burst), the frequencies of which are increased from pulse to pulse by a fixed increment $\Delta f = 25\,\text{MHz}$. Each pulse was $T = 50\ \mu\text{s}$ long, resulting in a burst duration $N \cdot T$ of 2 ms, while its total band $N \cdot \Delta f$ is 1 GHz positioned between 6 and 7 GHz, enabling a smallest resolution of 15 cm. The full waveform is 1.002 s. Afterward, they carried out the waveform spectral analysis and utilized specific considerations to justify the choice of the waveform parameters and to explain the operations of compensation and calibration in data processing. AQ10

In the experiment evaluation, they recruited real human volunteers who were allowed to move freely about the whole room. The sensor were fixed to the wall at a height of 1.5 m. Furniture and metallic shelves were deliberately included to enable the existence of clutter and reflections, mimicking a typical room setting. Falls were mimicked with two different human volunteers, with a similar 1.75 m height but different weights to enable the evaluation of different fall speeds. The first and second subjects' weights were 90 and 75 kg, respectively. However, only frontal falls have been evaluated at different locations at radial distances in the whole room, using an inflated mattress to avoid injuries. Also, only one person was present in the room at a time. The tagless localization evaluation showed that after applying the compensation and the calibration process, their system can perfectly distinguish the target's signal peak, which indicates the target's absolute distance, and will not be overwhelmed by the undesired reflections originating from the clutter and the antenna's cross coupling. Then, they validated whether their system can detect the fall event. Specifically, a data set was built containing 70 activities measured from two persons. In particular, 20 walking signals have been acquired for each person, who was allowed free movement in the whole room, and 30 fall signals have been acquired with each subject located at known distances from the antennas. The LS-SVM model was trained using the data of a single person (Target 1) and then validated using the data from the other person (Target 2). The above process was repeated two times since data from two persons were available. The results demonstrated that the LS-SVM model with the GA kernel, which incorporates time-dependent information, presented a success rate in distinguishing fall events from normal movements of 94.3% outperforming the linear and RBF kernels. This is consistent with the expectation since falls exhibit a time-dependent structure as the speed increases continuously until the sudden moment when it stops abruptly. An alternative method called dynamic time warping (DTW) combined with a Euclidean distance measure is frequently used to classify sequences of vectors. In order to compare the LS-SVM with GA solution to this standard method, they ran an additional experiment and the results showed that the GA kernel slightly outperforms the DTW alternative on their data set. They also pointed out that by further reducing the cross talk, it will be possible to increase the total receiver gain and, consequently, to improve the accuracy of velocity detection, besides the detection range extension. Moreover, the system's sampling rate influenced the accuracy of the speed detection, i.e., the higher it is, the more accurate is its detection. However, this will significantly complicate the system since the duration of the SFCW pulses must be shortened, and the ADC sample rate increased. This will involve higher power consumption and a larger number of transmitted frames to the base station. However, it is important to note that in their fall detection application, the main goal is to detect the changes in speed and not to determine how accurate is the value of the instantaneous speed.

AQ11 AQ12 AQ13 AQ14

To sum up, they proposed a new radar-based system for contactless fall detection and tagless localization in an indoor environment. This research work is in line with the growing need for novel healthcare solutions. The full system combined radar, wireless communications, and data-processing techniques to satisfy the European and FCC UWB spectrum masks. They proposed unique hardware structures and algorithms to address the practical problems, such as backscattering and cross talk. Experimental evaluations with real human subjects demonstrated accurate detection of the target's absolute distance and fall events.

11.1.2 Biometric authentication AQ15

Human authentication has been unprecedentedly important in the era of the Internet of Things (IoT) as IoT devices are becoming increasingly attractive targets for cybercriminals. Taking smartphone as an example, hundreds of millions of Americans have had their private or financial information compromised and more than 12 new people are hacked each second [21,22]. Meanwhile, it is proven that Internet-connected cars can be compromised, and hackers can carry out any number of malicious activities, including taking control of the vehicle system and unlocking the doors [23]. Wearables can also become a source of threat since hackers can use the motion sensors embedded in smartwatches to steal information you're typing, or gather health data from health tracker devices you might be using. Therefore, how to securely protect IoT devices without interrupting user activities has achieved great attention.

