mobile communications series

# SOFTWARE-DEFINED RADIO for ENGINEERS


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**Library of Congress Cataloging-in-Publication Data**
A catalog record for this book is available from the U.S. Library of Congress.

**British Library Cataloguing in Publication Data**
A catalog record for this book is available from the British Library.

ISBN-13: 978-1-63081-457-1

**Cover design by John Gomes**



10 9 8 7 6 5 4 3 2 1

*Dedication*

To my wife Lauren
—Travis Collins

To my wonderful children, Matthew, Lauren, and Isaac, and my patient wife, Michelle—sorry I have been hiding in the basement working on this book. To all my fantastic colleagues at Analog Devices: Dave, Michael, Lars-Peter, Andrei, Mihai, Travis, Wyatt and many more, without whom Pluto SDR and IIO would not exist.
—Robin Getz

To my lovely son Aidi, my husband Di, and my parents Lingzhen and Xuexun
—Di Pu

To my wife Jen
—Alexander Wyglinski

# Contents

CHAPTER 11

# Applications for Software-Defined Radio

Until now, the focus of this book was on understanding and mastering the tools of building a successful communication system using software-defined radio technology. Both theoretical concepts regarding the various building blocks of a communication system and practical insights on how to implement them have been extensively covered. The question one might be asking at this point is: What can I do with SDR? Indeed, SDR is a very powerful tool for designing, exploring, and experimenting with communication systems, but how can one wield this tool to innovate and create? In this chapter, two applications are discussed that significantly benefit from the versatility and performance of SDR: *cognitive radio* and *vehicular networking*. In particular, two approaches for implementing the intelligence and learning in cognitive radio will be discussed; namely, *bumblebee behavioral modeling* and *reinforcement learning*. As for vehicular networking, we will focus on the IEEE 802.11p and IEEE 1609 standards that define *vehicle-to-vehicle* and *vehicle-to-infrastructure* within vehicular ad hoc networks (VANETs). The goal of this chapter is to provide the reader with insights on how SDRs can be employed in these advanced applications.

## 11.1 Cognitive Radio

The concept of cognitive radio, whose term was coined in 2000 by Joseph Mitola [1], is a powerful methodology for performing communications where each radio within the network has the capability to sense its environment, adapt its operating behavior, and learn about new situations on-the-fly as they are encountered (see Figure 11.1). As a result of cognitive radio's ability to sense, adapt, and learn, it requires the communication system it is operating on to be highly versatile. Consequently, SDR technology is very well suited for implementing cognitive radio-based communication systems.

Although SDR seems to be a great fit for cognitive radio applications, there are several design and implementation considerations that need to be addressed. Referring to Figure 11.2, we see how the cognitive radio engine forms a layer on top of the baseband processing portion of the SDR platform. The baseband processing can be one of several computing technologies, such as general purpose microprocessor systems, FPGAs, DSPs, GPUs, ARM, and other embedded computing technologies. In fact, it might even be possible to have a SDR with several types of baseband processing technologies co-existing on the same system. Given a computing technology for a specific SDR system, one needs to be mindful that not all SDRs are built the same and that each computing technology has its advantages and disadvantages. For instance, FPGAs are not easily reprogrammable,

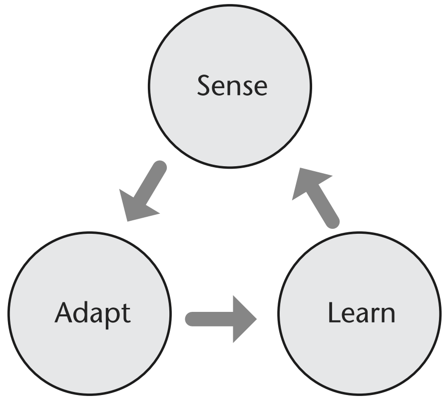


**Figure 11.1** The sense, adapt, learn cycle of cognitive radio. This cycle is what differentiates cognitive radio from those that are purely automated or adaptive because of the presence of learning in this functional cycle.

which means they are not well suited for communication system operations that frequently change. On the other hand, they are very suitable for those applications requiring raw computational speed. Choosing the right computing hardware can significantly affect the performance of your cognitive radio.

