Chapter 13

Wireless Sensing

While wireless has revolutionized mobile data communications, it also plays a major role as a sensing technology. Meteorologists routinely use wireless signals to scan the atmosphere for weather forecasts, astronomers use radio to probe deep space, geologists use radio frequencies for remotely sensing various Earth phenomenon, and airport authorities are increasingly using wireless signals at security gates to detect prohibited materials concealed by passengers. Recently, scientists are discovering techniques to monitor human activities and even vital signs, such as heart and breathing rates, simply by analysing the wireless signals reflected by the human body. These advancements have created the potential for wireless to penetrate the growing mobile and IoT sensing market. This chapter explains the working principles of the popular wireless sensing tools and techniques targeted at the IoT market.

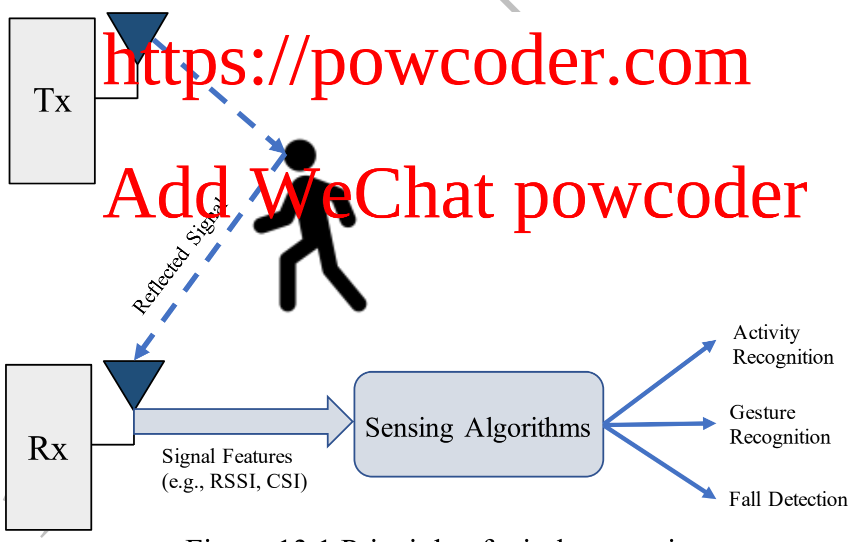


Figure 13.1 Principle of wireless sensing.

13.1 Motivation for Wireless Sensing

Sensing is fast becoming an indispensable technology for modern living. There is a push to integrate various types of sensors in the environment for seamlessly detecting human contexts to realise more natural and effortless living. For example, sensors embedded into wearable devices, such as wrist bands, can continuously monitor the user's activity levels and vital signs, offering 24x7 low-cost health and fitness care for many groups of citizens including high-risk individuals. Low-cost cameras can be deployed in aged care facilities to help detect diagnostic movements or falls of elderly occupants.

While wearable sensors and cameras can be very effective for sensing human contexts in smart environments, they have several disadvantages. Wearable sensors are not always convenient to carry or worn and they need to be regularly recharged adding additional maintenance burden on the user. Cameras on the hand frees the user from such burdens but they intrude user privacy and do not work without line-of-sight. As radio signals can penetrate walls, they offer a more ubiquitous sensing than cameras and unlike the cameras, they do not record privacy details. Wireless sensing can work with ambient radio signals and hence eliminates the need to wear sensors on the body. Due to these distinct advantages, wireless sensing is fast becoming a critical technology for smart living.

13.2 Principle of Wireless Sensing

Figure 13.1 illustrates the overall working principle of wireless sensing [COMST2021]. Human body reflects wireless signals. As such, human activities cause changes in wireless signal reflections, which in turn causes variations in received signals, e.g., the amplitude and phase of the signal. Carefully designed algorithms therefore can distinguish one human activity or state from another by measuring and analyzing various features, such as received signal strength, time of flight, etc., of the received signals.

13.3 Types of Sensing Signals

There are two dominant types of wireless signals that are currently used for mobile sensing: WiFi and radar. The actual techniques of sensing are different for these two types of signals. While WiFi sensing can sense humans and the environment directly from the existing signals used for communications, radars use signals specifically designed and dedicated for sensing. These two types of mobile sensing are explained in the remaining of this chapter.

13.4 WiFi Sensing

WiFi sensing refers to systems that try to detect human states from the WiFi signals reflecting from the human body. Working principle of WiFi sensing system is illustrated in Figure 13.2 where an existing access point (AP) or WiFi router transmits WiFi packets, while a receiver, such as a laptop, extracts specific signal information for sensing. RSS and channel state information (CSI) are dominant signal information currently used for WiFi sensing.

