Radar for health care: Recognizing human activities and monitoring vital signs

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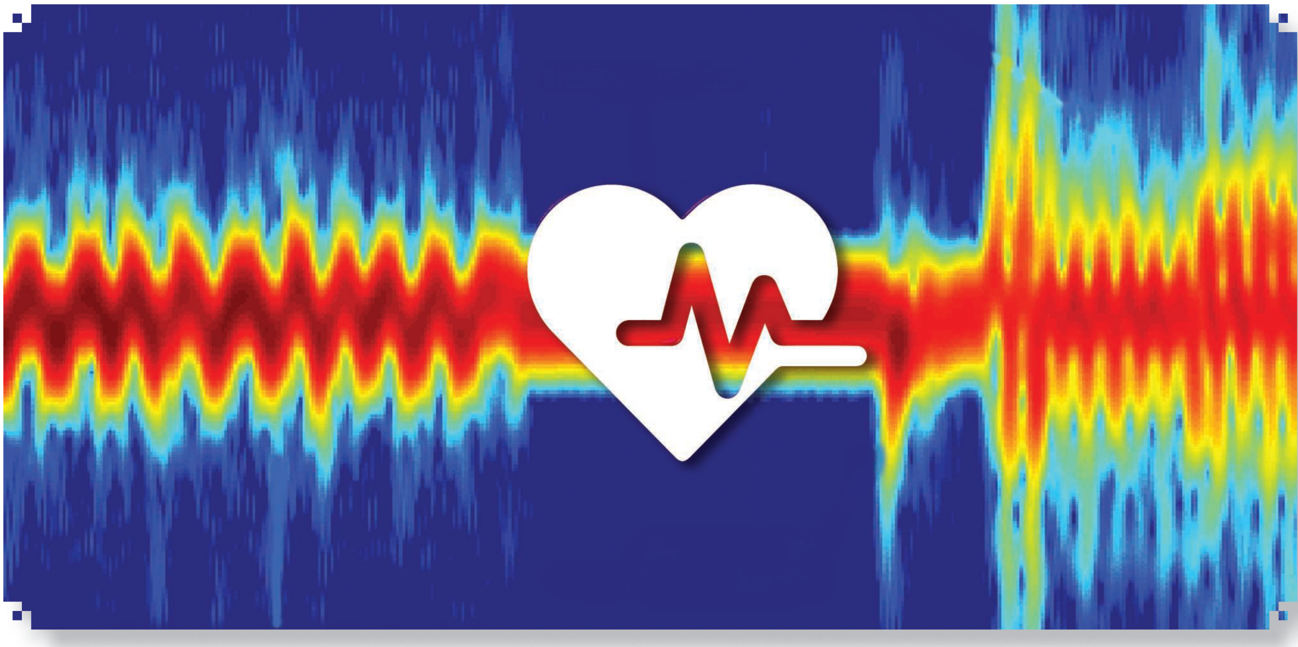

Radar is typically associated with defense and military applications, such as the detection and monitoring of ship and aircraft traffic in certain areas. For example, many of us have seen the antennas near the runways of airports while traveling, rotating to scan the surrounding space and discover airplanes approaching or leaving.

However, in recent years, radar has started to gain significant interest in many fields beyond defense and air-traffic control, opening new frontiers in radar. Emerging applications of radar sensing include automotive radar (on vehicles to help them navigate around obstacles and other vehicles), human-gesture identification (to identify the complex gestures performed by human users to interact with smart objects without tapping screens or pushing buttons), and the health-care domain (to estimate vital signs, such as respiration and heartbeat, and to monitor our level of activity at home).

Radar is ceasing only to be of interest to a niche community of researchers and users in the defense sector and becoming a relevant subject for a wide audience of students in electronic engineering and computer science, researchers and academics, entrepreneurs, and policy makers. Radar sensing intersects and relates to many skills and disciplines, from manufacturing of chips and components operating at the desired frequency to electromagnetic wave propagation, from manufacturing and integration on printed circuit boards to power management, from radar-specific signal processing to machine-learning algorithms applied to radar data. For this reason,

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it is very likely that engineering professionals will have to deal with some aspects of radar sensing as part of the design and development of a larger system, be that a smart vehicle, mobile phone, tablet, or a suite of sensors for new smart homes.

In this article, we focus on the health-care applications of radar systems and radar sensing, which are among the most innovative and somewhat different from the traditional, defense-oriented applications that are commonly associated with radar.