The current widely applied security defense is the so-called human authentication, which is a mechanism to secure the access of an IoT device by determining whether a person is who he or she claims to be. Among different kinds, biometric authentication is believed to be more secure because it is a "what you are" factor based on unique individual characteristics. Two types of biometric properties have been proliferating in customer devices. Specifically, physical biometrics emphasizes the unique physiological attributes in human body, which include fingerprints [24], facial recognitions [25], and eye scans (iris [26], retina [27]). Behavioral biometrics, on the other hand, represents the way people do things and the typical examples are keystroke rhythms [28], gait patterns [29] and handwritten signatures [30].

Because of the unobtrusive and sensitive nature of radar sensing, researches begin to explore the usage of radar in human identification for better usability and performance. For instance, one nascent work instrumented a system that can identify a subject accurately by using the MIMO array sensor for the safety mon- AQ16
itoring [31]. The authors set an 8×8 MIMO radar array around the target, and observed waves reflected and scattered from the target. As depicted in Figure 11.4, a single-pole 64 throw (SP64T) switch was used at the transmitting side. A CW signal at 2.47125 GHz was used, and transmitted power at the antennas was set to -12 dBm. The CW signal was later split to the receiver side since accurate synchronization between transmitting and receiving sides is required. At the receiver side, the received signals were input to a downconverter unit by way of an LNA. The downconverted baseband signals (I_1, $Q_1 \sim I_8$, Q_8) were digitized by a DAQ unit AQ17
with sampling frequency of 20 kHz. The snapshot rate for the MIMO channel is determined by the switching speed of the SP64T. In the experiment, the rate for

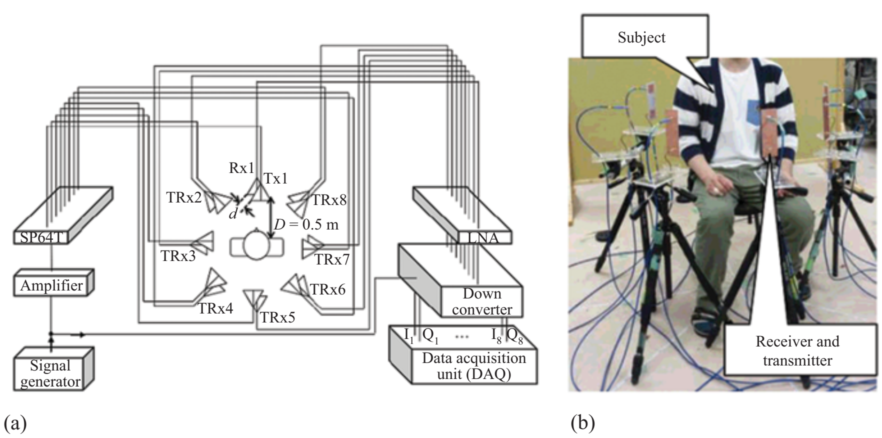


Figure 11.4 The system setup of the proposed radar MIMO array in [31]. (a) The system diagram. (b) The experiment setup AQ18

taking a snapshot of the MIMO channel was set to 100 Hz. In their experiment, they found that the target generates a time-variant channel due to respiration and heartbeat. Based on the spatial and temporal characteristics of the measured channel, the system was able to identify different subjects. Their experiments were carried out in an indoor environment to evaluate the recognition performance of the system. The results show that the proposed method can identify eight individuals and reject four impostors with 0% equal error rate. This work has proved the feasibility of detecting human biometrics through the reflected radar signals.