Figure 13.2 WiFi sensing using existing WiFi infrastructure.

13.4.1 Sensing with RSS

RSS is a single scaler power value in dBm reported for the entire wireless channel irrespective of the number of OFDM subcarriers within the channel. Humans can affect RSS in different ways; they can block the LoS between the transmitter and the receiver, or they can act as an additional source of reflection. Blocking of LoS would directly reduce the signal strength, while the reflection would cause variation in the overall received signal power as all reflected rays are combined at the receiver to produce the received signal. Thus, the presence, location, and activities of the human would create distinct patterns in RSS time series, which can detect using appropriate algorithms.

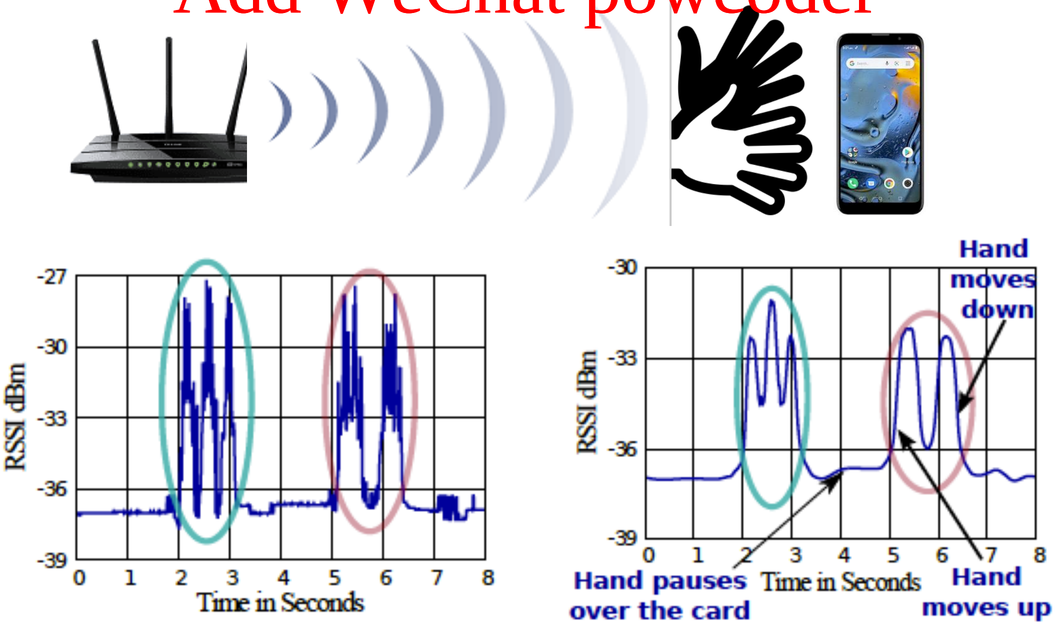


Figure 13.3 Gesture detection from WiFi RSS. Hand gestures conducted near a mobile phone receiving WiFi packets from an AP (top). Raw (bottom left) and denoised RSS (bottom right) time series for moving a hand up and down over the mobile phone [YOUSSEF2015]

Figure 13.3 shows an example of hand gesture detection using WiFi RSS. It shows that raw RSS data is very noisy due to complex propagation and interaction of the signals with surrounding objects. Raw RSS time series therefore is 'denoised' or 'smoothed' first before gesture patterns can be detected.

The major advantage of using RSS for sensing is that it is widely and readily available as most mobile devices measure and report RSS for all received WiFi packets. Thus, no special hardware/software is needed for WiFi sensing with RSS. The downside is that commodity WiFi chips provide low RSS resolutions hence only coarse activities can be detected with limited accuracies. For example, RSS can be used to detect a few hand gestures, but it is not good for detecting more fine-grained activities such as detecting gestures of sign language or detecting daily activities of the residents.