If we study Figure 11.2 more closely, we can see that the cognitive radio engine consists of several inputs (sensed environment, expected performance metrics, available radio configurations), an output (radio configuration to be implemented), and a feedback loop. At the heart of the cognitive radio engine is the decision-making process, which determines the best possible radio configuration to be implemented based on past experiences, available radio configurations, sensed environmental parameters, and desired performance metrics. The decision-making process is often implemented using *machine learning*, of which there is a plethora of choices to select. To understand the design considerations for a cognitive radio engine, let us look at each of these elements more closely.

Machine learning techniques have been extensively studied to either partially or entirely automate the (re)configuration process (see [2–6] and references therein). However, the solutions produced by these techniques often require some knowledge of the wireless device and the target networking behavior (e.g., high data rates, high error robustness, and low network latency [7]). Nevertheless, machine learning techniques are well suited to handle scenarios possessing a very large device configuration solution space [4–6].

One major issue affecting cognitive radio systems is the accuracy of their decisions, which are based on the quality and quantity of input information to the cognitive radio engine. Thus, with more information available to the system, this enables the cognitive radio engine to make better decisions such that it achieves the desired user experience more precisely. Referring back to Figure 11.2, three types of parameters employed by a cognitive radio system exist:

1. *Device Configurations*: A collection of parameters that can be altered to change the current operating state of the device. Note that several potential configurations may not be possible to implement, and are thus disallowed by the adaptation algorithm.

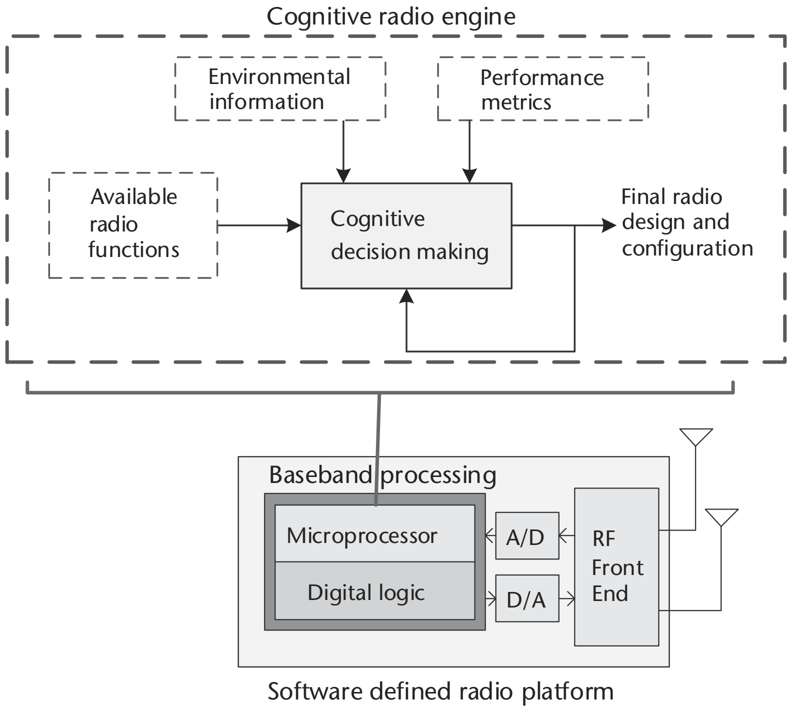


**Figure 11.2** Concept diagram of a cognitive radio engine operating on a software-defined radio platform.

2. *Environmental Parameters*: These parameters represent the information about the current status of the device as well as its sensed wireless environment using external sensors.
3. *Target Networking Experience*: These metrics approximately describe the average human user's experience when operating the wireless networking device. The goal of the any cognitive radio is to achieve the best-possible value for a given metric.

Since all applications operate in different environments and possess different requires, a solution produced by the cognitive radio engine for one application that achieves superior performance might yield unacceptable performance when that same solution is applied to a different application.

The definition of an optimal decision is a combination of device configuration and environmental parameters that achieve the target networking experience better than any other combination available. Defining a proper list of parameters constituting a device configuration to be employed by a cognitive radio system is of prime importance. A well-constructed list consists of common wireless parameters that each possess a large impact on the target networking behavior. Table 11.1 shows a list of nine transmission parameters commonly used in wireless networking devices.

