POWER CONTROL AND MULTI-TARGET IDENTIFICATION IN COGNITIVE WIRELESS NETWORKS

by

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To my family

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ABSTRACT

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Recent research results have shown that cognitive wireless networks (CWN) have the potential to alleviate spectrum scarcity problem resulting from current policies for radio resource allocation management and dramatically improve the overall performance of communication systems. Unlike conventional wireless networks, which lack the flexibility and adaptation in their operations, CWNs exploit cognitive radio technology which provides cognitive wireless devices with the ability to sense the situation, adapt to the environment and take appropriate actions correspondingly.

There have been many challenges in building a fully functional CWN. New developments and approaches need to be proposed to allow radio users to share primary licensed spectrum without harming the primary users. This thesis aims to address the problem of transmit power control in the scenario of spectrum sharing. We design a transmit power control system using Fuzzy Logic System to provide cognitive radios with the ability to coexist with primary (licensed) users in the same frequency band. With the built-in fuzzy power controller, a cognitive radio is able to opportunistically adjust its transmit power in response to the changes of the interference level to primary user (PU), the distance to PU and its received power difference at the base station (BS) while satisfying

the requirement of sufficiently low interference to PU. We increase the reliability of our power control scheme by using linguistic knowledge of transmit power control (TPC) obtained from a group of network experts. The outcome of this study show that the proposed fuzzy power control scheme leads to significant performance improvement in average transmit power consumption and average outage probability compared with the fixed-step power control scheme.

A new application of CWNs may be found in radar sensor networks wherein cognitive radios act as cognitive radars. Our key purpose is to deal with multiple targets within a required surveillance region in a robust and cost-effective manner. Thus, we focus on the problem of jointly classifying and identifying multiple targets in radar sensor networks where the maximum number of categories and the maximum number of targets in each category are obtained a priori based on statistical data. The actual number of targets in each category and the actual number of target categories being present at any given time are assumed unknown. We then propose a joint multi-target identification and classification (JMIC) algorithm for radar surveillance using cognitive radars. The existing target categories are first classified and the targets in each category are then identified. We also show that the proposed JMIC algorithm is a well-suited approach to surveillance activities in the future cognitive radar sensor networks.

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CHAPTER 1

INTRODUCTION

1.1 Cognitive Wireless Networks

Cognitive wireless networks have generated a great deal of interest recently as newly emerging technologies that are very likely to be implemented in next generation wireless networks. The positive aspect of using cognitive wireless networks is the ability to sense and automatically adapt to the environment, recognize and wisely process all collected information received at receivers. To ensure competitiveness of cognitive wireless networks in the next few years and beyond, further enhancement in technologies needs to be considered. A continued evolution and optimization of new developments, approaches and applications is also necessary in order to maintain competitiveness in term of both performance and cost.

This thesis is written in an effort to introduce two applications of cognitive wireless networks. The first application is cognitive wireless network in connection with cognitive radio technology. A new power control scheme is proposed to allow cognitive radios to use any available licensed spectrum without infringing upon the rights of primary users or operate in a reliable and efficient manner without causing harmful interference to licensed operations. The second application is cognitive radar sensor network wherein cognitive radios work as cognitive radars. A new algorithm is presented to address the problem of jointly classifying and identifying multiple targets in radar sensor networks where the maximum number of categories and the maximum number of targets in each category are obtained a priori based on statistical data. However, the actual number of targets in each category and the actual number of target categories being present at any given time are unknown. We will provide a brief introduction for each application as follows.

1.1.1 Cognitive Radio Networks

1.1.1.1 The Motivation for Cognitive Radio

There are many factors that motivate the evolution and deployment of cognitive radio technology applications. Major factors can be summarized as follows.

First and foremost, recent research projects have clearly shown that the current usage of the radio spectrum is severely inefficient. Most of the assigned channels are only occupied for a short duration of time while the demand for communications coming from unlicensed users is high. Since radio spectrum is a valuable public resource, the fact that some licensed users own the spectrum that they do not use is not desirable. Therefore, it becomes increasingly imperative to search for an efficient solution to solve the problem of unallocated spectrum scarcity as well as the problem of inefficient usage of allocated spectrum.

Besides, the ability to move the operations of a radio in all frequency bands is very enticing to public users. Thus, an implementation of a new device that allows these users to have dynamic use of the spectrum has become necessary. This device must know all the the rules in each frequency band and be able to adjust its transmission parameters in response to these rules.

In addition to technical factors as mentioned above, economic factors also have some effects on the motivation for cognitive radios. Capital investment on a new unused spectrum is sometimes too high for investors to receive licensed allocations in a particular geographic area while it is not likely that significant economic profits can be made on new applications in this spectrum. As a result, investors tend to focus their investments on low-cost equipments and the larger, more profitable marketplaces.

Last but not least, the current state-of-the-art advance in radio technology has promisingly shown that it is possible to implement a practical cognitive radio in various wireless applications at a reasonable cost. These cognitive radios will have the ability to work on any available frequency spectrum and intelligently adapt to their environment.

1.1.1.2 Cognitive Radio Definitions

Cognitive radios are intelligence cell phones or smart radios that have the ability to operate at variable data transmission rates, various modulation formats, different channel coding schemes and transmit power levels. Unlike regular radios, cognitive radios can adjust their transmitter parameters in any given channel situation based on interactions with the surrounding environment. It is noted that the power of a cognitive radio lies in its cognition. A cognitive radio can make intelligent decisions on how and when to utilize a particular part of a spectrum or the whole spectrum for communications. In order to have a reliable and efficient communication, a cognitive radio should be built to do the following tasks:

- Stay tuned to any available channel in all possible frequency bands.
- Establish and perform network communications.
- Implement channel sharing and power control protocols.
- Employ adaptive transmission bandwidths, data rates, and error correction schemes to obtain the best possible throughput.
- Implement adaptive antenna steering to focus transmitter power in a required direction to optimize received signal strength.

In term of conceptual forms, cognitive radio can be classified as "Full Cognitive Radio" and "Spectrum Sensing Cognitive Radio" [15]. In full cognitive radio, every possible parameter is observed for a decision on transmission and/or parameter change while in spectrum sensing cognitive radio, only the RF spectrum is considered.

It is also noted that in order to be able to dynamically use the spectrum, a cognitive radio incorporates four capabilities which can be listed as follows [5], [37].

- *Flexibility*: The waveform and the configuration of a cognitive radio can be changeable.
- *Agility*: A cognitive radio can change the frequency band in which it will operate.

- *Sensing*: A cognitive radio can observe the state of the system and self-aware of its environment.

- *Networking*: Communications can take place between multiple nodes. Networking enables interactions which may be useful for sensing to obtain a better understanding of the environment from the combination of many measurements or useful for adaptation to make a better decision on using the spectrum over an individual radio.

1.1.1.3   The Challenges to Cognitive Radio Network Deployment

Cognitive radio is a newly emerging technology which has a very short history. Many research projects needs to be done to make this technology really mature and become real applications in next generation wireless networks. That is, many technical hurdles have to be overcome before cognitive radios can be commercially deployed.

The challenges may come from the implementation of cognitive radios since cognitive hardware and software platforms should be developed in connection with new concepts and algorithms. Protocol and architecture designs also need to be studied. In addition, experimental measurements and deployments are very necessary to ensure successful operations for cognitive radios.

The specification of the protocols and etiquettes is another challenge for technicians and regulators. The regulators have the responsibility to specify how users are allowed to use a spectrum. They need to be assured that protocols are robust under all conditions, and that cognitive radios follow the regulatory policy and create no harmful interference to primary users. Besides, it is still unclear whether we can assure that device failure will cause no great impact on the primary licensed networks. However, we can admit that success in cognitive radio deployment will lead to significant improvements in spectrum efficiency and bring a fundamental change to the global radio spectrum allocation in the future.

1.1.2   Cognitive Radar Sensor Networks

1.1.2.1   The Motivation for Cognitive Radar

In radar sensor networks, a radar is able to locate a target such as a ship or a aircraft by obtaining information about the azimuth and elevation of the target. However, when a radar has to deal with multiple targets, determining the ranges of all targets at the same time is not an easy task.

A sequence of position estimates may be used to estimate the velocity of a target. It is also expected that the ability of extracting information about the changes of velocity of multiple targets is a step toward the evolution of radar technology.

Nowadays, providing a powerful multiple target identification capability for military applications is widely recommended. Features of multiple targets should be wisely collected and many complex neural computations need to be implemented. This means that a radar must learn to be cognitive. As mentioned by Haykin in [43], to be cognitive, a radar must be able to *"learn from continuing interactions with the environment and intelligently use the information extracted by the receiver on targets under surveillance, all of this being done on-the-fly during the different phases of the target-track sequence."*

1.1.2.2   Cognitive Radar Definition

A definition of cognitive radar reported by Haykin can be found in [43] as follows:

"Cognitive radar is an intelligent system that is aware of its surrounding environment (i.e., outside world), uses prior knowledge as well as learning through continuing interactions with the environment, and thereby adapts both its receiver and transmitter in response to statistical variations in the environment in real-time so as to meet specific remote-sensing objectives in an efficient, reliable, and robust manner."

1.1.2.3   The Challenges to Cognitive Radar Network Deployment

A network of cognitive radars is critically important to relax the requirements of intensive computations on a single cognitive radar, improve the reliability of any information processing and speed up the adaptation process of cognitive radars.