13.4.2 Sensing with Channel State Information (CSI)

In wireless communications, the received signals are never the exact replicas of their transmitted counterparts. Factors such as distance-related path loss, atmospheric absorption, reflection and scattering from various objects, etc. affect the amplitude and phase of the signal during its travel from the transmitter to the receiver. Conceptually, it is said that the signal travels through a wireless *channel*, *h*, which has a particular channel frequency response (CFR) function, *h(f)*, which determines the amplitude and phase response for each individual frequency, *f*, contained within the signal. This concept is illustrated in Figure 13.4. The received signal for frequency *f* at any time instant, *t*, is obtained by multiplying the CFR with the transmitted signal as follows:

$$y(f,t) = h(f,t) \times x(f,t) + n \qquad (13.1)$$

where *n* is the receiver noise independent of the transmitted frequencies. The CFR, *h(f,t)*, expresses the amplitude and phase changes using the complex number, $Ae^{j\theta}$, where A and θ, respectively, represent the changes in amplitude and phase, and $j=\sqrt{-1}$. A is often measured in dB and θ in radians. As illustrated in Figure 13.5, $Ae^{j\theta}$ can be geometrically plotted in a 2D graph as $(a+jb)$, where $A = \sqrt{a^2 + b^2}$ *and* $\theta = \tan^{-1}\frac{b}{a}$.

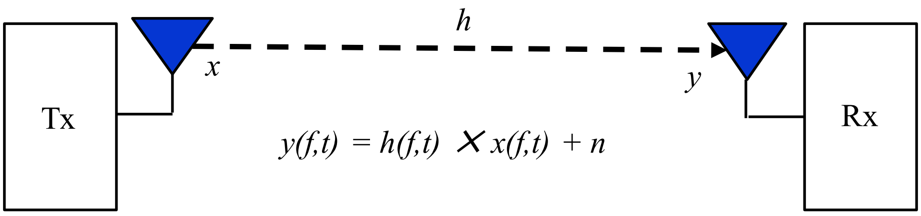


Figure 13.4 Channel frequency response for wireless communications.

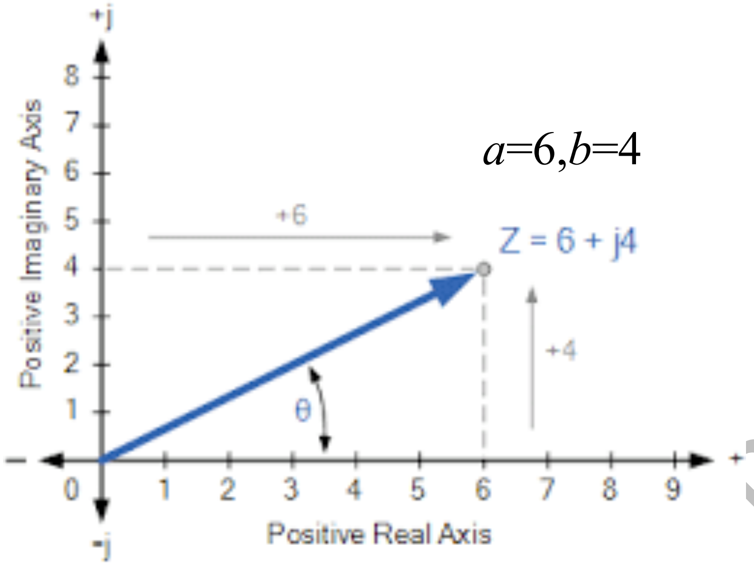


Figure 13.5 Geometric plot of the complex CSI. The x-axis plots the real part while the y-axis plots the imaginary part of the complex CSI number.

The complex number $Ae^{j\theta}$, is also known as the channel state information (CSI), which is used to estimate the wireless channel between the transmitter and the receiver. CSI estimation is a very important function at the physical layer of wireless communication systems, because it helps the system to adjust for the changes inflicted by the channel on the transmitted signal. For example, in WiFi, the packet preamble contains known signals, which is compared with the received signals to estimate CSI at the receiver; the receiver then uses the CSI to decode data symbols in the packet payload. The receiver may also provide CSI feedback to the transmitter, e.g., in 802.11n, so the transmitter can adjust the data rates (modulation and coding) or configure the power and phase parameters of the MIMO transmission more precisely.

In most commercial devices, CSI is produced and consumed inside the WiFi chip at the physical layer and cannot be accessed at user or application layer, which limits CSI-based WiFi sensing to some extent. However, some commercial WiFi chips, such as Intel 5300 and Atheros 9390 do provide CSI for selected subcarriers, usually for 30 subcarriers which is adequate for fine-grained sensing.

By configuring a WiFi transmitter to transmit packets at a fixed rate, a receiver can obtain a CSI time series for **each subcarrier** at a target sampling rate, e.g., 100 packets/s leads to CSI sampling at 100Hz for each of the N time series, where N is the number of subcarriers for which CSI is estimated. For receiving devices with multiple (M) antennas, each antenna produces N CSI time series for a given transmitting antenna.