One research team also presented an interesting work [32] and we hereafter introduce their work in detail. They pointed out that existing biometric authentications often follow the principle of one-step validation. After the initial login, there is no further identification procedure as long as the device remains active. This is mainly because the existing biometrics (e.g., fingerprint reading, iris scanning, or face recognition) are often intrusive and disruptive so that users are only willing to perform the authentication once at the beginning of the usage. Consequently, an impostor can gain physical access to the device if the legitimate user leaves it unlocked and unattended. For this reason, this is critical to propose a continuous authentication scheme.

After the wide exploration, the team placed their attention on the cardiac motion, which is a periodical three-dimensional (3D) automatic heart deformation caused by the unique self-excitement of the cardiac muscle in individuals [33] (Figure 11.5). The cardiac motion is unique (i.e., distinguishable across subjects), AQ19
non-volitional (i.e., unknown to the user), secure (i.e., difficult to counterfeit), and present in all living individuals (i.e., intrinsic liveness). However, they identify three main challenges before further utilizing it as a secure human biometric: (1) How to obtain the high-resolution cardiac motion information unobtrusively? (2) How to extract invariant geometric-based features for each heart with regard to

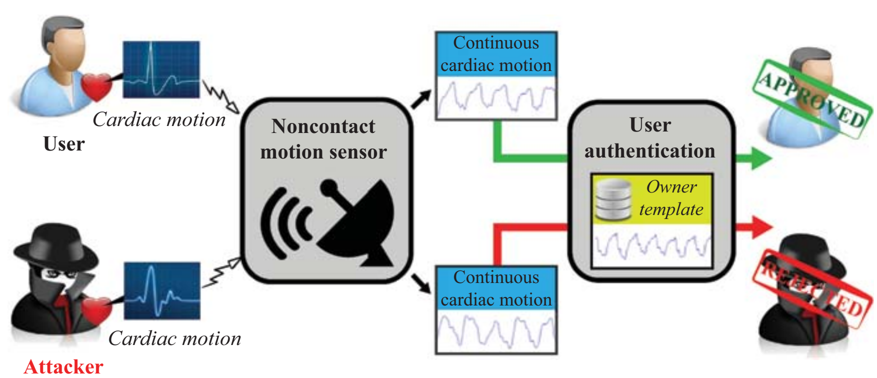


Figure 11.5 Cardiac Scan directly and continuously detects the heart motion via the Doppler radar signal. The system utilizes the micro-motion signal as the unique human biometric to secure the account security through the entire login session [32]

the cardiac motion mechanism? (3) How to examine the usability and security of the continuous authentication scheme?

11.1.2.1 Noncontact cardiac motion sensing

Noncontact monitoring of human body motion, such as respiration and heartbeat rates using a Doppler radar motion sensor, has gone through a few decades of scientific study [34–38]. Efforts have been devoted to the development of radar front-end hardware, signal processing algorithms, and system on-chip/on-board integration. Compared with other techniques such as noncontact laser vibrometer [39] and infrared imager [40] that can only detect motion at body surface, it has been shown that the Doppler radar sensor can directly measure the motion of internal organs [41] and heart [42,43]. However, research results in those works are incomprehensive for a real authentication system; e.g., the impact of random body movement is not considered. Although random body movement and clutter noise still require significant efforts to resolve, some progress has been achieved [44,45] and preliminary clinical studies have been reported [46]. However, existing cancellation approaches either compromise the quality of the baseband signals [44] or require sweeping the carrier frequency and adjusting the target position [45], which is not applicable to capture the high-fidelity cardiac motion in a real-world setup.