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New health-care needs and provisions

The adoption of radar sensing and other technologies in the domain of health care is related to the new needs in care and welfare provision arising from the rapidly aging population worldwide. Estimates from the World Health Organization and United Nations report that 30% of the world population will be older than age 65 by 2050, and in the United Kingdom, the Office for National Statistics expects the proportion of people more than 85 years old to double during the next 20 years. With aging, the incidence of multiple chronic health conditions (or multimorbidity) and the likelihood of such critical, life-threatening events as strokes or falls increases.

Statistics from the U.K. charity Age UK show, for example, that "falls and fractures in people aged 65+ account for more than 4 million hospital bed days each year in England alone, and the health-care cost associated with fragility fractures is estimated at £2bn a year." The challenges to manage these conditions on an increasing segment of the population are combined with budget pressure on public health-care systems, making the traditional approach of intensive care provided in highly specialized hospital structures potentially unsustainable. In addition to the economic argument, prolonged periods in hospitals can also be unpleasant for patients and their families and come with risks of exposure to antibiotic-resistant bugs and other infections.

Therefore, in recent years, there has been very significant interest in using the most advanced technologies to provide integrated care in private home environments, which is often referred to as *assisted living technologies*. This has two primary objectives. First, preserving as much as possible the autonomy and independence of older citizens in their own familiar environments and avoiding hospitalization and the rupture of the familiar routine and daily habits that are very important for the welfare of people. Second, promoting a proactive approach to health care, whereby technology can provide continuous reliable monitoring and timely identification of subtle signs related to worsening health conditions rather than reacting only when there are very serious symptoms.

Why use radar technology?

What can radar contribute as a technology for health care? Radar is good at identifying the presence of people, tracking them as they move in a certain area, and characterizing these movements, from the bulk motion of the whole body to the smaller movements of individual body parts, such as the head or limbs, down to the very small movements of chest and abdomen while breathing or even the heart beating. Radar research has primarily worked in two directions when it comes to health care:

- estimation and monitoring of vital signs, such as respiration rate and heartbeat using radar systems and data
- monitoring of daily activity patterns using radar data, looking at their regularity and the time it takes to perform them.

The second bullet point includes ensuring that people perform fundamental activities, such as food preparation/intake or personal hygiene; identifying anomalies in the normal pattern, such as increased access to the bathroom overnight; and detecting any critical event that may occur and require prompt response, such as falls.

Before describing the details of radar systems for these applications, it is worth asking, why radar rather than other technologies proposed in recent years? These include video cameras (in normal colors or in thermal and depth modalities), wearable sensors either as stand-alone devices worn at the wrist or embedded into smartphones, and sensors embedded in the ambient, including acoustic (microphones), pressure (pads over floor tiles), infrared (revealing presence of objects in close proximity), and presence or switch sensors for doors, windows, drawers, and electric appliances.

Each sensing technology can be evaluated on different metrics. First of all, the quality and accuracy of its information and performance (how good and useful is the obtainable information?) and the field of view and range of action (how far can it sense the environment?). Then other aspects, such as cost (of installation and maintenance), reliability, number of units required, and users' perception and acceptance, which are very important for health-care applications. Will the users—potential patients and their families and carers—accept these sensing technologies in their homes, and will they comply with any instructions or procedures they are supposed to follow for the system to work properly?

Perceived privacy is a rather important aspect to consider, especially for deployment of the specific sensing technology in potentially sensitive environments, such as bedrooms or bathrooms. Any type of camera can be regarded as privacy invasive but will provide useful information, whereas ambient sensors

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can be embedded in the built environment but are not too informative on their own. Figure 1 provides a summary of this potential dilemma between privacy and information, with a possible classification of assistive living technologies as a function of their perceived privacy and richness of the information provided.

In this context, radar has two main advantages.

- Unlike cameras, no optical images or videos of the monitored subjects are recorded by radar systems, making them less problematic in terms of privacy. However, the level of information they can provide is still very rich, as we will discuss.
- Unlike wearable sensors, radar systems do not require users to wear, carry, or interact with any additional electronic device or modify their daily routine and behavior, which is an advantage for acceptance of this technology.

With respect to practical deployment of radar systems—in particular, their feasibility in terms of miniaturization, cost, and infrastructures—we may be in a transition period, where more research evidence emerges on their usefulness for health-care applications, but they are not yet to the point of being mass-produced and widely available like cameras or wearables. Technology development in electronics and market push from the autonomous vehicles sector (automotive radar) is making radar systems more compact (radar on chip) and driving costs down, as reported by Li and colleagues in their recent review papers on portable/integrated radar in 2017 and 2018.