While CSI time series provide more detailed frequency-dependent channel information, it becomes overwhelming to detect patterns from so many individual time series. Often, some **dimensionality reduction**, such as Principle component Analysis (PCA), is performed on the large number of CSI time series to produce a **single CSI time series** [WIDANCE2017], which is then used to detect patterns for human activities. The dimensionality reduction pre-processing is illustrated in Figure 13.6.

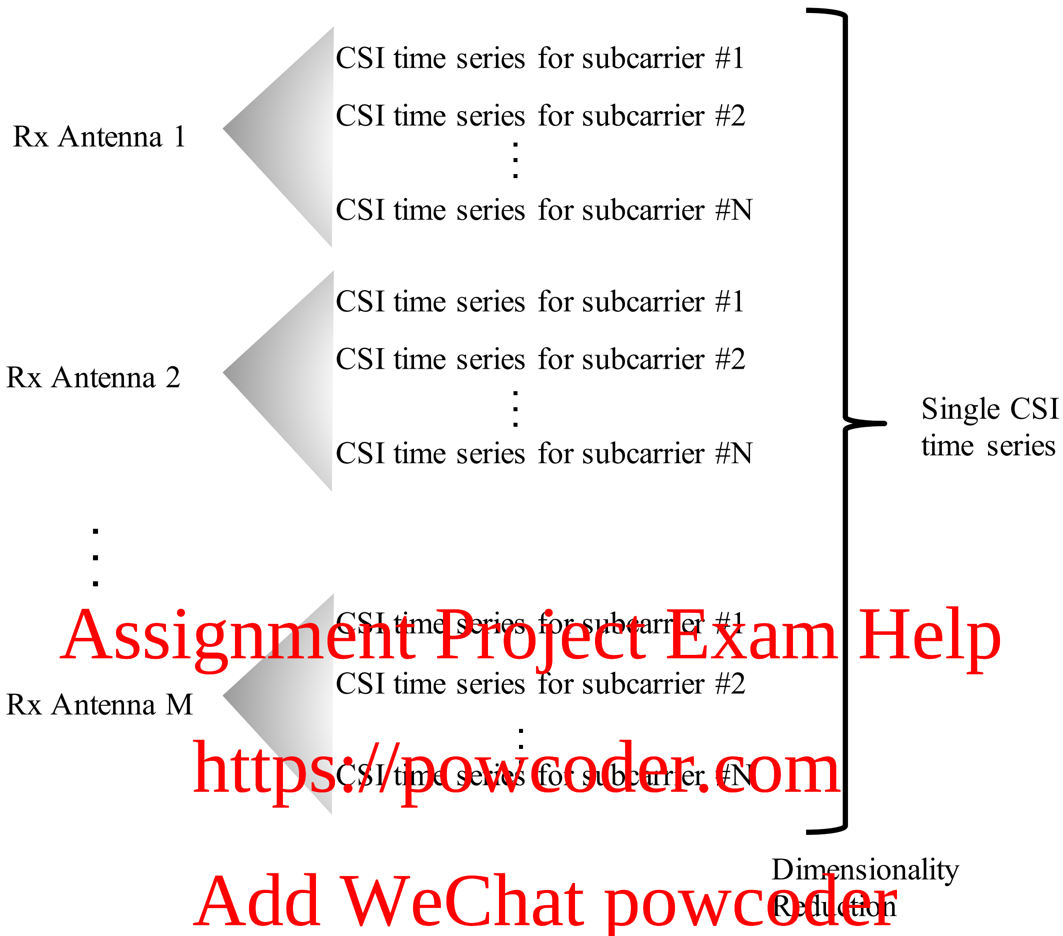


Figure 13.6 Dimensionality reduction of CSI time series.

While CSI provides both amplitude and phase values, the phase values are typically very noisy due to frequency drifts in oscillators. This phenomenon is particularly pronounced in WiFi receivers due to low-cost electronics compared to cellular (3G, 4G etc.) receivers. Therefore, phase values of the WiFi CSI are often ignored and sensing is performed exclusively using CSI amplitudes. Future generations of WiFi radios designed to work with very high modulations, such as 4096 QAM in the proposed 802.11be, are expected to provide cleaner phase values as they will require more strict phase noise control for correctly detecting very small phase differences between symbols. Figure 13.7 shows examples of CSI amplitude and phase time series collected from a 802.11n WiFi receiver for different human activities. We can see that different activities have distinct amplitude patterns while the phase values are too noisy.