Although a network of cognitive radars looks very promising, we can see that many technical issues currently remain unaddressed to guarantee the integrity, efficiency and reliability of the network. Many challenges need to be get over before cognitive radar networks can be implemented for practical surveillance purposes.

1.2   Thesis Organization

This thesis is organized as follows.

Chapter 1 covers the brief introduction of cognitive wireless networks. Cognitive radio networks and cognitive radar networks are then introduced in term of motivations, definitions and challenges.

Chapter 2 describes the scenario in which cognitive radios must follow a particular transmit power control scheme to coexist with primary licensed users in the same frequency band without violating the rights of these users. We then propose a fuzzy power controller for cognitive radios. With this fuzzy controller, a cognitive radio is able to opportunistically adjust its transmit power in response to the changes of the interference level to primary user (PU), the distance to PU and its received power difference at the base station (BS) while satisfying the requirement of sufficiently low interference to PU. Simulation is implemented to obtain the average transmit power increase and the average outage probability. Simulation results show that using the proposed fuzzy power control scheme, we can decrease average transmit power consumption and achieve lower average outage probability compared with the fixed-step power control scheme.

Chapter 3 investigates the problem of jointly classifying and identifying multiple targets in radar sensor networks where the maximum number of categories and the max-

imum number of targets in each category are obtained a priori based on statistical data. However, the actual number of targets in each category and the actual number of target categories being present at any given time are unknown. It is assumed that a given target belongs to one category and one identification number. The target signals are modeled as zero-mean complex Gaussian processes. We propose a joint multi-target identification and classification (JMIC) algorithm for radar surveillance using cognitive radars. The existing target categories are first classified and then the targets in each category are accordingly identified. Simulation results are presented to evaluate the feasibility and effectiveness of the proposed JMIC algorithm in a query surveillance region.

Finally, chapter 4 completes this thesis with a brief summary of contributions and future works to facilitate cognitive radios and cognitive radars to fulfill their potentials and become recognized and successful in industry.

CHAPTER 2

EFFICIENT POWER CONTROL SCHEME IN
COGNITIVE RADIO NETWORKS

2.1 Introduction

Cognitive radio [26] has been considered as an efficient approach to opportunistic spectrum sharing between primary (licensed) users and cognitive radio users. However, in order to have such opportunistic spectrum sharing, cognitive radio must be able to intelligently adapt to the behavior of primary user (PU). If PU vacates its frequency band, a cognitive radio or secondary user (SU) which is sensing will know and, if necessary, occupy this band to transmit signals. While doing transmission, the SU still has to sense unused frequency bands and detect when the PU reclaims its band. There are two options for the SU when the PU reclaims its band [29]: (1) the SU will free the band and jump to another available spectrum band, and (2) the SU still stays in this band altering its transmit power to avoid harmful interference to the PU. Given these options, we may have the following question: Is it necessary for the active SU to immediately jump to another available frequency band when the PU reclaims transmission? We can easily figure out that with an immediate frequency jumping, SU communication is unexpectedly interrupted. The SU will have to wait to be assigned a new frequency band to continue its transmission session. Obviously, this takes time and hence degrades the secondary system performance. On the other hand, without immediate jumping, the SU will still stay in the frequency band and adjust its transmit power without creating harmful interference to the PU. This option leads to the following questions: How will the SU adjust its transmit power? What is the opportunistic transmit power control (TPC) scheme for the SU in this case? This thesis will give answers to the above questions.

Notably, under the constraint that no excessive interference to the PUs is generated, TPC decision-making for SUs is still a daunting task when efficient communications of PUs as well as SUs are taken into consideration. Studies on TPC are progressing to investigate the best scheme for a workable SU system. In [28], game theory has been used to alter SU power level but no clear explanation has been given about choosing appropriate objective function to model the situation [1] wherein SUs are free to set their power levels in an ALOHA network. Haykin [42] applied water-filling to control the transmit powers of SUs subject to the constraint that the interference limit is not violated, however all target transmission rates must be known and lie within a permissible rate region. Looking for another approach, Hoven and Sahai [35] focused on the SU transmit power variation using received SNR as a proxy for distance. Although no excessive interference to PUs is created, efficient operation of the SU is not considered.

In this work, we design a TPC system using Fuzzy Logic System (FLS) to provide SUs the ability to opportunistically coexist with PUs in the same frequency band. With this built-in fuzzy power controller, a SU is able to dynamically adjust its transmit power in response to the changes of the interference level caused by the SU to the reclaiming PU, the distance from the SU to the reclaiming PU and the received power difference of the SU at the base station (BS) while still guaranteeing an acceptable QoS for the PU. Besides, to increase the reliability of this power control scheme, we set up the fuzzy rules based on linguistic knowledge of TPC obtained from a group of network experts rather than a single expert. The transmit power control ratio obtained from the output of the FLS is used to dynamically adjust the transmit power of the specific SU. Using this proposed fuzzy power control scheme, we can reduce the number of frequency hops, thereby successfully minimizing SU communication interruption. We use Monte Carlo simulations to obtain the average transmit power increase and the average outage probability. Simulation results show that, with the proposed scheme, lower average transmit power increase and lower average outage probability can be achieved compared with the fixed-step power control scheme.

The rest of the chapter is organized as follows. In Section 2.2, we briefly present the FLS and then introduce the fuzzy power control system for cognitive radios. In Section 2.3, we design the membership functions and collect linguistic knowledge of TPC to implement fuzzy power control. We describe the proposed fuzzy power control scheme and generate the decision surface for TPC in Section 2.4. In Section 2.5, we analyze simulation results. Finally, conclusions are given in Section 2.6.

2.2 System Model

2.2.1 Fuzzy Logic System

When an input $\mathbf{x} = \{x_1, x_2, ..., x_p\}$ is applied to a FLS [24] as shown in Fig. 2.1, the inference engine computes the output set corresponding to each rule. The defuzzifier then computes a crisp output y from these rule output sets. Consider a p-input 1-output FLS, using singleton fuzzification, center-of-sets defuzzification [23] and "IF-THEN" rules of the form [13]

$$R^l: \text{IF } x_1 \text{ is } F_1^l \text{ and } x_2 \text{ is } F_2^l \text{ and ... and } x_p \text{ is } F_p^l,$$

$$\text{THEN } y \text{ is } G^l$$

Assuming singleton fuzzification, when an input $\mathbf{x}' = \{x_1', x_2', ..., x_p'\}$ is applied, the degree of firing corresponding to the lth rule is computed as

$$\xi_{F_1^l}(x_1') \star \xi_{F_2^l}(x_2') \star ... \star \xi_{F_p^l}(x_p') = \mathcal{T}_{i=1}^p \xi_{F_i^l}(x_i') \tag{2.1}$$

where $\star$ and $\mathcal{T}$ both indicate the chosen t-norm. There are many kinds of defuzzifiers. In this thesis, we focus, for illustrative purposes, on the center-of-sets defuzzifier. It computes a crisp output for the FLS by first computing the centroid, c_{G^l}, of every consequent set G^l, and, then computing a weighted average of these centroids. The weight corresponding to the lth rule consequent centroid is the degree of firing associated with the lth rule, $\mathcal{T}_{i=1}^p \xi_{F_i^l}(x_i')$, so that

$$y_{cos}(\mathbf{x}') = \frac{\sum_{l=1}^M c_{G^l} \mathcal{T}_{i=1}^p \xi_{F_i^l}(x_i')}{\sum_{l=1}^M \mathcal{T}_{i=1}^p \xi_{F_i^l}(x_i')} \tag{2.2}$$

where M is the number of rules in the FLS.
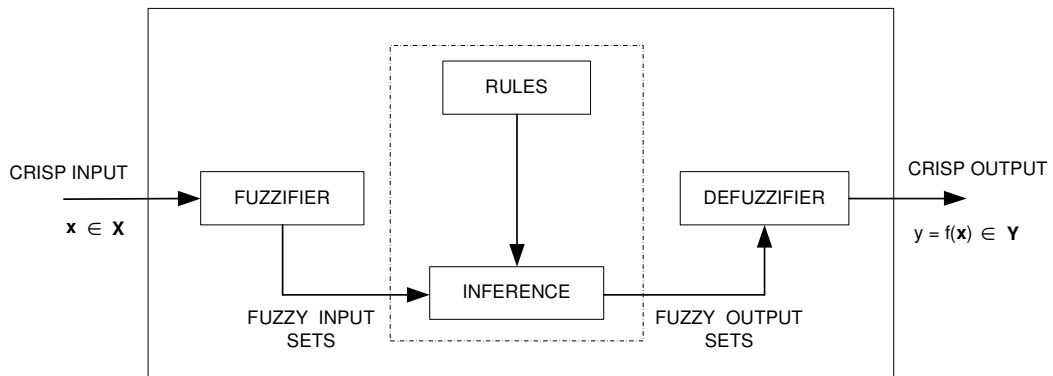
Figure 2.1: Fuzzy logic system

2.2.2 Fuzzy Power Control System

In this thesis, we assume that a fixed point-to-multipoint wireless air interface as specified in [6] is used for the cognitive radio system. In this system, the BS manages all SUs in its cell and no SU is allowed to transmit before receiving authorization from BS. Based on these considerations, we design a fuzzy power control system for SUs as shown in Fig. 2.2. The sensing and analyzing processor will smartly implement the following tasks:

- Sense the stimuli from the radio environment.
- Detect the available unused frequency bands.
- Collect information about the interference level caused by the SU to the reclaiming PU.
- Estimate the distance from the SU to the reclaiming PU.
- Compute the difference between the actual received power of the SU at the BS and the target received power at this BS.