Principles of radar systems

The basic principle of any radar system consists of transmitting and receiving sequences of electromagnetic waves, modulated in suitable waveforms. By collecting and analyzing the received radar waveforms, one can extract information on the targets of interest that may be present in the area under test and it will reflect back to the transmitter part of the radar waveforms. The typical comparison involves such animals as bats or dolphins, which can emit and receive acoustic waves (ultrasounds) to gain awareness of their surroundings and locate their prey. They operate on similar principles (transmission and reception of waves) but different physical mechanisms (acoustic waves in nature, electromagnetic waves for man-made radar systems).

In their very basic form, radar systems have a transmitter and receiver to generate, condition, and receive electromagnetic waves; antennas to transmit and receive the radar waveforms; and a digital processing core to manipulate and store the radar data through suitable radar signal processing. Figure 2 shows some examples of radar systems from our research laboratory at the University of Glasgow, United Kingdom, which are used for research in the health-care domain. They operate across different frequencies, from 5.8 GHz [Fig. 2(e)] up to 60 GHz [Fig. 2(c)]. Note the small size of these devices, with the largest ones [Fig. 2(d) and (e)] being approximately 15 × 20 × 3 cm, showing how modern radar systems can be easily miniaturized for unobtrusive indoor applications.

Basic principles of radar signal processing in health care

The two main applications of radar sensing in the health-care context are classification of human activities and monitoring of vital signs. Both can be related to the detection and characterization of movements of body parts of the subject, either large movements of the whole body and limbs while performing daily activities or very small movements of the chest (for respiration monitoring) and internal organs (for heartbeat monitoring or blood pressure).

Once the presence of a subject is detected, the typical signal processing on the radar data aims to characterize these movements in three domains: range (as the distance at which the subject and his or her body parts are located with respect to the radar), time (as the evolution over

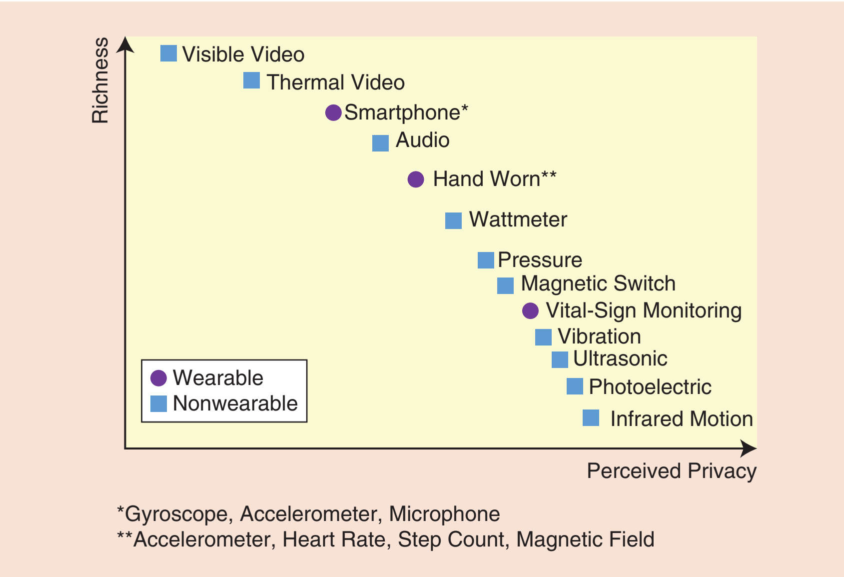

FIG1 The classification of sensing technologies for assisted living as a function of richness of information and perceived privacy. (Source: Debes et al. 2016; used with permission.)

time of the position of the subject and any change to his or her movements), and velocity (as the speed at which these changes happen, whether controlled and regular or with sudden acceleration and deceleration). Velocity and its changes are typically measured by radar systems through the Doppler effect, which is a change in the frequency of the received radar waveforms (Doppler frequency shift) due to the movement of the target. For example, in the case of someone walking indoors, if the person is moving toward the radar, the Doppler shift will be positive because more electromagnetic wavefronts will be scattered back to the radar in a unit of time. The opposite, negative Doppler shift, will happen for movements away from the radar.

Unlike wearable sensors, radar systems do not require users to wear, carry, or interact with any additional electronic device or modify their daily routine and behavior.

Measuring velocity, therefore, means calculating the frequency components of the received waveforms in radar signal processing, and this can be done using Fourier analysis, in particular fast Fourier transform (FFT) algorithms. Figure 3 shows the signal processing chain for an example of data where a person was walking back and forth in front of a radar system. The initial stage of radar signal processing is the temporal sequence of digitized received raw radar data. These are typically organized in a matrix form, where each individual radar pulse will include range bins, digitized samples related to the distance of a possible target, and the sequence of radar pulses will be associated with time, according to the temporal sequence of these pulses. This matrix is typically called a *range–time-intensity* (*RTI*) *matrix*.