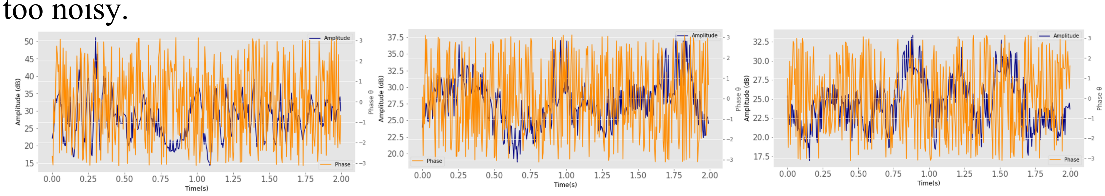


Figure 13.7 CSI time series for three different human activities; Leg Swing (left),

hand Push&Pull (middle), and Hand Swipe (right). The amplitude (blue) shows distinct patterns while the phase (yellow) is too noisy to be useful.

13.5 Radar Sensing

Radar stands for **RA**dio **D**etecting **A**nd **R**anging. As the name suggests, it is a technology to detect objects and estimate the range of the object, i.e., how far the object is from the transmitter, using radio signals. Traditionally, radars have been used to detect and track objects at long ranges such as aircrafts, ships, and cars as well detecting rains. With advancements in low-power electronics and miniaturizations, radar technology is now penetrating the mobile and IoT consumer market giving these consumer devices greater sensing capability to realize the vision of smart living [TI-RADAR]. These compact radars have much enhanced sensing capabilities than WiFi; they can sense distance, speed, direction of movement, and sub-millimeter motions.

13.5.1 Principle of Radar Sensing

The fundamental principle of radar is illustrated in Figure 13.8. Radar uses a single device instrumented with a transmitting and a receiving antenna synchronized by the same clock. It works by transmitting a directional wireless signal through the transmitting antenna and then measuring the signal reflected by the target object at the receiving antenna, which allows it to accurately compute the time of flight (ToF). The range is then computed by multiplying the ToF by the speed of light.

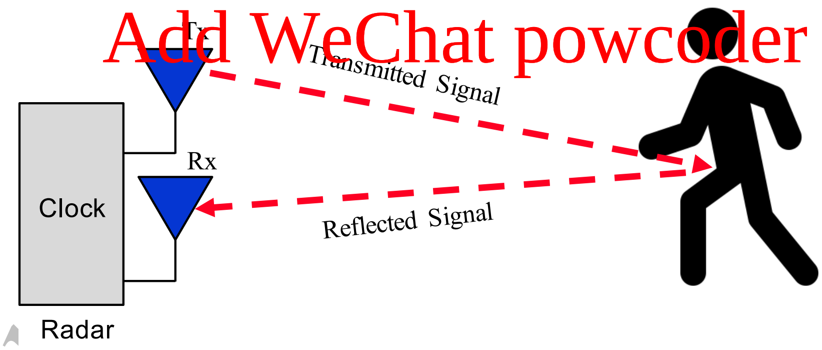


Figure 13.8 Fundamental principle of radar.

13.5.2 Range and Resolution

The range of a radar refers to the detection or coverage range, i.e., the maximum distance from which a radar can reliably detect and estimate the range of an object. Range therefore basically relates to 'how **far** the radar can see'. Resolution, on the other hand, refers to its ability to separate two or more targets at different ranges within the same bearing. Resolution therefore relates to 'how **clearly** the radar can see'. Usually, longer range radars have lower resolution and vice-versa. The concepts of range and resolution of a radar are illustrated in Figure 13.9. We note that both the range and the resolution are measured in units of distance, such as in meters or millimeters.

Fundamentally, the resolution directly depends on the bandwidth of the radar signal as follows [RADAR-NATURE]:

$$\text{Resolution} = \frac{c}{2B} \text{ meter} \qquad (13.2)$$

where c is the speed of light in m/s and B is the bandwidth in Hz.