The FLS is used to dynamically adjust the transmit power control ratio of the specific SU according to the changes of three following antecedents (ANT):

- ANT 1: The interference level caused by the SU to the reclaiming PU.
- ANT 2: The distance from the SU to the reclaiming PU.
- ANT 3: The received power difference of the SU at BS.
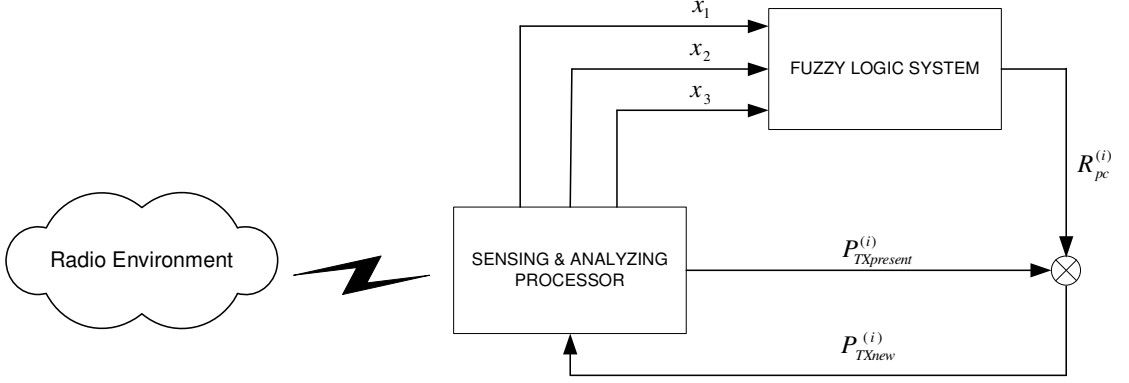
Figure 2.2: Fuzzy power control system for cognitive radio

The new transmit power level is obtained by multiplying the present transmit power and the power control ratio obtained from the output of the FLS together. The transmit power control ratio of the ith secondary user $R_{pc}^{(i)}$ is defined as:

$$R_{pc}^{(i)} = \frac{P_{TXnew}^{(i)}}{P_{TXpresent}^{(i)}} \tag{2.3}$$

where $P_{TXnew}^{(i)}$ is the new transmit power level and $P_{TXpresent}^{(i)}$ is the present transmit power level of the ith SU. We can express $R_{pc}^{(i)}$ in dB domain as follows:

$$
\begin{aligned}
R_{pc}^{(i)}(dB) &= 10 \log \frac{P_{TXnew}^{(i)}}{P_{TXpresent}^{(i)}} \\
&= P_{TXnew}^{(i)}(dBm) - P_{TXpresent}^{(i)}(dBm) \tag{2.4}
\end{aligned}
$$

To fully assist the task of collecting information about the interference level, we recommend that interference level $P_I^{(i)}$ caused by the ith SU is estimated by the reclaiming PU. The estimated value is then immediately sent to the primary BS which is managing the PU and from the primary BS to a real time database which can be accessed by the secondary BS. This BS will finally send the information to SU via a common control channel. We also suggest that the distance d_i from the ith SU to the reclaiming PU can be estimated based on the empirical propagation formula for the path loss. Using the path loss, the received power $P_I^{(i)}$ of the ith SU at the reclaiming PU can be expressed in terms of the transmit power $P_{TXpresent}^{(i)}$ as follows:

$$P_I^{(i)} = \frac{\alpha}{d_i^\beta} P_{TXpresent}^{(i)} \tag{2.5}$$

From (2.5), we can calculate the distance d_i

$$d_i = \sqrt[\beta]{\alpha \frac{P_{TXpresent}^{(i)}}{P_I^{(i)}}} \tag{2.6}$$

where β is path-loss exponent and α is attenuation parameter.

2.3 Fuzzy Power Controller Design

We design a fuzzy power controller to dynamically adjust the transmit powers of SUs. First, three antecedents mentioned in Section 2.2 are characterized as linguistic variables. To present the interference level caused by the SU to the reclaiming PU, we use linguistic variable x_1 with the term set *low, moderate,* and *high.* The variable x_2 used to represent the distance from the SU to the reclaiming PU is in the set *near, moderate,* and *far.* The received power difference of the SU at the BS is presented by the variable x_3 which specifies *negative, zero,* and *positive.* The consequent, i.e., the transmit power control ratio of the SU is divided into seven levels: *highly decrease (HD), moderately decrease (MD), slightly decrease (SD), remain unchanged (RU), slightly increase (SI), moderately increase (MI),* and *highly increase (HI).*

Then, we use trapezoidal membership functions (MFs) to represent *low, near, negative* and *high, far, positive.* Triangle MFs are chosen for *moderate, zero.* For the consequent, we choose trapezoidal MFs to represent *HD* and *HI.* Triangle MFs are used for *MD, SD, RU, SI, MI.* The MFs for three antecedents and consequent are shown in Fig. 2.3 and Fig. 2.4.

Finally, in order to increase the reliability of the fuzzy power controller, we decide to set up the fuzzy rules based on linguistic knowledge of TPC obtained from a group of network experts rather than a single one. Questions given to these experts in a survey were designed in the form as follows:
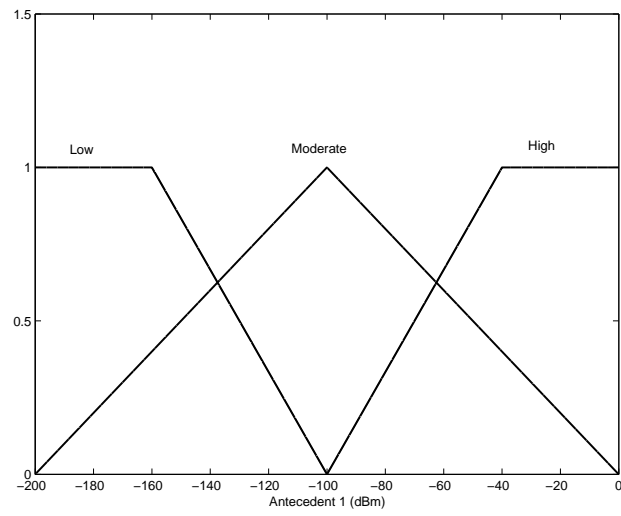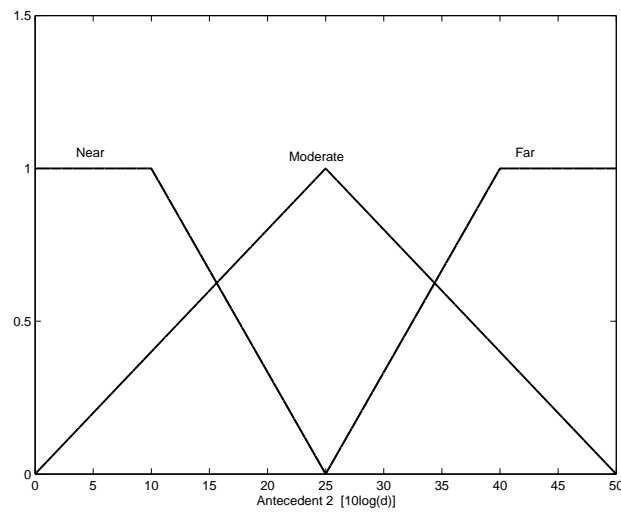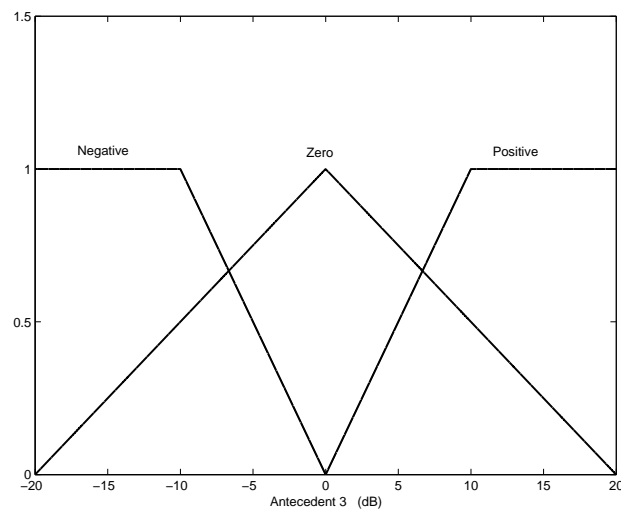
Figure 2.3: The membership functions used to represent the linguistic labels: (a) Antecedent 1, (b) Antecedent 2, and (c) Antecedent 3
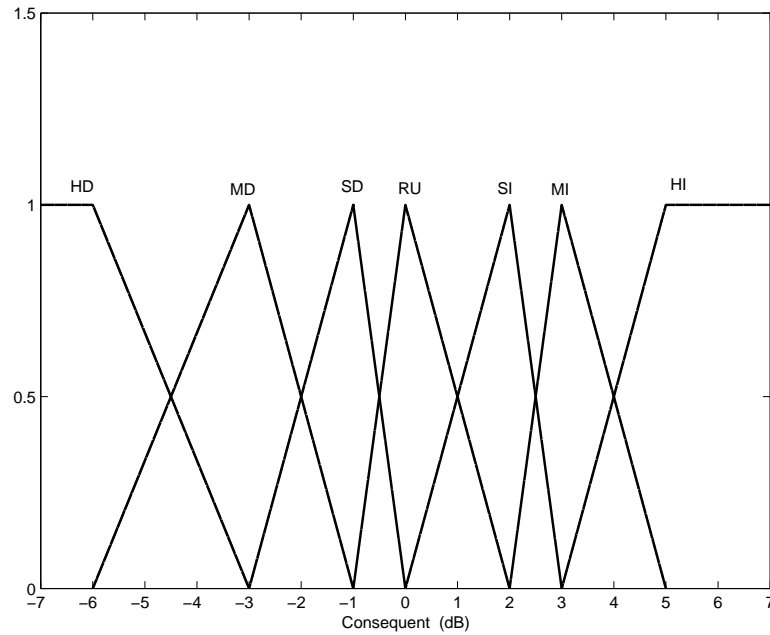
Figure 2.4: The membership function used to represent the consequent