Instead, this team proposed that DC-coupled interferometry radar and Doppler radar with digital intermediate frequency (digital-IF) architecture can avoid frequency-selective signal distortion and thus make it possible to recover accurate motion patterns using CW Doppler radar sensors. In detail, to monitor cardiac motion pattern, a smart DC-coupled CW radar sensor was employed by taking advantage of real-time signal processing and mixed-signal design in modern devices. For cardiac motion sensing, the DC offset due to reflection from other parts of the body not related to cardiopulmonary activities may easily saturate the receiver and create frequency-dependent distortion, and is an important factor for the central intelligence unit to handle. As shown in Figure 11.6, the DC-coupled adaptive tuning architecture includes radio frequency (RF) coarse-tuning and baseband fine-tuning. For RF tuning, the electronically controlled phase shifter and attenuator add a portion of the transmitted signal to the receiver signal to cancel most of the DC offset caused

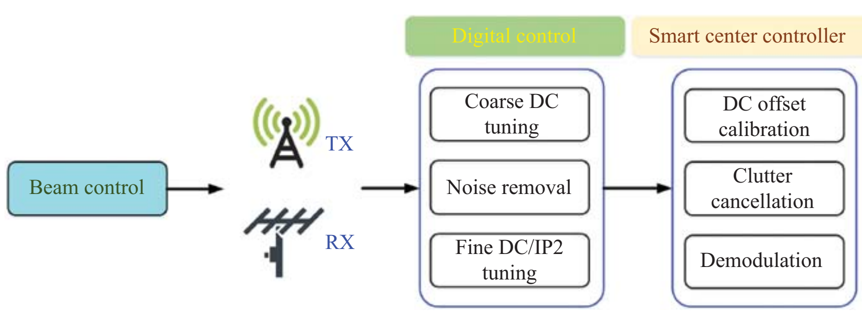


Figure 11.6 Doppler radar sensor with adaptive DC tuning proposed in [32]

by clutter reflections. However, due to quadrature imbalance, the phase variation of the received signals, and the limited resolution of the phase shifter and the attenuator, the RF tuning cannot completely remove all the DC offsets. To further eliminate the remaining DC offsets, a baseband fine-tuning block was implemented to dynamically adjust the amplifier bias to the desired level that allows the maximum dynamic range. With the above DC tuning realized by a smart center in real time, the radar will precisely measure cardiac motion pattern. The integration of the DC-tuning technique into portable devices will be addressed with the help of logic control circuits coordinated by the I2C bus and CMOS-integrated calibration DACs. AQ20 AQ21

Besides manipulating the penetration depth, radar carrier frequency also determines the modulation sensitivity. Therefore, they carried out experiments to compare the performance of carrier frequencies ranging from 2.4 to 40 GHz. It should be noted that increasing the carrier frequency beyond 40 GHz may not help because as the wavelength approaches physiological motion amplitude, strong nonlinear phase modulation will generate harmonic interference [47]. Moreover, cardiac sensing should be realized from different angles to obtain sufficient information for biometrics applications. Also, multiple radars around a subject may "probe" cardiac signals simultaneously. To achieve this, they believed that a radar can configure the radiation beam to precisely point at the location of interest. As shown in Figure 11.6, digital beam control was implemented on the radar front end. Conventional beamforming systems directly adjust the phase and amplitude of the signal of each element antenna. They demonstrated that it is much more convenient to simultaneously adjust the phase and amplitude in the complex domain than to adjust them separately. For a complex signal $x = \exp(-j2\pi ft)$ sent into each element antenna (where f is the signal frequency), a vector multiplier was used to realize phase and amplitude modulation by first splitting the signal into in- and out-of-phase components and then by multiplying each one using a variable gain amplifier. Finally, by adding the amplified in- and out-of-phase components together, complex modulation to the original signal can be achieved thus effectively realizing radar beam control. In their work, they used a laser pointer to indicate the beam direction by aligning the radar beam with the user.

Afterward, they elaborated on the radio signal processing schemes and correspondingly investigated user authentication methods to achieve secure and usable authentication results. As depicted in Figure 11.7, their proposed approach was