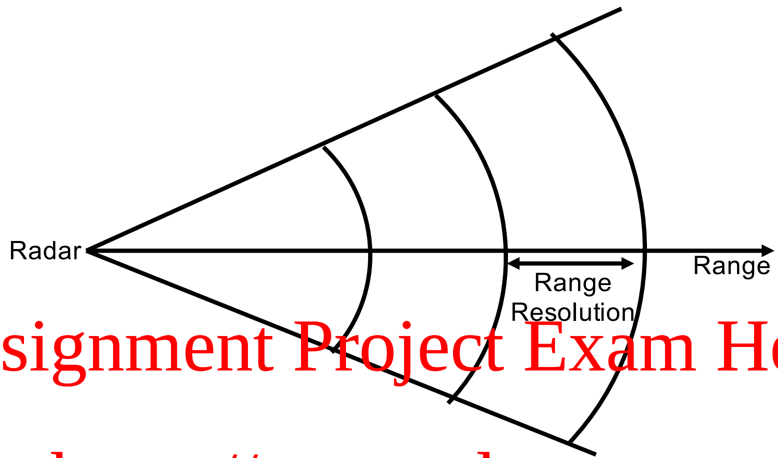


Figure 13.9 Illustration of range and resolution of radar.

13.5.3 Types of Radar Signals

Radars are specifically designed for sensing and cannot be generally used as communication devices. This contrasts with WiFi sensing, which can sense with commodity WiFi devices and signals designed for data communications.

There are two major types of radar signals: **Pulse** vs. **FMCW.** Pulse radars are usually used for long-range detections; they are bulky, power hungry and used by large infrastructure such as weather stations, aircraft control tower, cars, and so on. FMCW is lightweight, energy-efficient and used in mobile devices such as mobile phones and IoTs.

13.5.4 Pulsed Radars

A pulse is a very short signal on the order of µs or ns, which is transmitted with very high peak power on the order of kW or MW. These high-power pulses are suitable for long-range applications, e.g., aircraft detection and tracking. Radar antennas are highly **directional** and usually rotate continuously to provide 360° coverage for applications such as aircraft detection in control towers.

Pulses are transmitted periodically with tens or hundreds of pulses per sec, while the transmitter remains completely silent in between pulse transmissions. As pulse durations are extremely short compared to the silence periods, the average power consumption of pulsed radars is considerably lower than the peak pulse power. While the transmitted pulse powers are high, the received pulses are very weak as illustrated in Figure 13.10.

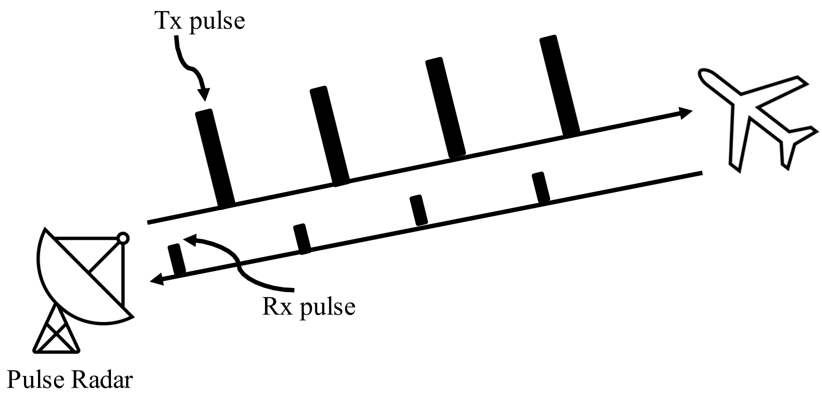


Figure 13.10 Pulsed radar.

Wider pulses contain more energy; hence they provide longer detection range, but echoes from multiple objects can overlap yielding low resolution. Since *B* is inversely proportional to pulse width, the resolution of pulsed radars can be obtained as:

$$Resolution = \frac{c \times \omega}{2}\ meter \qquad (13.3)$$

Where ω is the pulse width in meter. Thus, narrower pulses have higher resolution at the expense of shorter range and higher bandwidth requirements.

With advanced signal processing, it is possible to measure the frequency of the received pulses, which enables Doppler shift calculations. Thus, radars can also calculate the radial **velocity** of the target and detect whether the target is moving closer and farther from the radar.

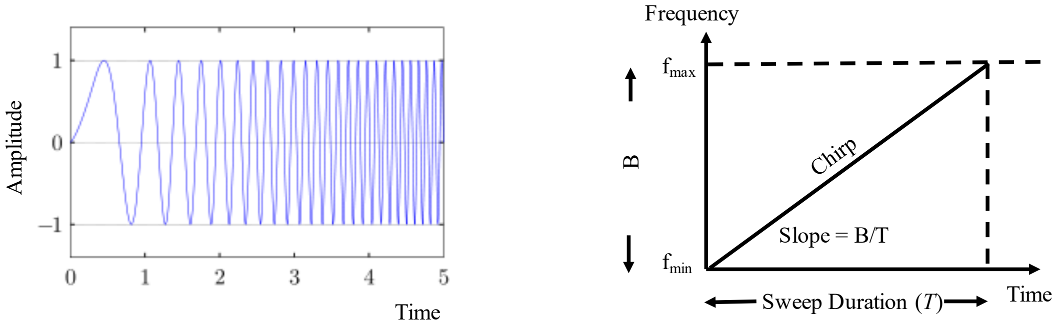
For large objects, such as aircrafts, pulses get reflected by different parts of the object body. With advanced signal processing, it is then possible to detect the **shape** of the target and identify them.