Environmental parameters inform the system of the surrounding environment characteristics. These characteristics include internal information about the device operating state and external information representing the wireless channel environment. Both types of information can be used to assist the cognitive radio

**Table 11.1** Several Common Wireless Networking Device Configuration Parameters*

| *Parameter* | *Description* |
|---|---|
| Transmit power | Raw transmission power |
| Modulation type | Type of modulation |
| Modulation index | Number of symbols for a given modulation scheme |
| Carrier frequency | Center frequency of the carrier |
| Bandwidth | Bandwidth of transmission signal |
| Channel coding rate | Specific rate of coding |
| Frame size | Size of transmission frame |
| Time division duplexing | Percentage of transmit time |
| Symbol rate | Number of symbols per second |

* From [5, 8].

in making decisions. These variables along with the target networking experience are used as inputs to the algorithm. Table 11.2 shows a list of six environmental parameters that can affect the operational state of a cognitive radio device.

The purpose of a machine learning-based cognitive radio system is to autonomously improve the wireless networking experience for the human operator. However, improving this experience can mean several different things. Much research is focused on improving the accommodation of many wireless users within the same network. Other important aspects include providing error-free communications, high data rates, limiting interference between users, and even the actual power consumption of the wireless networking device, which is extremely important in mobile applications. As shown in Table 11.3, we have defined five common target networking experiences that guide the cognitive radio to a specific optimal solution for the cognitive radio system.

The target experiences presented in Table 11.2 represent the means for guiding the state of the cognitive radio-based wireless system. The cognitive radio makes use of these experiences through relationships that describe how modifying the device parameters achieve these objectives. To facilitate the decision making process, each target networking experience must be represented by a mathematical relationship that relates a device configuration and environmental parameters to a scalar value that describes how well this set achieve the specific goal [5, 8]. These functions will provide a way for the cognitive radio to rank combinations of configurations and environmental parameters, ultimately leading to a final decision.

Note that it is possible to specify several target networking experiences simultaneously, with the final score being represented by a numerical value. In this case, the individual scores of the target experiences are weighted according to their importance in the specific application and summed together, forming the final overall score [5].

### 11.1.1 Bumblebee Behavioral Model

So far we have focused on the framework surrounding the decision making process of a cognitive engine, but we have not really explored the different approaches for decision making on the radio itself. Consequently, let us explore two potential approaches for performing the decision making operation. The first approach is a *biologically inspired* method based on the behavior of bumblebees [9].

When people talk about cognitive radio, they hear the word cognitive and associate it with some sort of human intelligence that is driving the decision making

**Table 11.2** Several Common Wireless Networking Environmental Parameters*

| *Parameter* | *Description* |
|---|---|
| Signal power | Signal power as seen by the receiver |
| Noise power | Noise power density for a given channel |
| Delay spread | Variance of the path delays and their amplitudes for a channel |
| Battery life | Estimated energy left in batteries |
| Power consumption | Power consumption of current configuration |
| Spectrum information | Spectrum occupancy information |

* From [5, 8].

**Table 11.3** Several Common Wireless Networking Target Experiences*

| *Objective* | *Description* |
|---|---|
| Minimize bit error rate | Improve overall BER of the transmission environment |
| Maximize data throughput | Increase overall data throughput transmitted by radio |
| Minimize power consumption | Decrease amount of power consumed by system |
| Minimize interference | Reduce the radio interference contributions |
| Maximize spectral efficiency | Maximize the efficient use of the frequency spectrum |

* From [5, 8].

process. However, this might actually be overkill in terms of the performance we are seeking and the significant cost associated with the computational complexity. As a result, several researchers have instead focused on lifeforms with simpler cognitive capabilities as the basis for their cognitive radio engines as well as decision-making processes employed in other applications. Over the past several decades, researchers have investigated the behavior of ant colonies and honeybees as the basis for intelligent and efficient decision-making. These lifeforms possess the characteristic of being social animals, which means they exchange information with each other and perform an action that yields the best possible reward. However, ant colonies and honeybees suffer from being socially dependent lifeforms, which means that the actions of one entity is completely dependent on those of the collective. When translating these biologically inspired decision-making processes to cognitive radio and SDR, this yields a very challenging operating environment. Suppose that each radio operates a cognitive radio engine that collects information on its environment as well as information from nearby radios. As a result of this extensive information, we would expect that the radio would make excellent decisions on its own configuration. However, if these socially dependent models are used, this also constrains how these decisions are made on a per-radio basis.