IF *the interference level caused by the SU to the reclaiming PU is moderate, and the distance from the SU to the reclaiming PU is near, and the received power difference of the SU at the BS is negative,* THEN *the transmit power control ratio of this SU will* _____.

Six network experts were requested to choose a consequent using one of the seven linguistic variables. The questions used in this survey are summarized in Table 2.1. As an example, answers from a randomly-chosen expert are specified in this table. The results collected from the completed survey are captured in Table 2.2.

2.4 Opportunistic Power Control Decision

As previously mentioned, we consider the case wherein the SU will not immediately jump to another available frequency band when the PU reclaims transmission. We then design an opportunistic TCP scheme for the SU to coexist with the reclaiming PU in the primary frequency band.

Table 2.1: The questions of TPC for cognitive radio. Answers from a randomly-chosen expert are given as an example.

Question #	Ant1	Ant2	Ant3	Consequent
1	low	near	negative	SI
2	low	near	zero	RU
3	low	near	positive	MD
4	low	moderate	negative	MI
5	low	moderate	zero	RU
6	low	moderate	positive	MD
7	low	far	negative	HI
8	low	far	zero	RU
9	low	far	positive	SD
10	moderate	near	negative	SI
11	moderate	near	zero	RU
12	moderate	near	positive	MD
13	moderate	moderate	negative	SI
14	moderate	moderate	zero	RU
15	moderate	moderate	positive	MD
16	moderate	far	negative	SI
17	moderate	far	zero	RU
18	moderate	far	positive	SD
19	high	near	zero	MD
20	high	near	positive	HD
21	high	moderate	zero	SD
22	high	moderate	positive	HD
23	high	far	zero	SD
24	high	far	positive	HD

Table 2.2: Histograms of expert responses about TPC for cognitive radio.

Rule #ℓ	HD	MD	SD	RU	SI	MI	HI	$\overline{\beta_l}$
1	0	0	0	0	3	3	0	2.5
2	0	0	0	6	0	0	0	0.3333
3	1	3	2	0	0	0	0	-3.0444
4	0	0	0	0	1	5	0	3.0555
5	0	0	0	6	0	0	0	0.3333
6	0	3	3	0	0	0	0	-2.3333
7	0	0	0	0	0	2	4	4.7407
8	0	0	0	5	1	0	0	0.5555
9	0	1	5	0	0	0	0	-1.6666
10	0	0	0	0	6	0	0	1.6667
11	0	0	0	6	0	0	0	0.3333
12	2	3	1	0	0	0	0	-3.7555
13	0	0	0	0	4	2	0	2.2222
14	0	0	0	6	0	0	0	0.3333
15	1	4	1	0	0	0	0	-3.3778
16	0	0	0	0	3	3	0	2.5
17	0	0	0	6	0	0	0	0.3333
18	0	3	3	0	0	0	0	-2.3333
19	0	4	2	0	0	0	0	-2.6666
20	6	0	0	0	0	0	0	-5.6
21	0	2	4	0	0	0	0	-2.0
22	5	1	0	0	0	0	0	-5.2222
23	0	1	5	0	0	0	0	-1.6666
24	4	2	0	0	0	0	0	-4.8444

Under the constraint that no harmful interference to the reclaiming PU is created, the SU is allowed to increase its transmission power with distance as it moves further from the PU. The SU near the PU must be quieter. The SU must jump to another available unused frequency band if it introduces excessive interference level to the PU. Cognitive radio system is point-to-multipoint as assumed in Section 2.2. A target received power is required at the BS to achieve equal signal strengths of the SUs. We denote the target received power at the BS as $P_{RX_{tar}}$. Thus, the received power difference $\triangle P_{RX}^{(i)}$ of the ith SU at the BS is given by:

$$\triangle P_{RX}^{(i)} = P_{RX}^{(i)} - P_{RX_{tar}} \tag{2.7}$$

where $P_{RX}^{(i)}$ is the actual received power of the ith SU at the BS.

If $\triangle P_{RX}^{(i)} < 0$, i.e., the actual received power of the ith SU at the BS is less than the target received power, then the ith SU will have to increase its transmit power under the constraint that the interference to the PU is not excessive. Otherwise, if $\triangle P_{RX}^{(i)} > 0$, this SU will have to decrease its transmit power. Based on the survey, the SU must jump to another unused frequency band for communications in the following cases:

- Interference level to the reclaiming PU is *high*, distance to the reclaiming PU is *near* and the received power difference is *negative*.

- Interference level to the reclaiming PU is *high*, distance to the reclaiming PU is *moderate* and the received power difference is *negative*.

- Interference level to the reclaiming PU is *high*, distance to the reclaiming PU is *far* and the received power difference is *negative*.

Since there are 3 antecedents and each antecedent has 3 fuzzy sub-sets, the number of rules can be set up for this FLS is $3^3 = 27$ rules. However, we have three cases in which SU must jump to another frequency band. Thus, the total number of rules we need to set up is finally 24 rules which determine 24 questions in the survey as specified in Table 2.1.

In our approach to forming a rule base, we chose a single consequent for each rule. To do this, we averaged the centroids of all the responses for each rule and used this average in place of the rule consequent centroid. This led to rules that have the following form:

R^l: IF *the interference level caused by the SU to the reclaiming PU* (x_1) is F_1^l and *the distance from the SU to the reclaiming PU* (x_2) is F_2^l and *the received power difference of the SU at the BS* (x_3) is F_3^l, THEN the transmit power control ratio of the SU (y) is $\overline{\beta_l}$.

$$\overline{\beta_l} = \frac{\sum_{i=1}^{7} w_i^l c_i}{\sum_{i=1}^{7} w_i^l} \qquad (2.8)$$

in which w_i^l is the number of experts choosing linguistic label i for the consequent of rule l ($i = 1,..., 7$; $l = 1,..., 24$) (Table 2.2) and c_i is the centroid of the ith consequent set ($i = 1, ..., 7$). All 24 $\overline{\beta_l}$ values are listed in Table 2.2. The entries from the second to the eighth column correspond to the weights w_1^l, w_2^l, w_3^l, w_4^l, w_5^l, w_6^l and w_7^l. For every input (x_1, x_2, x_3), the output is computed using

$$y(x_1, x_2, x_3) = \frac{\sum_{l=1}^{24} \xi_{F_1^l}(x_1)\xi_{F_2^l}(x_2)\xi_{F_3^l}(x_3)\overline{\beta_l}}{\sum_{l=1}^{24} \xi_{F_1^l}(x_1)\xi_{F_2^l}(x_2)\xi_{F_3^l}(x_3)} \qquad (2.9)$$