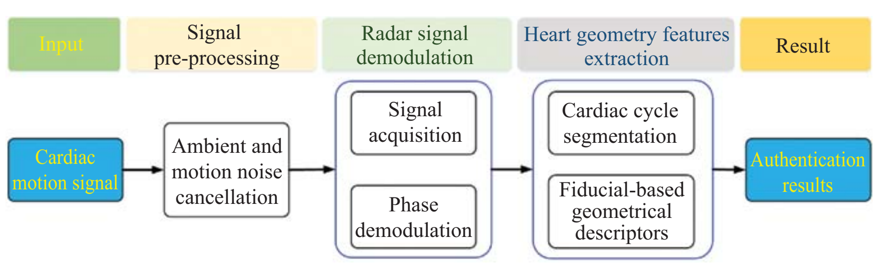


Figure 11.7 The flowchart of Cardiac Scan, a heart-biometric-based continuous user authentication system [32]

mainly comprised of three modules. First, the original sequential signal was preprocessed for noise reduction. The noise includes low-band components (e.g., baseline wander), high-band components (e.g., power-line interference), and unpredictable-band components (e.g., arbitrary motion in the scene). Considering diverse and known frequency bands of the noise spectrum, we have addressed the noise-level reduction in two areas: one-pass noise-reduction techniques (e.g., a Butterworth BPF) and adaptive noise-canceling techniques. Second, they performed de-noising-aware radar signal demodulation by investigating an extended DACM algorithm to avoid the phase unwrapping problem. Their proposed algorithm computes a derivative to the arctangent-demodulated phase information and reconstructs the desired phase information, which represents cardiac motion. Third, they extracted fiducial-based descriptors from the periodical signal segments. The fiducial-based method extracts intrinsic geometrical descriptors (e.g., temporal, amplitude, area, or angle) from fiducial points in the cardiac motion signal. Specifically, fiducial points are the biomarkers with physical meanings in clinics during the cardiac motion cycle. Fiducial points contain the biological information that is unique and nonvolatile for individuals, and are also independent of the sensor location or state of the individual such as anxiety, nervousness, or excitement. Lastly, they obtained authentication results. Note that the existing heart-based biometrics, such as ECG, is recording the electrical activity of the heart, whose AQ22
descriptors are extracted on the basis of the QRS complex [48]. As a new biometric AQ23
modality, their noncontact cardiac motion is substantially different from the typical ECG signal in that it is a direct heart motion activity measured by an RF sensor.

To elaborate the system usage, they devised three scenarios in particular for Cardiac Scan enabled continuous authentication, including *Authentic user is present*, *Authentic user leaves*, and *Adversary is present*.

Authentic user is present

When an authentic user has logged into the system and is present within the range of the radar sensor, Cardiac Scan is able to detect sensed cardiac motions are from the same person who was initially authorized. Thus, the permission of using the system for the user can be continuously granted without any interruption, unless the user logs off intentionally or leaves, as shown in Figure 11.8(a). By designing the false negative tolerance, Cardiac Scan allows one single "classified as adversary" event given that the classification results just before and after this event are both positive as "classified as authentic user." In case two or more than two consecutive "classified as adversary" events occur, though it has a low probability, Cardiac Scan will log out the initial user. Under such circumstance, the user is asked to confirm its identity again using other complementary existing biometrics system, such as PIN, fingerprint, or face.

Authentic user leaves

When the authentic user is away from the system and the radar sensor has detected the user's absence, as shown in Figure 11.8(b), Cardiac Scan will first check whether the user has logged off and the system has been locked up. If so, Cardiac Scan will classify the user's absence as a legitimate action and no further action needs to be taken. Otherwise, the system is at risk of unauthorized access, hence

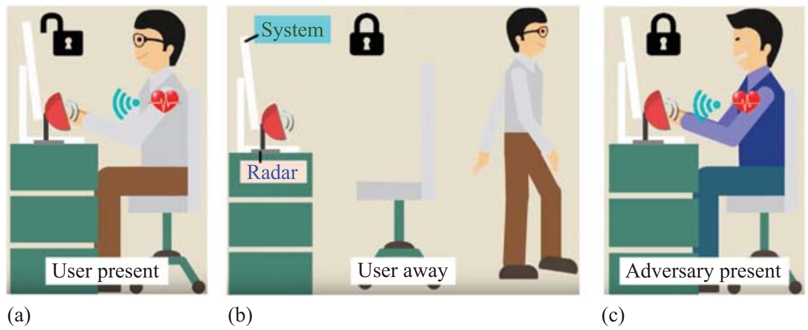


Figure 11.8 Continuous authentication scenarios: (a) Authentic user is present and the system remains unlocked. (b) Authentic user leaves and the system locks up. (c) Adversary is present and the system locks up. Green screen means the system is unlocked and red screen means the system is locked [32] AQ24

necessary actions such as locking the session, logging out the original user, or notifying the administrator [49], which depend on the system policy, have to be considered to address the security risks.