Bumblebees are also social lifeforms that operate within a collective. However, unlike honeybees and ant colonies, bumblebees are socially independent by nature since they collect information from their environment and share information with each other, but they make their own decisions without control from the collective. It is this sort of flexility that makes bumblebees ideal for operating environments that could potentially change quickly over time. As for employing the bumblebee behavioral model in cognitive radio, it is well suited for operating environments where the network topology changes frequently, the channel conditions and spectral availability changes as a function of time, and the number of radios that are part of the network changes. Consequently, having each radio running a cognitive engine based on a bumblebee behavioral model is great since they gather information about the environment and then act to enhance their own performance.

In order to implement a bumblebee behavioral model for a cognitive radio engine, we need to leverage *foraging theory* on which bumblebees and many other lifeforms employ when gathering resources [9]. Essentially, foraging theory is a form of resource optimization employed by lifeforms to gather food, hunt prey, and seek shelter, along with various other operations. In the case of bumblebees, it is possible to map their activities and interpretations of the world that surrounds them to a wireless communication environment employing software-defined radio. For example, Table 11.4 presents the mapping between bumblebee behavior and perceptions to that of a vehicular ad hoc network that is dynamically accessing spectrum. It can be observed that many of the actions described for bumblebees possess some degree of similarity with those of a cognitive radio-based vehicle network.

### 11.1.2 Reinforcement Learning

Another decision-making process that has been receiving significant attention lately is reinforcement learning, which is a form of machine learning. As shown in Figure 11.3, reinforcement learning employs an agent that takes as inputs the reward of the previous action and the associated state and determines a new action. This action could be anything, but for the purposes of building cognitive radio engines the actions would mostly be specific radio configurations such that the performance of the communication system will be acceptable for the prevailing operating conditions, such as a dispersive wireless channel. At the receiver, the resulting reward associated with the action is calculated, which defines how well or how poorly the action was chosen. It is sent back via overhead channel to the agent in order to close the feedback loop such that the agent can adjust future actions (recall the feedback loop in the cognitive radio engine, as seen in Figure 11.2).

Although the structure described in Figure 11.3 appears to be straightforward, the one concern is about the overhead channel that is needed to close the loop. If there was some way of minimizing the impact of the overhead channel in this framework, this reinforcement learning approach could be made to be more robust. As a result, one approach for minimizing the overhead channel impact while still maintaining decent performance is to employ a neural network. The neural network is essentially a black box that can be trained using a large amount of data in order to create a complex input-output relationship in lieu of a closed-form mathematical expression. Referring to Figure 11.4, we can see an example of how a neural network

**Table 11.4** Several Definitions in Connected Vehicular Communications and Their Equivalent Definitions in Bumblebees*

| *Vehicles* | *Bumblebees* |
|---|---|
| In-band interference | Bees foraging on the same floral species |
| Out-of-band interference | Bees foraging on alternative floral species |
| Minimum channel energy level | Maximum nectar level per floral species |
| Computation/process time | Handling/searching time |
| Latency vs. reliability | Sampling frequency vs. choice accuracy |
| Switching cost/ time between channels | Switching cost/time between floral species |
| Channel activity over time | Floral species occupancy over time |
| Channel-user distribution | Bee distribution across floral species |

* From: [9]

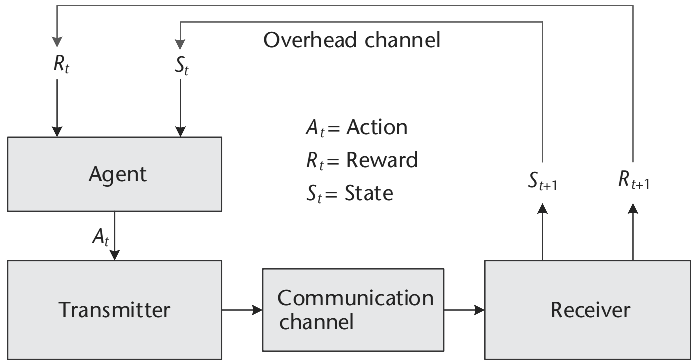


**Figure 11.3** Concept diagram of a reinforcement learning approach for intelligently adapting a communication system to its operating environment [10].