By repeating these calculations for $\forall x_1 \in$ [-200, 0], $\forall x_2 \in$ [0, 50] and $\forall x_3 \in$ [-20, 20], we received a hypersurface $y(x_1, x_2, x_3)$. In order to obtain the decision surface, we fixed the variable x_2 and considered x_1 and x_3 as random variables in their definition domains. Two cases were investigated. First, we set $x_2 = 15$ and changed two other variables. We obtained a decision surface $y(x_1, 15, x_3)$ as shown in Fig. 2.5a. Similarly, we then let $x_2 = 45$ and obtain another surface $y(x_1, 45, x_3)$ as shown in Fig. 2.5b. From Fig. 2.5, we see that although a SU has a small distance to the reclaiming PU, its transmit power control ratio can be higher than some SUs having further distance to the reclaiming PU.
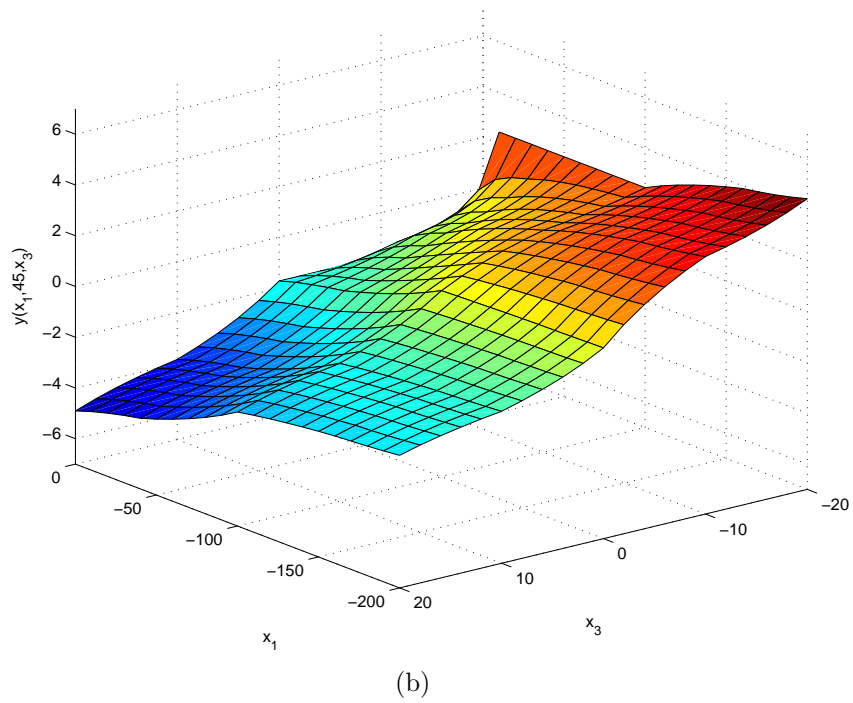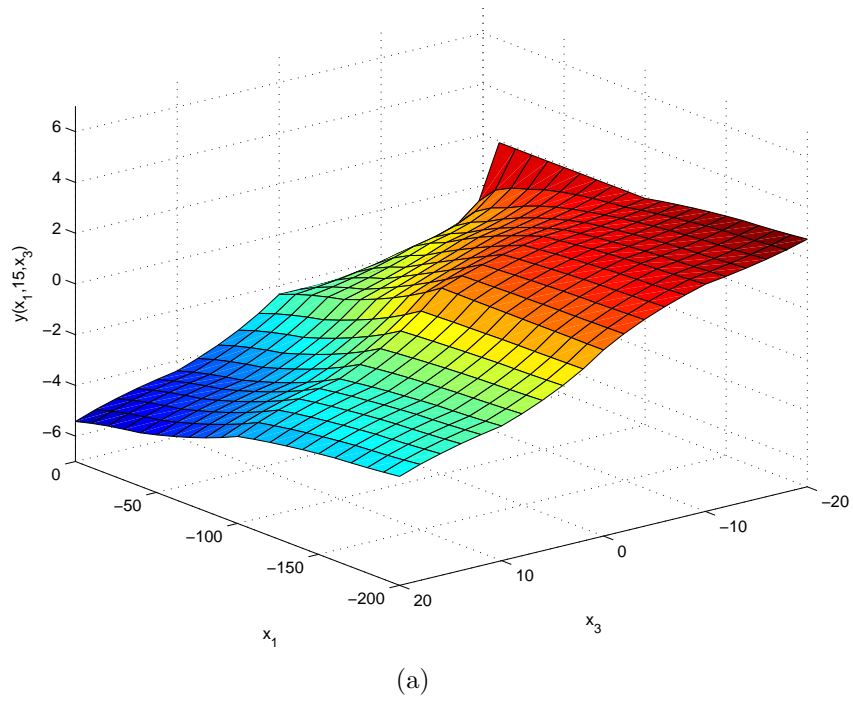
Figure 2.5: TPC decision surface for fixed distance to the reclaiming PU: (a) $x_2 = 15$ and (b) $x_2 = 45$.
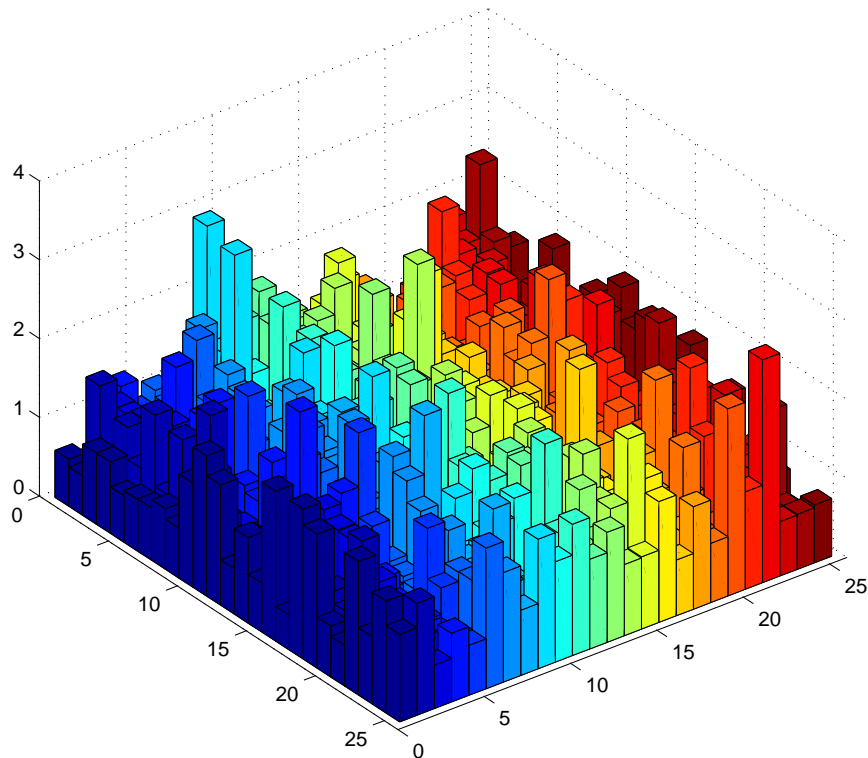
Figure 2.6: TPC ratios of 625 SUs within the radius of 50 km. The SU with maximum TPC ratio has distance: 47.903, interference: -184.89, and received power difference: -19.948. The SU with minimum TPC ratio has interference: -16.615, distance: 1.6219, and received power difference: 19.11 using fuzzy power control scheme.

2.5 Simulation Results

We randomly generated 625 SUs within a radius of 50 km from a BS. Each SU has the interference level to its corresponding reclaiming PU in [-200, 0] and its received power difference at the BS in [-20, 20]. The distance of each SU to the its reclaiming PU is taken as $10\log(d)$ resulting [0, 50] scale. We applied (2.9) to compute the transmit power control ratio for each SU as illustrated in Fig. 2.6.

We then investigated the average transmit power increase achieved using the proposed scheme. We ran the simulations with different number of active SUs within the radius of 50 km for 10^5 times. The step of 1 dB was used for the fixed-step scheme. The average transmit power increase using our scheme compared with the average transmit power increase using fixed-step scheme is shown in Fig. 2.7a. Our simulation results show that our fuzzy power control scheme has better performance compared to the fixed-step
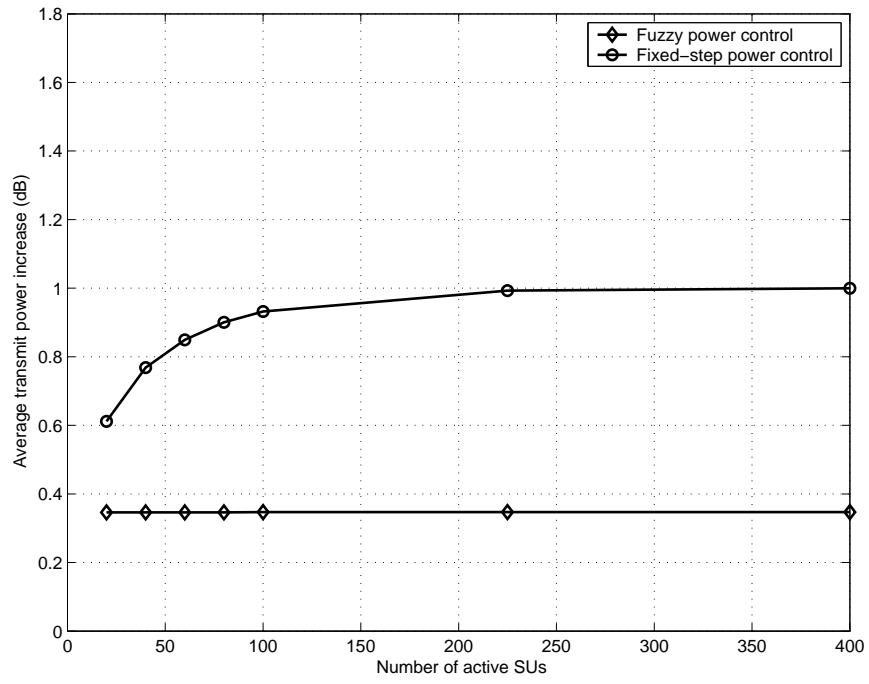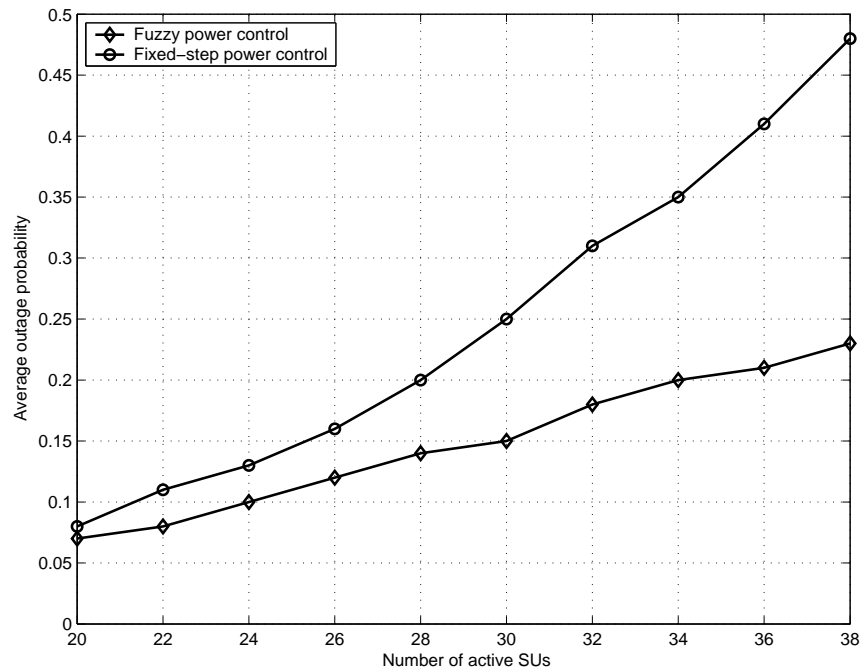
Figure 2.7: Comparison between two power control schemes for cognitive radios: (a) Average transmit power increase, (b) Average outage probability.