13.5.5 FMCW Radars

FMCW stands for Frequency Modulated Continuous Wave. As the name suggests, unlike narrow pulses, FMCW transmits continuous signals, but it modulates the frequency of the transmitted signal in a special way that helps detect the ToF [TI-RADAR]. Basically, the frequency modulation follows a linear chirp as shows in Figure 13.11 (a), where the frequency is increased at a constant speed over time. In the time-frequency representation (Figure 13.11(b), the chirp appears as a straight line. As we can see, the chirp sweeps the entire bandwidth, from the minimum frequency to the maximum frequency, within a specified chirp sweep duration. The sweeping speed is basically given by the slope, S, as:

$$S = \frac{B}{T} \qquad (13.4)$$

Where B is the bandwidth in Hz and T is the chirp sweeping duration in second.



(a) (b)

Figure 13.11 Linear chirp in amplitude-time (a) and frequency-time (b).

So, how does a chirp transmission help FMCW radar measure the ToF? As shown in Figure 13.12, this is achieved by measuring the instantaneous frequency difference, Δf, between the transmitted chirp and the received chirp. The reason that there exists a frequency difference at any given time instant between these two signals is because there is a time delay, ToF, between them. Given that the frequency difference is basically the product of the slope of the chirp and the ToF, we have:

$$ToF = \frac{\Delta f}{S} \qquad (13.5)$$

The range is then obtained as:

$$Range = ToF \times c = \frac{\Delta f \times c}{S} \qquad (13.6)$$

Using the same chirp concepts, FMCW radars can detect two or more objects located at different distances but at the same bearing. This is possible as each object reflects the chirp with slight delays from each other. Figure 13.13 shows the chirp transmissions and receptions at the radar when two objects are located at the same bearing but at different distances.

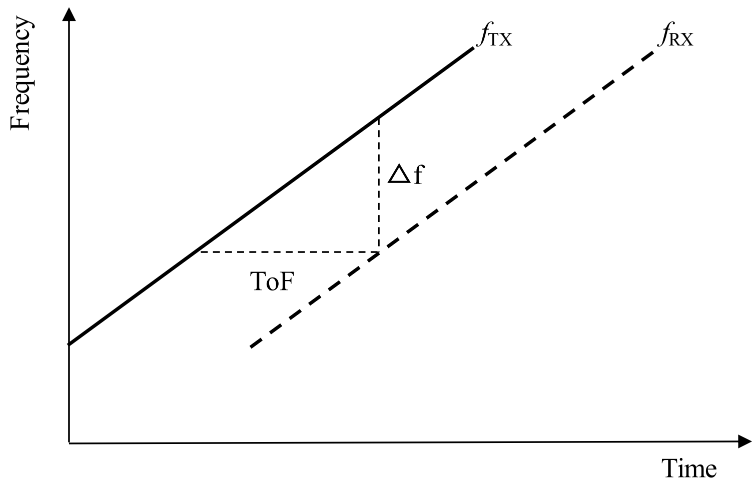


Figure 13.12 Principle of FMCW radar.

Let us now derive the resolution of FMCW radars. Let us consider two objects along the same bearing but with a difference of Δd meters from each other. If we denote the instantaneous frequency difference between the received chirps from these two objects with Δf, then we have:

$$\frac{\Delta f}{2\Delta d/c} = S = \frac{B}{T} \qquad (13.7)$$

where $2\Delta d/c$ is the difference between the round-trip times of the two objects. According to the frequency detection principle, which relates to Fast Fourier Transform, two frequencies within a signal can be distinguished if $\Delta f > 1/T$, where T is the observation time of the signal. Thus replacing Δf with $1/T$ in Eq. (13.7), we obtain:

$$\Delta d = \frac{c}{2B} \qquad (13.8)$$

It is interesting to note that the resolution of FMCW radar obtained in Eq. (13.8) is identical to the resolution of the pulsed radar, which depends only on the bandwidth. This means that FMCW resolution does not depend on the slope of the chirp.