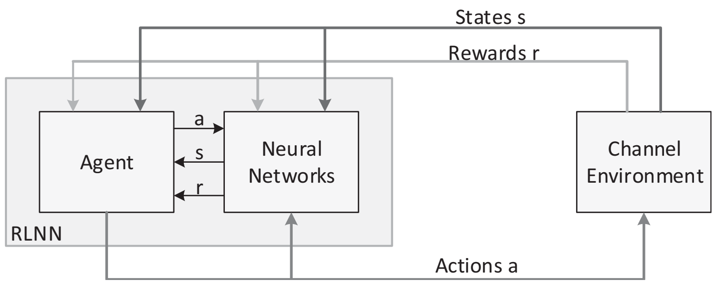


**Figure 11.4** Hybrid reinforcement learning framework for communication systems [11].

can be employed within the reinforcement learning framework in order to assist the agent in deciding actions based on past rewards and states. It turns out that if the neural network is sufficiently trained such that it mathematically models associated rewards of the communication channel, it can be used to run the reinforcement learning agent until the channel conditions significantly change such that the neural network needs to be retrained.

## 11.2 Vehicular Networking

With some insight regarding cognitive radio, let us now proceed with exploring an application where cognitive radio combined with SDR technology can truly be a game-changer: *vehicular networking*.

Vehicular networking has been extensively researched over the past several decades [12], especially with respect to vehicle-to-vehicle (V2V) and vehicle-to-infrastructure (V2I) communications [13–16]. Given the complex nature of the operating environment, including a rapidly changing network topology [17], time-varying physical characteristics of the propagation medium [18, 19], and the need for a robust medium access control (MAC) protocol [20], vehicular networking is a challenging research area being addressed by both academia and industry.

IEEE 802.11p (*Dedicated Short Range Communications* or DSRC) and IEEE 1609 (*Wireless Access in Vehicular Environments* or WAVE) are ratified standards for the implementation of V2V and V2I network architectures [13, 16, 20–23]. Given that these standards are relatively simple extensions of the popular IEEE

802.11 family of wireless networking architectures, the ability to deploy compliant wireless devices is relatively inexpensive. However, unlike indoor environments employing Wi-Fi, vehicular networking environments are much more complex, introducing problems not experienced previously by the Wi-Fi community.

VANETs are one type of *mobile ad hoc networks* (MANETs) that specifically addresses scenarios involving moving ground vehicles. Three types of VANET applications include [16]

- *Road safety applications*: Warning applications and emergency vehicle warning applications. Messages from these applications possess top priority.
- *Traffic management applications*: Local and map information.
- *Infotainment*: Multimedia content based on the traditional IPv6 based internet.

In a VANET architecture, both V2V and V2I links may exist in order to support the communications within the network. In V2V, each vehicle is equipped with an *onboard unit* (OBU) where V2V communications is conducted between the OBUs of each vehicle mainly for road safety applications and traffic management applications [24]. The measurements for V2V DSRC are available from [15]. In V2I applications, roadside infrastructure might be equipped with a *road side unit* (RSU). In order to support these V2V and V2I communications within a VANET, two standardized protocols exist for VANETs: IEEE 802.11p and IEEE 1609. Figure 11.5 provides a graphical representation of the protocol stack of a vehicular radio unit employing IEEE 802.11p and IEEE 1609.

Referring to Figure 11.5, IEEE 802.11p [13] specifies the PHY and MAC layers, while the upper layers are defined by the IEEE 1609.x protocols. IEEE 802.11p possesses many similar characteristics relative to the IEEE 802.11-2012 standard [23]. However, to reduce the communications latency in a highly dynamic vehicular communications environment, the MAC layer needs to be defined in such a way that it can support rapid changes in the networking topology and the need for low-latency communications. Consequently, both IEEE 802.11p and IEEE 1609.4 define new characteristics for the MAC layer. For instance, in IEEE802.11 the wireless nodes could form a service set (SS) such that the nodes possess the same *service ID* (SSID) and share communications. The network possessing an