Adversary is present

In this scenario, an unauthorized adversary (the dark one in Figure 11.8(c)) is present and close to the system, and the system has been logged in initially by an authentic user. This can happen when the authentic use is forced to be present or the adversary takes over the system before the system automatically locks up when the authentic user leaves. Therefore, immediate action is demanded to keep the adversary outside the system and prevent the leakage of sensitive information. In this case, Cardiac Scan will immediately log out the initial user and lock up the system once the false negative tolerance threshold Th_{nt} is exceeded.

In the experiment, they conducted a pilot study to prove identifiability in cardiac motion. A Doppler radar vital sign detection system was developed for the study. As shown in Figure 11.9, a subject sat in a chair in a relaxed condition. The customized Doppler radar sensor was placed in front of the subject with a distance of 1 m and the sampling frequency was 20 Hz. An iPhone was placed close to a radar to record the subject identity and label the ground truth. Motion compensation was carried out for the baseband complex signal obtained from subjects who breathed normally but randomly moved their body. A pulsed sensor (UFI 1010 pulse transducer) was attached to the subject's finger to provide a heartbeat reference, and a chest belt (UFI 1132 piezo-electric respiration transducer) was used to provide a respiration reference. Seventy-eight healthy subjects (46 males and 32 females) without heart disease participated in the study. Each subject has 20 trials, and each trial lasts 8 s including 8 to 10 cardiac cycles. In total, there are 14,886 cardiac cycle samples in the evaluation. AQ25

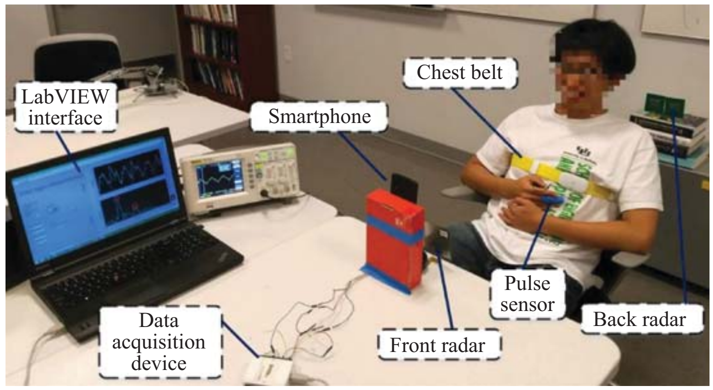


Figure 11.9 Experimental setup for cardiac motion sensing. A subject is sitting one meter away from both radar sensors, a chest belt and a pulsed sensor is attached to the subject [32]

They first studied the effectiveness of random body movement compensation because the subject will perform free movements in the practical continuous monitoring system. Compared with cardiac motion, body movement may result in a large perturbation to the output DC offset, and thus confuse the radar demodulation algorithm or even saturate the baseband circuit. In the experiment, the time-domain signal had fluctuations due to the random body motion as shown in Figure 11.10(a). This phenomenon was first observed in [50] and the authors observed the strong near-DC spectral components and found that the heartbeat was invisible in the spectrum as shown in Figure 11.10(b). Simply reducing the front-end gain, as adopted in some communication systems, does not work because the radar will lose the sensitivity to the weak cardiac motion signal.