In Fig. 3, as the person is walking back and forth in front of the radar, a diagonal zigzag pattern can be seen in the RTI image, with the echo of the person moving away from the radar (range bins increasing over time) and then back toward it (range bins decreasing over time). As mentioned previously, FFT can be applied to characterize the velocity of the target through its Doppler effect. If a single FFT is applied across the time dimension of the RTI, that is, across the sequence of radar pulses, a new matrix called *range–Doppler* (*RD*) can be obtained.

In the example in Fig. 3, both positive and negative Doppler contributions can be seen as the person was moving toward the radar

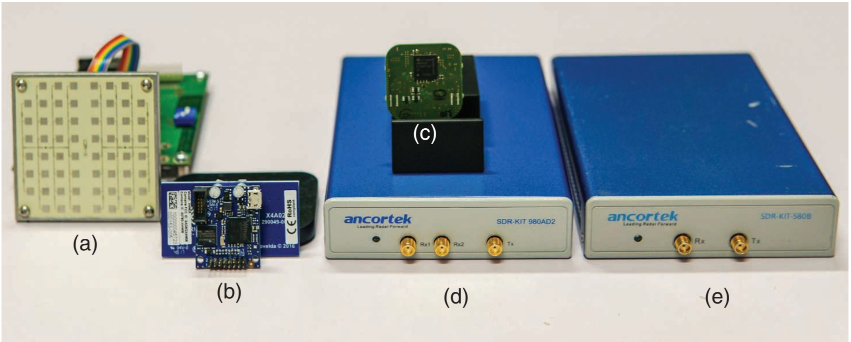

FIG2 Examples of radar systems used at the University of Glasgow for health-care applications including human activity classification and monitoring of vital signs. (a) Continuous wave (CW) 24-GHz radar, (b) ultrawideband (UWB) X-band radar, (c) frequency-modulated continuous wave (FMCW) 60-GHz radar, (d) FMCW 9.8-GHz radar, and (e) FMCW 5.8-GHz radar. (CW, FMCW, and UWB are related to the specific type of waveform transmitted and received by the radar. Additional information is available in the "Read More About It" section.)

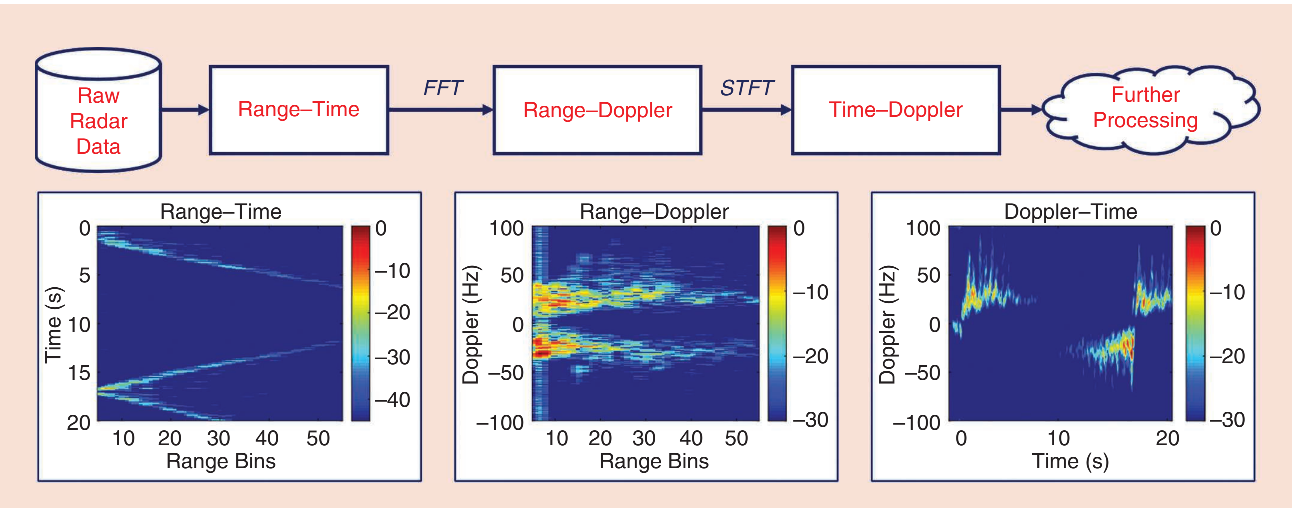

FIG3 The typical signal processing chain for radar data, with examples of range–time, range–Doppler, and Doppler–time patterns for a person walking back and forth in front of the radar.