scheme. Our average transmit power increase in each case is lower than that of fixed-step scheme. Therefore, using the proposed scheme, we can save the power of the whole system, especially in the case the number of active SUs is increased. Besides, our scheme has a stable performance because when the number of active SUs is increased from 20 users to 400 users, the average transmit power increase difference is just approximately 0.23% while the difference for fixed-step scheme is 63.47%.

Fig. 2.7b, finally, shows a comparison of average outage probabilities between the proposed scheme and the fixed-step scheme for different number of active SUs. The average outage probability is defined as:

$$\overline{P_o} = \frac{1}{N} \sum_{i=1}^{N} P_o^{(i)} \tag{2.10}$$

where N is the number of active SUs and $P_o^{(i)}$ is the outage probability of the ith SU:

$$P_o^{(i)} = P_r\{SINR^{(i)} < SINR_{th}\} \tag{2.11}$$

Simulation results were obtained for N active secondary users after 100 runs. For the same number of active SUs, the outage probability of our fuzzy scheme is smaller than that of the fixed-step scheme. The outage probability of our power control scheme increases with the number of active SUs but more slowly than the corresponding probability of fixed-step power control scheme.

2.6 Conclusion

In this chapter, we propose a novel power control system design using the fuzzy logic system to opportunistically control the transmit power of cognitive radio in the case cognitive radio has a desire for coexistence with primary user. The linguistic knowledge of transmit power control based on three antecedents is obtained from a group of network experts, so that an acceptable decision can be achieved. Simulation results show that, using the proposed scheme, we can achieve lower average outage probability and lower average transmit power increase compared to fixed step scheme, thereby improving the

performance and decreasing power consumption of the whole network. Moreover, our proposed scheme is an efficient solution not only to reduce the spectrum handoff duration for cognitive radios since cognitive radios can continue their transmissions while looking for new spectrum bands, but also to improve the performance of cognitive radios by allowing cognitive radios to use reclaimed band and other unused bands for multi-band transmissions. Therefore, we believe that our proposed scheme is promising to be implemented in future cognitive radio networks.

CHAPTER 3

JOINT MULTI-TARGET IDENTIFICATION AND CLASSIFICATION IN COGNITIVE RADAR SENSOR NETWORKS

3.1 Introduction

The importance of providing multiple target identification and classification (MTIC) capabilities for military applications is widely recognized nowadays. When the total number of targets present in tactical battlefields is increased, classifying as well as identifying these targets will become a very challenging task. Measurements received from multiple radar sensors should be collected and processed in an efficient and robust manner to obtain the most meaningful information for identification and classification. Therefore, collaborative processing algorithms at the fusion center are in urgent need to successfully achieve this ultimate goal.

Many algorithms have been suggested to handle the task of multiple target identification and classification. In [8], a Gaussian Mixture Model (GMM) classifier was proposed to distinct categories in a semi-structured outdoor environment. For radar target identification, a multi-feature decision space approach was discussed in detail in [21]. Other approaches to the problem of target identification were presented in [16] applying two statistical-based techniques Bayesian and Dempster-Shafer to develop radar target identification algorithms. Distributed multi-class classification with fault-tolerance capability was studied in [52]. Collaborative classification algorithms [7] were applied to single target scenarios and then extended to more complex scenarios of multiple targets.

Multiple target identification and classification have become major concerns in radar surveillance applications. Usually, this task is implemented based on wideband radars or imaging radars [53]. In this thesis, we address the problem of MTIC for radar surveillance using cognitive radars. Cognitive radars, as presented in [44] and [43], con-

tinuously interact with the environment, intelligently collect data and thereby efficiently adapt to statistical variations in the environment in real-time so as to achieve reliable surveillance where the likelihood of the presence of targets is high. Cognitive radars are showing promise in home health care, rescue and homeland security applications [43], [54]. Such applications were studied in [44], [54].

We consider the scenario wherein the total number of targets K is unknown in a region of interest and a query regarding the classification of these targets and the identification of the targets in each category is inquired. This is the general surveillance scenario since each target belonging to one distinct category as in [22] is no longer considered. In this work, targets may now have the same category but different identification numbers. In order to perform this higher complexity version of surveillance scenario, we assume that each given target belongs to one distinct pair of one target category and one identification number. Based on statistical data, we then reasonably assume that the maximum number of target categories M and the maximum number of targets N in each category are a priori known parameters. However, the actual number of existing target categories and the actual number of targets present in each category at any given time are unknown. It is assumed that there are R cognitive radar sensors in the query region.

Within the above-described framework, we propose a joint multi-target identification and classification (JMIC) algorithm for radar surveillance. Firstly, the existing target categories are classified based on $M^\star$-ary hypothesis testing where $M^\star = 2^M$. Note that, $M^\star$ hypotheses correspond to all possibilities we may have regarding to the presence or absence of each category. Thereafter, based on the result obtained from classification specifying which target categories exist, we identify targets present in each detected category. Targets in a category are identified based on their identification numbers or identification indices. Therefore, $N^\star$ ($N^\star = 2^N$ - 1) hypotheses are set up corresponding to all scenarios of presence or absence of each target identification index. Numerical

results based on simulated data are finally presented to demonstrate the feasibility and effectiveness of the proposed JMIC algorithm in a query surveillance region.

The rest of the chapter is organized as follows. In Section 3.2, we provide a framework and formulate the multi-target classification and identification problem in a cognitive radar network. In Section 3.3, we propose the joint multi-target identification and classification algorithm. Simulation results are presented in Section 3.4. Finally, Section 3.5 concludes the chapter.

3.2   System Description and Problem Formulation

The general system architecture for MTIC problem used in this work is shown in Fig. 3.1. This architecture accommodates the deployment of R cognitive radar sensors (CRSs). These sensors will collect and then send all the target signals to the fusion center. There are K targets in the region of interest. Each target is considered as a point source and target signals are modeled as zero-mean complex Gaussian processes [22]. All measurements from sensors are combined to reduce the impact of target signal variability. At any given time, the measurements in distinct cognitive radar sensors are approximately independent.

It is assumed that at most M distinct target categories and N targets in each category are present in the surveillance region in the observation duration. However, the actual existing number of target categories is unknown. Therefore, we set up 2^M hypotheses corresponding to all possible scenarios of presence or absence of each target category. We denote these hypotheses by H_k ($k = 0, 1, ..., 2^M - 1$). Target categories are denoted by i ($i = 1, 2, ..., M$) and in each ith category, targets are identified by the identification indices j ($j = 1, 2, ..., N$). We use the parameter $b_{ij} \in \{0, 1\}$ to denote the event in which target of category i, index j is absent or present. Specifically,