Example 13.1

Question: What is the resolution of a 24GHz FMCW radar operating within the ISM band from 24 GHz to 24.25 GHz

Solution:
Bandwidth (B) = 24.25 – 24 = 0.25GHz
Speed of light (c) = $3\text{x}10^8$ m/s
Resolution = c/2B = $(3\text{x}10^8)/(2\text{x}0.25\text{x}10^{9)}$ = 60cm

---

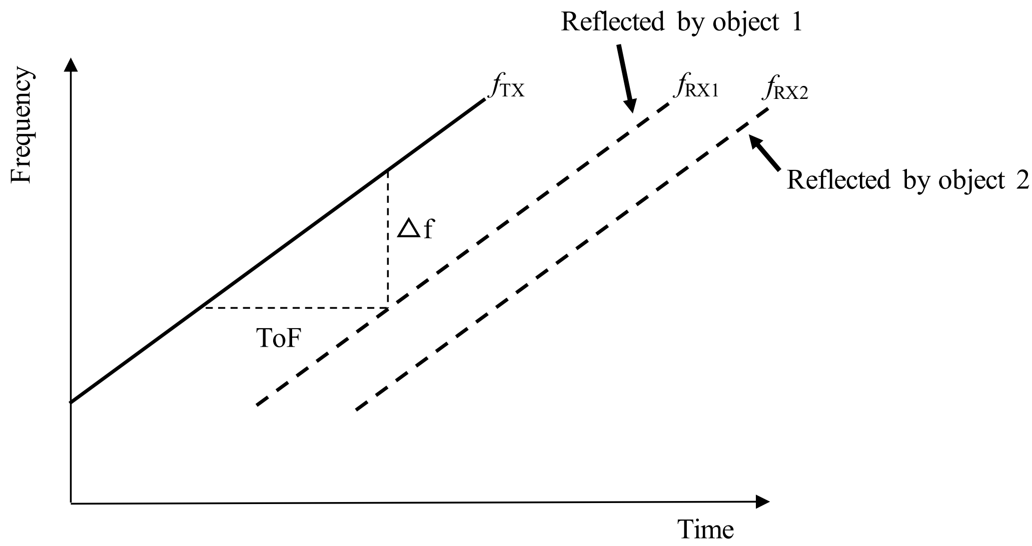


Figure 13.13 Transmitted and received chirps in the presence of two objects.

13.6 Chapter Summary

1. Wireless signals are good for both communication and sensing
2. Two major types of wireless sensing: WiFi Sensing and Radar Sensing
3. Using RSS and CSI, WiFi can be used for many human sensing and monitoring applications
4. RSS is readily available, but cannot provide fine-grain sensing
5. CSI can provide fine-grain sensing, but modifications required to access CSI in commodity WiFi devices
6. Radar can provide accurate range and motion information; more sophisticated sensing applications are possible with radars, but they require dedicated infrastructure for sensing
7. Millimeter wave FMCW radars have emerged as a popular low-cost, small form-factor IoT sensing device with applications in many IoT domains: health, smart home, smart industry, smart transport, etc.

References

[COMST2021] I. Nirmal, A. Khamis, M. Hassan, W. Hu and X. Zhu, "Deep Learning for Radio-Based Human Sensing: Recent Advances and Future Directions," in *IEEE Communications Surveys & Tutorials*, vol. 23, no. 2, pp. 995-1019, Second quarter 2021, doi: 10.1109/COMST.2021.3058333.

[YOUSSEF2015] H. Abdelnasser, M. Youssef and K. A. Harras, "WiGest: A ubiquitous WiFi-based gesture recognition system," *2015 IEEE Conference on Computer Communications (INFOCOM)*, 2015, pp. 1472-1480, doi: 10.1109/INFOCOM.2015.7218525.

[TI-RADAR] "mmWave Radar Sensor," Texas Instrument. https://www.ti.com/sensors/mmwave-radar/overview.html [accessed 28 October 2021]

[WIDANCE2017] Kun Qian, ChenshuWu, Zimu Zhou, Yue Zheng, Zheng Yang, Yunhao Liu, "Inferring Motion Direction using Commodity Wi-Fi for Interactive Exergames," CHI 2017.

[RADAR-NATURE] Komissarov, R., Kozlov, V., Filonov, D. *et al.* Partially coherent radar unties range resolution from bandwidth limitations. *Nature Communications* **10,** 1423 (2019). https://doi.org/10.1038/s41467-019-09380-x

End of Chapter 13 (Wireless Sensing)