One of the challenges researchers are investigating is avoiding false alarms for fall detection tasks when the subject sits or bends down.

(positive Doppler) and away (negative Doppler). This matrix characterizes the overall Doppler due to the macromovement of the person but does not say anything about how the body and its parts were moving over time. To achieve this, a different signal-processing technique, called *short-time Fourier transform* (*STFT*) can be used to generate Doppler–time patterns, also called *spectrograms*. The STFT performs several FFTs on the data using shorter, overlapped time windows, so that each FFT produces a column of the spectrogram over time. The key parameters of this operation are the duration of the short FFT window, the overlap factor, and the type of window (for example, a Hamming window, a very typical one), because these parameters significantly affect how the final Doppler–time pattern appears.

There is positive and negative Doppler in the pattern in Figure 3; each contribution has a central, more intense signature (red and yellow color) due to the movement of the torso and main body, and less intense streaks (light blue) due to the limbs. When a person is walking, the movement pattern typically presents a bulk movement of the main body and torso, with additional back-and-forth oscillating movements of the arms. This is what is visible in the Doppler–time pattern in Fig. 3. Finally, in the context of human activity recognition, further processing after generating the patterns in Fig. 3 typically consists in using machine learning to teach an algorithm how to automatically classify patterns related to different activities, as different human activities will exhibit different patterns in the three radar domains described thus far.

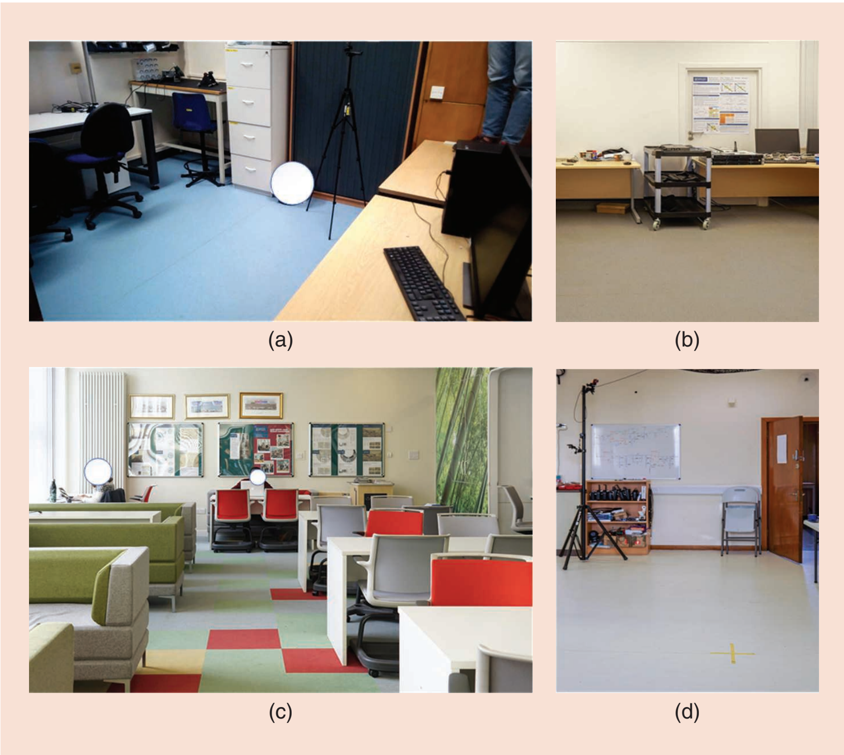

FIG4 Examples of environments (laboratory and common rooms) at the University of Glasgow, where the results presented in the "Examples of Results" section were generated. The (a) small laboratory, (b) large laboratory/experimental area, (c) large common room, and (d) another view of the large laboratory/experimental area.

Examples of results

In this section, we present a few representative results in the context of human activity recognition and monitoring of vital signs. Figure 4 shows some of the environments at the University of Glasgow where the experimental data were collected to generate such results. These range from a small laboratory environment [Fig. 4(a)] to larger laboratory and experimental areas [Fig. 4(b) and (d)] to a large common room [Fig. 4(c)].

Figure 5 shows six Doppler–time patterns for six different activities performed by the same subject while facing the radar, as recorded by a radar system operating in C-band (5.8 GHz) at the University of Glasgow. The six activities include sitting on a chair [Fig. 5(a)], standing up from a chair [Fig. 5(b)], bending to tie shoelaces [Fig. 5(c)], bending to pick up an object [Fig. 5(d)], crouching and standing back up [Fig. 5(e)], and falling frontally after tripping [Fig. 5(f)].