Because biomedical radar can detect cardiac motion from four sides of a human body, multiple radars can be installed at different locations around the human body to cancel out random body motion based on the different patterns of body motion and cardiac motion [44]. In the view of the two radars, the heartbeat-and-respiration-caused body movements are in phase, while the random body movements are out of phase. For example, in case of two radars detecting from the AQ26
front and the back of the body, when the body is drifting toward one radar, it is moving away from the other; whereas heartbeat presents similar expansion/contraction patterns to the two radars [?]. Therefore, random body motion creates an AQ27
opposite Doppler frequency shift to the signals of the radars, while cardiac motion leads to the same polarity. By properly combining the low-speed baseband signals from the radars, one type of motion can be canceled and the other type will be enhanced. Figure 11.10(c) shows the results after random body motion cancellation, where not only are the near-DC interferences suppressed but also the heartbeat signal is clearly visible based on the proposed solution. Moreover, respiration signal can also be identified within a range of frequencies which is the most prominent peak than the other peaks in the spectrum.

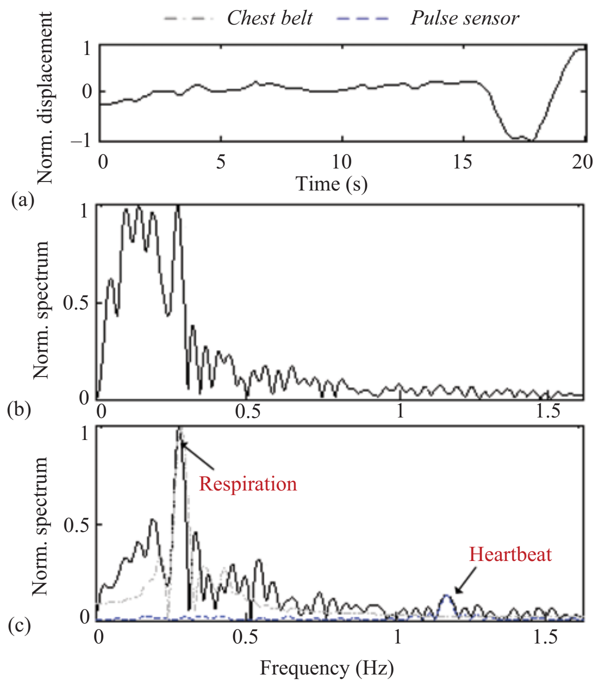


Figure 11.10 (a) Time-domain signal of 20 s under random body motion; (b) Spectrum without random body motion cancellation; (c) Spectrum with the random body motion cancellation [50]

They also emphasized that the baseband output of each radar has very low frequencies because human physiological motion is very slow (no more than a few hertzs). In the meantime, the "coherence detection" feature of the radar is maintained at the front end of each individual radar to achieve a sub-millimeter-scale detection sensitivity, which is not affected by the synchronization among different radars. Therefore, for practical noncontact cardiac password applications, either wired or wireless secure data communication can transfer the data to a central computing unit signal processing.

Afterward, they verified the validity of the collected data from their system. When the radar sensor detects the cardiac motion, the fingertip sensor simultaneously collects a signal as the ground truth signal. Both the radar sensor and fingertip pulse sensor were sampled at 20 Hz. They observed that the cardiac motion circles are in similar shape with the corresponding fingertip signal which is served as the ground truth. The detected cardiac motion signals appeared periodically, each of which precisely matches the peaks in the fingertip signal. To this end, they verified that Cardiac Scan could accurately detect the cardiac motion signal in a noncontact way. Then, they evaluated the performance, usability, and vulnerabilities in practice of Cardiac Scan. Here, we'd like to introduce the vulnerability study to demonstrate the robustness of their radar sensing system for authentication. AQ28

Investigating the vulnerability of Cardiac Scan is crucial. Although cardiac motion is invisible and might possess better safety and security than other authentication approaches (e.g., PIN and fingerprint), it could become fallible under direct or spoofing attacks [51]. One immediate attack approach is the presentation of human characteristics to the acquisition device, including different living traits (i.e., zero-effort impostor attempts that try to take advantage of the false acceptance rate of biometric systems) [52]. Specifically, they discussed one advanced spoofing approach, i.e., replay attack.