$$b_{ij} = \begin{cases} 0 & \text{if target of category } i, \text{ index } j \text{ is absent} \\ 1 & \text{if target of category } i, \text{ index } j \text{ is present} \end{cases}$$
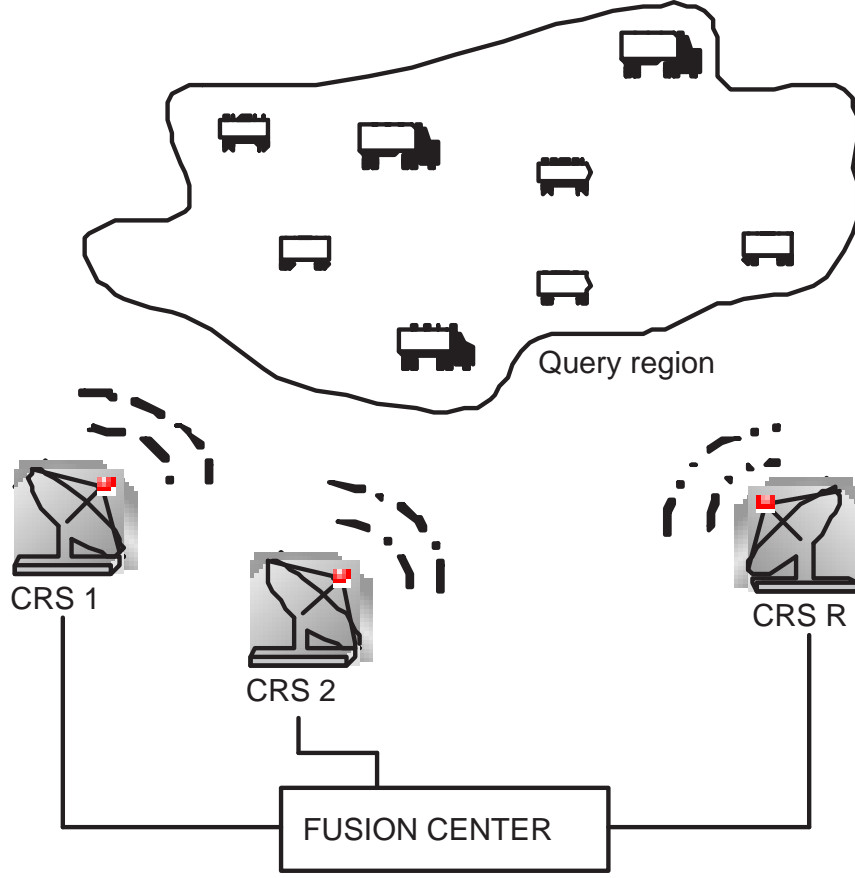
Figure 3.1: System architecture for JMIC algorithm

Classification and identification parameters are given in Table 3.1 wherein each row represents one target category and each column represents one target index. The probability of target of category i, index j being absent $P(b_{ij} = 0)$ is denoted by p_{ij}, i.e., $P(b_{ij} = 0) = p_{ij}$. Hence, the probability of presence of this target $P(b_{ij} = 1)$ is: $P(b_{ij} = 1) = 1- p_{ij}$.

We employ hypothesis H_0 for scenario of no category being present, hypothesis H_1 for scenario of category 1 being present,..., and hypothesis H_{2^M-1} for scenario of all M categories being present. We assume that the total number of targets K in the region

Table 3.1: Classification and Identification Parameters

	Index 1	Index 2	Index 3	...	Index N
Category 1	b_{11}	b_{12}	b_{13}	...	b_{1N}
Category 2	b_{21}	b_{22}	b_{23}	...	b_{2N}
Category 3	b_{31}	b_{32}	b_{33}	...	b_{3N}
$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$
Category M	b_{M1}	b_{M2}	b_{M3}	...	b_{MN}

of interest is unknown. In the case of K = 0, i.e., there is no target in the surveillance region, hypothesis H_0 is chosen. The prior probability of hypothesis H_0 is given by:

$$
\begin{aligned}
P(H_0) &= \text{P \{no category present\}} \\
&= P(\forall b_{1j} = 0; \forall b_{2j} = 0; ...; \forall b_{Mj} = 0), \\
&\qquad \text{for } j = 1, 2, ..., N
\end{aligned}
\tag{3.1}
$$

Since the possibilities for presence or absence of targets are independent, we have

$$
\begin{aligned}
P(H_0) &= P(\forall b_{1j} = 0).P(\forall b_{2j} = 0)...P(\forall b_{Mj} = 0) \\
&= (p_{11}.p_{12}...p_{1N})(p_{21}.p_{22}...p_{2N})...(p_{M1}...p_{MN}) \\
&= \prod_{j=1}^{N} p_{1j} \cdot \prod_{j=1}^{N} p_{2j} \ldots \prod_{j=1}^{N} p_{Mj}
\end{aligned}
\tag{3.2}
$$

Similarly, the prior probability of H_1 is given by:

$$
\begin{aligned}
P(H_1) &= \text{P \{category 1 present\}} \\
&= P(\text{at least one } b_{1j} = 1; \forall b_{2j} = 0; ...; \forall b_{Mj} = 0) \\
&= P(\exists \text{ one } b_{1j} = 1).P(\forall b_{2j} = 0)...P(\forall b_{Mj} = 0) \\
&= (1 - \prod_{j=1}^{N} p_{1j}) \cdot \prod_{j=1}^{N} p_{2j} \ldots \prod_{j=1}^{N} p_{Mj}
\end{aligned}
\tag{3.3}
$$

Generally, we obtain the prior probability of hypothesis H_k in the form as follows:

$$
P(H_k) = \prod_{i=1}^{M} [b_i^{(k)} (1 - \prod_{j=1}^{N} p_{ij}) + (1 - b_i^{(k)}) \prod_{j=1}^{N} p_{ij}]
\tag{3.4}
$$

where $b_i^{(k)}$ takes the value of 0 when category i is absent, otherwise $b_i^{(k)}$ takes the value of 1 when category i is present under hypothesis H_k.

3.3 Joint Multi-target Identification and Classification Algorithm

Joint multi-target identification and classification algorithm consists of two steps. In the first step, multiple target classification is implemented to investigate which target categories are present within the entire surveillance region. Then, in the second step, based on classification results, we identify targets in each detected category using their identification indices. Our JMIC algorithm relies on the framework previously presented in Section 3.2.

3.3.1 Multiple Target Category Classification

The $M^\star$-ary hypothesis testing problem is given by:

$$H_k : \mathbf{z}_l = \mathbf{s}_l + \mathbf{n}_l, \qquad k = 0, 1, ..., 2^M - 1 \tag{3.5}$$

where $\mathbf{z}_l$ is a feature vector of dimension D collected by the lth ($l = 1, 2, ..., R$) cognitive radar sensor. It is assumed that target signals have the same energy, i.e., these signals are modeled as zero-mean complex Gaussian vectors with covariance matrix $\boldsymbol{\Sigma}_m$. Thus,

$$\mathbf{s}_l \sim \mathcal{CN}(0, \boldsymbol{\Sigma}_{s_{lk}}), \quad \text{where} \quad \boldsymbol{\Sigma}_{s_{lk}} = \sum_{i=1(i \in H_k)}^{M} \sum_{j=1}^{N} b_{ij} \boldsymbol{\Sigma}_m \tag{3.6}$$

Signals are corrupted by zero-mean complex white Gaussian noise.

$$\mathbf{n}_l \sim \mathcal{CN}(0, \sigma_n^2 \mathbf{I}). \tag{3.7}$$

Under hypothesis H_k, the probability density function of the feature vector $\mathbf{z}_l$ is given by:

$$
\begin{aligned}
P(\mathbf{z}_l | H_k) &= p_k(\mathbf{z}_l) \\
&= \frac{1}{\pi^D |\boldsymbol{\Sigma}_{z_{lk}}|} \exp\left\{-\mathbf{z}_l^H \boldsymbol{\Sigma}_{z_{lk}}^{-1} \mathbf{z}_l\right\}
\end{aligned}
\tag{3.8}
$$

where $\boldsymbol{\Sigma}_{z_{lk}} = \boldsymbol{\Sigma}_{s_{lk}} + \sigma_n^2 \mathbf{I}$

We denote $P(H_k)$ by δ_k. The decision rule for the multiple target classifier is therefore given by:

$$\hat{k} = \arg \max_{k=0,1,...,M^\star-1} p_k(\mathbf{z}_1, \mathbf{z}_2, ..., \mathbf{z}_R) \delta_k \tag{3.9}$$

Due to the conditional independence of $\mathbf{z}_l$, (3.9) can be expressed as:

$$\hat{k} = \arg \max_{k=0,1,\ldots,M^\star-1} \prod_{l=1}^{R} p_k(\mathbf{z}_l)\delta_k \qquad (3.10)$$

In terms of log-likelihood, we have

$$
\begin{aligned}
\Delta_k(\mathbf{z}_1, \mathbf{z}_2, \ldots, \mathbf{z}_R) &= \log \prod_{l=1}^{R} p_k(\mathbf{z}_l)\delta_k \\
&= \sum_{l=1}^{R} \log p_k(\mathbf{z}_l) + \log \delta_k \qquad (3.11)
\end{aligned}
$$

By substituting $p_k(\mathbf{z}_l)$ from (3.8) to (3.11) and omitting constants that do not depend on categories, we then obtain Δ_k in the following form, :

$$\Delta_k(\mathbf{z}_1, \mathbf{z}_2, \ldots, \mathbf{z}_R) = -R \log |\boldsymbol{\Sigma}_{z_{lk}}| - \sum_{l=1}^{R} \mathbf{z}_l^H \boldsymbol{\Sigma}_{z_{lk}}^{-1} \mathbf{z}_l + \log \delta_k \qquad (3.12)$$

The information about $\mathbf{z}_l$ is then sent from the lth ($l = 1, 2, \ldots, R$) cognitive radar sensor to the fusion center. The classifier at the fusion center then makes the final classification decision in the form:

$$
\begin{aligned}
\hat{k} &= \arg \max_{k=0,1,\ldots,M^\star-1} \Delta_k(\mathbf{z}_1, \mathbf{z}_2, \ldots, \mathbf{z}_R) \\
&= \arg \min_k \{ R \log |\boldsymbol{\Sigma}_{z_{lk}}| + \sum_{l=1}^{R} \mathbf{z}_l^H \boldsymbol{\Sigma}_{z_{lk}}^{-1} \mathbf{z}_l - \log \delta_k \}
\end{aligned}
$$

$$(3.13)$$

From (3.13), we map the integer value of $\hat{k}$ to binary value to obtain a category vector $\mathbf{c} = [c_1, c_2, \ldots, c_M]$ where c_i ($i = 1, 2, \ldots, M$) takes value of 1 corresponding to category i being present or takes value of 0 corresponding to category i being absent in the area of interest. The total number of target categories being present in the surveillance region is given by:

$$N_C = \sum_{i=1}^{M} c_i \qquad (3.14)$$

For example, if $\hat{k} = 5$, then we get $\mathbf{c} = [1, 0, 1, 0, \ldots, 0]$, i.e., only categories 1 and 3 are present within the surveillance region. Therefore, the total number of target categories being present N_C is 2.