It should be noted that the y-axis is expressed in velocity rather than Doppler shift. Activities that imply movement toward the radar, for example, bending down and falling, all have positive velocity in their patterns, and vice versa (for example, the sitting on a chair scenario, where the subject in this case sat down and leaned a bit back on the chair, therefore generating a significant negative Doppler shift). One of the challenges researchers are investigating is avoiding false alarms for fall detection tasks when the subject sits or bends down, as all of these activities produce a significant acceleration and a sudden velocity signature.

Another challenge is coping with the variability of movements and radar signatures with different subjects. Any algorithm will be inevitably trained on a subset of people, but everyone has his or her own characteristic way of moving and performing actions, depending on body type, posture, age, gender, and possible disabilities. The capability of capturing the general, universal

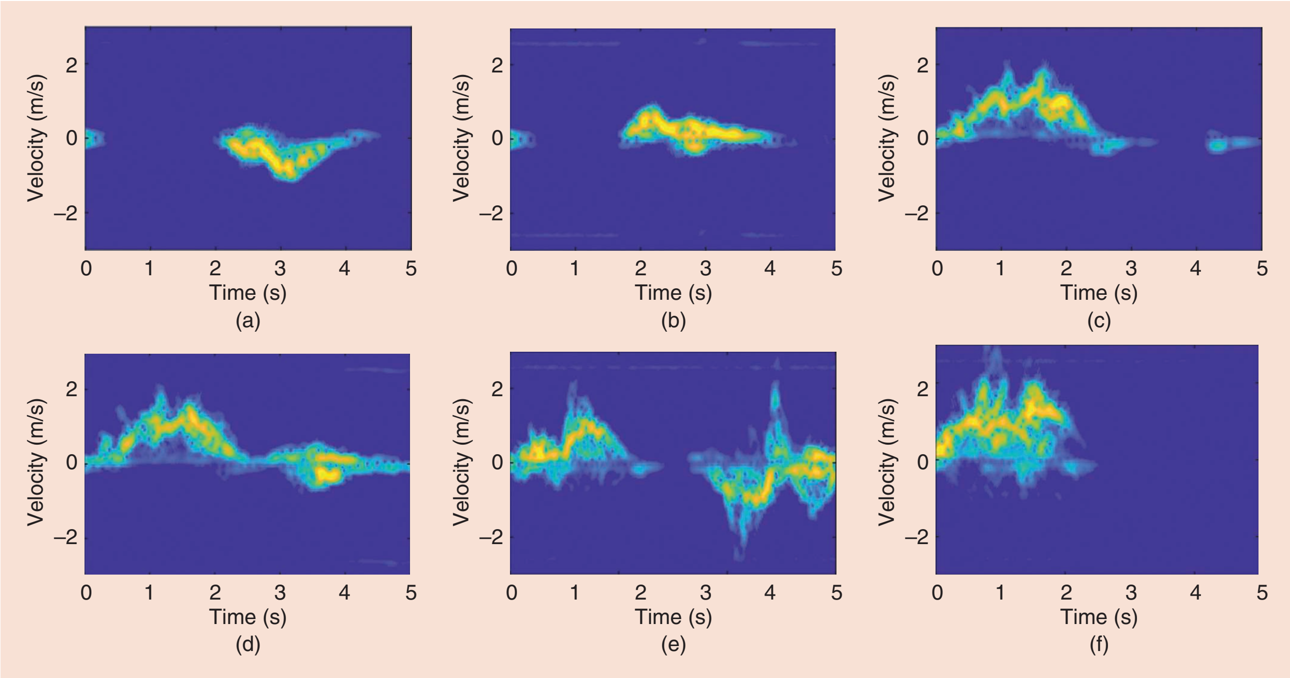

FIG5 An example of six velocity/Doppler–time patterns for six human activities recorded by radar. The subject (a) sitting on a chair, (b) standing up from a chair, (c) bending to tie shoelaces, (d) bending to pick up a pen, (e) crouching and standing back up, and (f) falling frontally.

features of the kinematics of human movements irrespective of the changes discussed is one of the outstanding research questions in this domain.