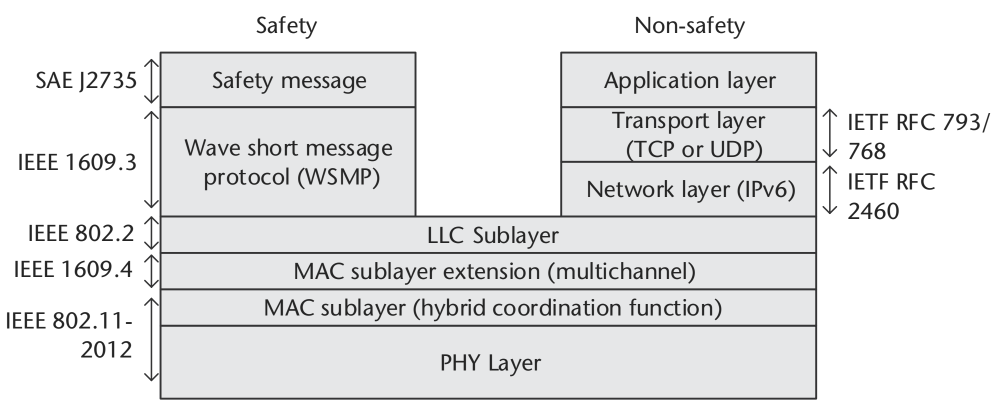


**Figure 11.5** Protocol stack for a vehicular communication system.

access point (AP) is referred to as a *basic service set* (BSS) while a network with no AP (i.e., an ad hoc network), is referred to as an *independent BSS* (IBSS). Several BSS could connect together to form an *extended service set* (ESS), while all the BSSs in one ESS can share the same *extended SSID* (ESSID). The problem with respect to a VANET is that the formation of a SS before the start of any communications may potentially be time consuming, which is not suitable for rapidly changing vehicular networking environments. To handle this issue, the IEEE 802.11p standard proposed an *out-of-context BSS* (OCB), where the OCB mode applies to multiple devices within the coverage area of a single radio link. In OCB mode, the vehicle can send or receive data any time without forming or being a member of an SS. Additionally, the IEEE 802.11p standard removed the authentication, association, and data confidentiality mechanisms from the MAC layer and moved them to an independent higher layer defined in IEEE 1609.2 [21]. Conversely, IEEE 802.11p still keeps the BSS mode, which is mainly used for infotainment applications via V2I communication.

For MAC, conventional IEEE 802.11 uses carrier sense multiple access (CSMA)/collision avoidance (CA). IEEE 802.11p still employs the CSMA mechanism, but it also employs a *hybrid coordination function* (HCF), which ensures the *quality of service* (QoS) via an *enhance defense cooperation agreement* (EDCA) defined in IEEE 802.11e. Data from the different services have different priorities depending on its importance. For instance, the performance of CSMA/CA and the proposed *self-organizing time division multiple access* (STDMA) mechanism demonstrates the lower occurance of dropped packets relative to CSMA/CA [25]. However, this paper does not fully consider the HCF mechanism (i.e., the QoS based EDCA and contention-free period (CPF)-based HCCA are not evaluated). A priority-based TDMA MAC mechanism designed to decrease the packet drop rate in a transmission was also proposed for WAVE [26].

The PHY layer of a VANET based on IEEE 802.11p is derived from the IEEE 802.11a standard with three different channel width options: 5 MHz, 10 MHz, and 20 MHz, among which 10 MHz is recommended. As with IEEE 802.11a, IEEE 802.11p uses OFDM including 52 carriers, which consists of 48 data carriers and 4 pilots, and 8-$\mu$s symbol intervals. The physical channel supports BPSK, SPSK, 16-QAM, and 64-QAM. In addition to IEEE 802.11p, IEEE 1609.4 defines multichannel behavior in the MAC layer [20]. Given that the PHY layer consists of seven channels, IEEE 1609.4 defines the channel switching mechanism among the CCH and SCHs. IEEE 1609.3 defines two types of messages in VANET: *Wave Short Message Protocol* (WSMP) and IPv6 stack [22]. IPv6 is usually for infotainment applications while the safety applications are transmitted via *WAVE Short Messages* (WSM). Additionally, SAE J2945 specifies the minimum communication performance requirements of the SAE J2735 DSRC message sets and associated data frames and data elements. In order to ensure interoperability between vehicles, SAE J2945 further defines BSMs sending rate, transmit power control, and adaptive message rate control.