Replay attack

One major risk of using biometrics is the danger that the biometric token can be intercepted and replayed by an unauthorized party. Compared to visual-based still biometrics (face/fingerprint/iris), the cardiac motion is more complex and dynamic to fake or replicate. However, there is still a chance to compromise Cardiac Scan under some extreme scenarios. For example, attackers might hack into the database and obtain cardiac motion patterns or engineer the same cardiac motion sensing device to extract a user's cardiac motion. The authors conducted this experiment to prove the possibility of a replay attack on Cardiac Scan if a legitimate user's cardiac signals are obtained by attackers. The team investigated the method of synthesizing cardiac motion and developed a programmable actuator to imitate the cardiac motion. As shown in Figure 11.11, a linear actuator (ZABER TNA08A50) and a linear translational stage (ZABER TSB28-1) were placed 30 cm from the cardiac motion-sensing device. The actuator was programmed to perform a harmonic back-and-forth motion toward the fixed position radar for mimicking cardiac motion patterns.

Anti-spoofing (liveness artifacts)

Given the above attack, the team also investigated a set of anti-spoofing approaches against a replay attack. The general idea of anti-spoofing is liveness detection [53,54]. Liveness detection has been applied to existing biometrics systems by using living traits of humans. Pan *et al.* proposed the method to extract liveness information through eye blinks in face recognition [55]. Wei *et al.* detected counterfeit iris through texture analysis [56]. In their work, they exploited the uniqueness of living traits in human cardiac motion to defend the above adversarial model.

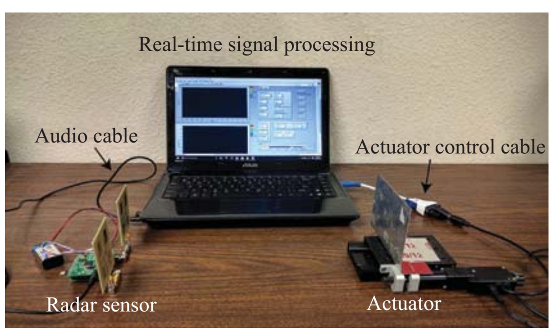


Figure 11.11 A linear actuator imitates cardiac motion as a replay attack [32]

Specifically, they tackled the challenge from two dimensions: hardware-based and software-based approaches. First, they integrated assisted sensors in Cardiac Scan, so that they can leverage additional information from these sensors to examine the legitimacy of subjects and capture the characteristics of multidimensional cardiac motions for liveness simultaneously. Specifically, the system employed multi-channel radars for noise reduction. Since the linear actuator only moves in rectilinear directions, the direction of arrival (DoA) [57] measurements with the linear actuator on these radars are different from DoA measured with real cardiac motion. Second, we have investigated software-based approaches. Based on the experiment, the sensor data from a live subject inevitably include vital sign (e.g., respiration) and other motion artifacts (e.g., body sway). Utilizing these vital sign detection and motion artifacts, liveness detection is conducted against the replay attack [58]. They programmed the actuator working with different moving amplitudes and frequencies to imitate cardiac motions of 12 subjects. All replay attacks were successfully rejected by the proposed liveness detection method.

Overall, their group prototyped a novel biomedical radar system, Cardiac Scan, featured with DC-coupled interferometry radar and Doppler radar with digital-IF architecture. Such a design can avoid frequency-select signal distortion and thus accurately recover the internal cardiac motion via remote sensing. Cardiac Scan represents a new security mechanism which significantly enhances the security level of the system by continuously monitoring the user's trait during the entire login session without compromising the usability. It holds the potential to transform existing authentication systems into a more undeceivable, disclosure-resistant, and user-friendly solution. Moreover, Cardiac Scan can be conveniently integrated with existing one-pass user verification techniques (e.g., personal identification number, fingerprint, iris scan, and face recognition) to enhance the continuous authentication capability of existing systems.

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