The activities in Fig. 5 were performed and collected as individual snapshots, with each activity separated from the others. In Fig. 6, the Doppler–time pattern of a sequence of six activities performed continuously, one after the other, is presented. The six activities are drinking a glass of water while standing, picking up an object from the floor, sitting on a chair, standing back up, walking back and forth, and falling frontally. The first four activities are fundamentally performed without much bulk movement of the body, so the Doppler signature is concentrated around the 0-Hz value, whereas the positive and negative contributions due to walking back and forth are visible between 20 and 30 s, with the final strong positive Doppler signature due to the fall at the end of the recording. Figure 6 introduces an additional challenge for research into activity recognition using radar signatures, which is the processing of a continuous stream of activities (and therefore data), where finding the transitions between them can be very challenging.

Another new application of radar systems and signal processing is the analysis of gait and locomotion parameters to identify any change or degradation of mobility metrics and capabilities. Figure 7 shows the velocity–time patterns for two subjects who are walking normally [Fig. 7(a) and (c)] and walking with a limp on one leg [Fig. 7(b) and (d)]. The two patterns are rather different, with a more-or-less symmetric Doppler signature produced by the legs for normal walking and an asymmetric pattern for the subject who is limping. Further research is being undertaken to extract more precise gait parameters from these signatures—for example, periodicity of the gait, mean velocity and acceleration, length of the strides—because these can have clinical value in assessing health conditions of patients at risk.

Finally, Fig. 8 includes an example of how radar can be used to monitor respiration rates of human subjects, which can be useful to assess respiratory conditions during sleep or the insurgence of further health conditions related to problems

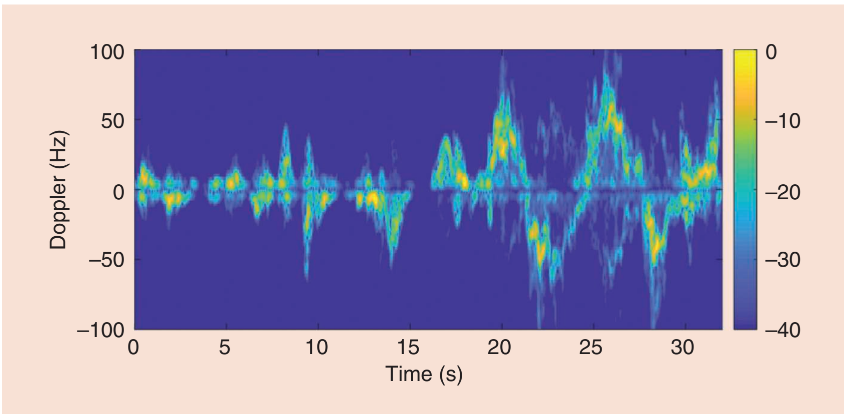

FIG6 A Doppler–time pattern for a sequence of six activities performed by a subject: drinking a glass of water while standing, picking up an object from the floor, sitting on a chair, standing back up, walking back and forth, and falling frontally.

Another new application of radar systems and signal processing is the analysis of gait and locomotion parameters.

in breathing. In this instance, a subject was sitting facing the radar at approximately 60 cm and simulating different respiration rates: 10 normal inhaling/exhaling cycles, followed by holding his breath for a few seconds, a deep exhaling, and finally a few cycles of fast breathing. The experimental setup is shown in Fig. 8(a), with a chair where the subject was sitting, the laptop controlling the radar, and the radar (occluded by the laptop in this case) facing the subject. The distinction between the different respiration rates and regimes is quite clear in the Doppler–time pattern [Fig. 8(b)], and the periodicity and regularity of respiratory movements can be extracted from these data.

Ongoing research within the radar community aims to validate monitoring of respiration rate on longer distances and more realistic conditions as well as extending capabilities to the monitoring of heartbeat and blood pressure. Outstanding challenges include investigating how robust the algorithms for radar-based vital signs monitoring are, in particular the effect of different orientations of the subject (frontal, back, side view, lying down rather than sitting) and the presence of layers of clothing (those worn by the subject themselves or the presence of bed linens, blankets, or curtains, for instance).

Conclusion

Although typically associated with large-scale, defense-related use to monitor ships and aircraft, radar has been employed in the past few years for a number of short-range, civilian applications. We have discussed and presented some examples of radar used to support health-care provisions, to help monitor vital signs of patients at risk and their daily activities, a useful proxy for their more general physical and cognitive well-being. Unlike cameras and wearables, radar does not collect sensitive images of the