SAE standards have been extensively used by the automotive industry with respect to safety message implementation. In particular, SAE J2735 defines 15 types of safety messages such as the *basic safety message* (BSM), *signal phase time* (SPT) message, and MAP message [16].

BSM is broadcast to surrounding vehicles periodically at a frequency of 10 Hz, announcing the state information of the vehicle such as position, speed, acceleration, and heading direction [27]. Selective broadcasting is used, where other cars at the edge of the DSRC transmit range will rebroadcast a message sent by another vehicle. When the orginal message sender receives the rebroadcasted message, it will cancel its own broadcast. The BSM message feature is mandatory in DSRC. Note that selective broadcasting for VANETs has been implemented in NS-3 [28]. In SAEJ2735, the BSM message consists of two sections: the basic section and the optional section [29]. The basic section includes position, motion, time, and general status of the vehicle information, which are always sent using a combination of the DER encoding and some octet binary large-object encoding [27]. The optional section is only sent when it is necessary. This section provides information to assist the receiving devices in further processing.

Vehicles within the DSRC range can share situational awareness information among each other via BSM, including scenarios such as

- *Lane Change Warning*: Vehicles periodically share situational information including position, heading, direction, and speed via V2V communication within the DSRC range. When a driver signals a lane change intention, the OBU is able to determine if other vehicles are located in blind spots. The driver will be warned if other vehicles do exist in the blind spot; this is referred to as *blind spot warning*. On the other hand, if no vehicles exist in the blind spot, the OBU will predict whether or not there is enough of a gap for a safe lane change based on the traffic information via BSMs. If the gap in the adjacent lane is not sufficient, a lane change warning is provided to the driver.
- *Collision Warning*: The vehicle dynamically receives the traffic info from BSMs and compares that information with its own position, velocity, heading, and roadway information. Based on the results of the comparison algorithm, the vehicle will determine whether a potential collision is likely to happen and a collision warning is provided to the driver.
- *Emergency Vehicle Warning*: Emergency vehicles transmit a signal to inform nearby vehicles that an emergency vehicle is approaching.

In addition to the regular safety messages, BSM messages can be also be used to transmit control messages. It can help in a cooperative collision warning environment [30], in a safety message routing application [17], or improve the power control [31]. For the emergency channels (i.e., Channel 172 and Channel 184), BSM can convey power control information to coordinate the transmission power on each channel. Conversely, the BSM can be used as inputs to the vehicle's control algorithms. The control messages are transmitted among the vehicles within the range.

Given these specifications and standards regarding VANET communications, it is possible for an individual to implement their own radios capable of V2V and V2I communications. Although the complexity of the radio design is significant since the entire protocol stack is extensive, the information is sufficient to create a radio compliant with IEEE 802.11p and IEEE 1609. The primary issues to be considered when implementing IEEE 802.11p and IEEE 1609 on a SDR platform include the computing performance of the radio itself, the bandwidth limitations in terms of achievable throughput, and the real-time functionality of every function across the protocol stack. Despite these challenges, the opportunity exists to construct these vehicular communication SDR systems that can network on the road in real time.

## 11.3 Chapter Summary

In this chapter, we briefly examined two real-world applications that can extensively leverage SDR technology: cognitive radio and vehicular networking. With respect to cognitive radio, we explored how to set up the cognitive radio engine on a SDR platform and presented at least two ways to construct the decision-making process using either a bumblebee behavioral model or a reinforcement learning approach. Regarding vehicular network, we presented a short introduction to the IEEE 802.11p and IEEE 1609 standards that can enable us to construct our own vehicular networks from scratch using SDR technology.

In this book, we have delved into the theoretical foundations of signals, systems, and communications, and then explored the real-world issues associated with communication systems and the solutions needed to mitigate these impairments, and finally presented several advanced topics in equalization and OFDM implementations before introducing real-world applications such as cognitive radio and vehicular networking. Of course, this book only scratches the surface of the entire communication systems domain, but it is hoped that this book will serve as a starting point for mastering this very important topic.

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