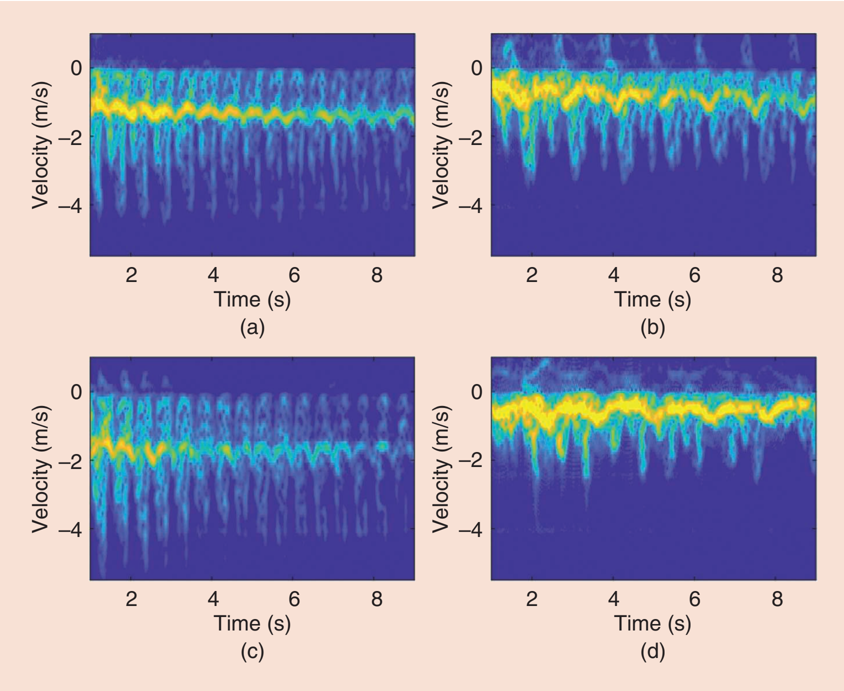

FIG7 The velocity–time patterns for two subjects walking normally and limping as recorded by a C-band radar. (a) Person A walking, (b) person A limping, (c) person B walking, and (d) person B limping.

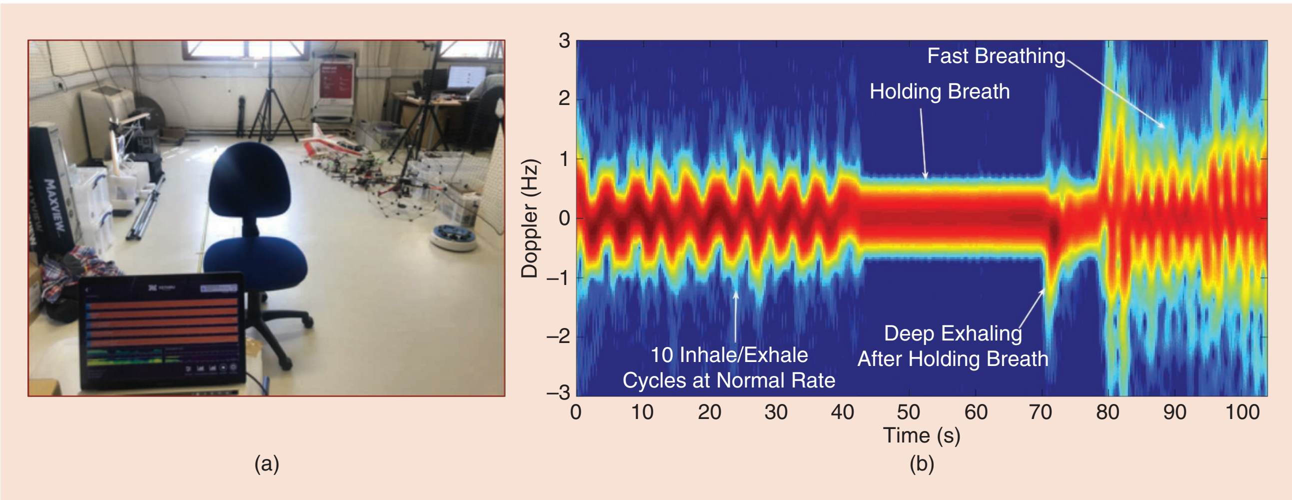

FIG8 (a) The experiment setup for (b) the Doppler–time pattern for a person sitting on a chair at 60 cm from the radar and simulating different respiration rates.

people monitored or require users to wear, carry, or interact with new devices that may be perceived as intrusive; it can, therefore, have significant advantages in terms of users' perception and compliance.

We have shown a few experimental results of the radar signatures for different human activities as well as an example of radar data tracking the respiratory rate of a monitored subject. The collection and full understanding of these data will be key to developing innovative signal processing and machine-learning algorithms to automate monitoring and consequently timely and proactive diagnostics for future healthcare provision.

Ongoing research within the radar community aims to validate monitoring of respiration rate on longer distances and more realistic conditions.

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Read more about it

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