3.3.2 Multiple Target Identification

Based on the estimated value $\hat{k}$, we realize which target categories have shown up in the surveillance region. However, we still have no information about the number of targets belonging to each category. Therefore, the second step of the JMIC algorithm is repeatedly applied to each detected category to identify targets in the surveillance region. We aim at searching all the targets using their jth indices. For each category i, we denote $H^i_{h,\hat{k}}$ to represent the hypothesis h ($h = 0, 1, ..., 2^N$ - 1), given category $i \in \mathbf{S}$ being present under hypothesis $H_{\hat{k}}$. Note that, $\mathbf{S}$ is a set of all categories i being present in hypothesis $H_{\hat{k}}$.

$$\mathbf{S} = \{i \text{ present in } H_{\hat{k}}\} \tag{3.15}$$

Since category i is estimated to be present, i.e, at least one target index j shows up in this category, thus, the scenario of no target index of category i being present is eliminated, i.e., $\mathrm{P}(H^i_{0,\hat{k}}) = 0$. Thus, we only have $N^\star = 2^N$ - 1 hypotheses corresponding to $h = 1$, 2, ..., $N^\star$. We choose $H^i_{1,\hat{k}}$ to represent the hypothesis of target index $\sharp 1$ of category $i \in \mathbf{S}$ being present, $H^i_{2,\hat{k}}$ to represent the hypothesis of target index $\sharp 2$ of category $i \in \mathbf{S}$ being present, ..., $H^i_{N^\star,\hat{k}}$ to represent the hypothesis of all targets index $\sharp 1, \sharp 2, ..., \sharp N$ of category $i \in \mathbf{S}$ being present.

We have

$$
\begin{aligned}
P(H^i_{h,\hat{k}}) &= P(H^i_h, H_{\hat{k}}) \\
&= P(H^i_h | H_{\hat{k}}) P(H_{\hat{k}})
\end{aligned}
\tag{3.16}
$$

The conditional probability of hypothesis $H^i_{1,\hat{k}}$ is given by:

$$
\begin{aligned}
P(H^i_1 | H_{\hat{k}}) &= \mathrm{P}\{\text{target index } \sharp 1 \text{ category } i \text{ present}\} \\
&= P(b_{i1} = 1; b_{i2} = 0; ...; b_{iN} = 0)
\end{aligned}
$$

$$\tag{3.17}$$

Because the possibilities for presence or absence of targets are independent, we have

$$
\begin{aligned}
P(H_1^i|H_{\hat{k}}) &= P(b_{i1}=1).P(b_{i2}=0)...P(b_{iN}=0) \\
&= (1-p_{i1}).p_{i2}...p_{iN}
\end{aligned}
\tag{3.18}
$$

Similarly, the conditional probability of hypothesis $H_{2,\hat{k}}^i$ is:

$$
\begin{aligned}
P(H_2^i|H_{\hat{k}}) &= \text{P \{target index \sharp 2 category } i \text{ present\}} \\
&= P(b_{i1}=0; b_{i2}=1;...;b_{iN}=0) \\
&= P(b_{i1}=0).P(b_{i2}=1)...P(b_{iN}=0) \\
&= p_{i1}.(1-p_{i2})...p_{iN}
\end{aligned}
\tag{3.19}
$$

In general, we obtain the conditional probability of hypothesis $H_{h,\hat{k}}^i$ as follows:

$$
P(H_h^i|H_{\hat{k}}) = \prod_{j=1}^{N}[b_{ij}^{(h)}(1-p_{ij}) + (1-b_{ij}^{(h)})p_{ij}]
\tag{3.20}
$$

where $b_{ij}^{(h)}$ takes the value of 0 when target index j of category i is absent, otherwise $b_{ij}^{(h)}$ takes the value of 1 when target index j of category i is present under hypothesis H_h^i given hypothesis $H_{\hat{k}}$.

We now set up $N^\star$ hypotheses:

$$
H_{h,\hat{k}}^i : \mathbf{z}_l^i = \mathbf{s}_l^i + \mathbf{n}_l^i, \qquad h = 1, 2, ..., N^\star
\tag{3.21}
$$

where $\mathbf{z}_l^i$ is collected by lth ($l = 1, 2, ..., R$) cognitive radar sensor regarding to ith category. Target signals of ith category are given by:

$$
\mathbf{s}_l^i \sim \mathcal{CN}(0, \boldsymbol{\Sigma}_{s_{l,h}^i}), \quad \text{where } \boldsymbol{\Sigma}_{s_{l,h}^i} = \sum_{j=1(j\in H_{h,\hat{k}}^i)}^{N} b_{ij}\boldsymbol{\Sigma}_m
\tag{3.22}
$$

Signals are corrupted by zero-mean complex white Gaussian noise.

$$
\mathbf{n}_l^i \sim \mathcal{CN}(0, \sigma_n^2\mathbf{I})
\tag{3.23}
$$

Under hypothesis $H^i_{h,\hat{k}}$, the probability density function of the feature vector $\mathbf{z}^i_l$ of category i is given by:

$$
\begin{aligned}
P(\mathbf{z}^i_l | H^i_{h,\hat{k}}) &= p_{h,\hat{k}}(\mathbf{z}^i_l) \\
&= \frac{1}{\pi^D |\boldsymbol{\Sigma}_{z^i_{l,h}}|} \exp\left\{-(\mathbf{z}^i_l)^H \boldsymbol{\Sigma}^{-1}_{z^i_{l,h}} \mathbf{z}^i_l\right\}
\end{aligned}
\tag{3.24}
$$

where $\boldsymbol{\Sigma}_{z^i_{l,h}} = \boldsymbol{\Sigma}_{s^i_{l,h}} + \sigma_n^2 \mathbf{I}$.

We denote $P(H^i_h | H_{\hat{k}})$ by α^i_h. From (3.16) and due to the conditional independence of $\mathbf{z}^i_l$, the identification decision rule is hence given by:

$$
\hat{h} = \arg \max_{h=1,2,\dots,N^\star} \prod_{l=1}^{R} p_{h,\hat{k}}(\mathbf{z}^i_l) \alpha^i_h \delta_{\hat{k}}
\tag{3.25}
$$

In terms of log-likelihood, we have

$$
\begin{aligned}
\Delta^i_k &= \log \prod_{l=1}^{R} p_{h,\hat{k}}(\mathbf{z}^i_l) \alpha^i_h \delta_{\hat{k}} \\
&= \sum_{l=1}^{R} \log p_{h,\hat{k}}(\mathbf{z}^i_l) + \log \alpha^i_h + \log \delta_{\hat{k}}
\end{aligned}
\tag{3.26}
$$

By substituting $p_{h,\hat{k}}(\mathbf{z}^i_l)$ from (3.24) to (3.26) and omitting constants that do not depend on target indices in each category, we have Δ^i_k in the following form:

$$
\Delta^i_k = -R \log |\boldsymbol{\Sigma}_{z^i_{l,h}}| - \sum_{l=1}^{R} (\mathbf{z}^i_l)^H \boldsymbol{\Sigma}^{-1}_{z^i_{l,h}} \mathbf{z}^i_l + \log \alpha^i_h + \log \delta_{\hat{k}}
\tag{3.27}
$$

The information about $\mathbf{z}^i_l$ is sent from the lth cognitive radar sensor to the fusion center. The identifier at the fusion center then makes the final identification decision:

$$
\begin{aligned}
\hat{h} &= \arg \max_{h=1,2,\dots,N^\star} \Delta^i_k \\
&= \arg \min_h \Big\{ R \log |\boldsymbol{\Sigma}_{z^i_{l,h}}| + \sum_{l=1}^{R} (\mathbf{z}^i_l)^H \boldsymbol{\Sigma}^{-1}_{z^i_{l,h}} \mathbf{z}^i_l - \log \alpha^i_h \\
&\qquad\qquad - \log \delta_{\hat{k}} \Big\}
\end{aligned}
\tag{3.28}
$$

From (3.28), we map the integer value of $\hat{h}$ to binary value to obtain a index vector $\mathbf{b}_i = [b_{i1}, b_{i2}, \dots, b_{iN}]$ where every component of $\mathbf{b}_i$ takes the value of 1 or 0. Component

$\sharp j$ takes value of 1 corresponding to the scenario of target index $\sharp j$ of category i being present. The total number of targets N_i in each category i is calculated by:

$$N_i = \sum_{j=1}^{N} b_{ij} \qquad (3.29)$$

Following the example previously described in classification step, for i = 1, if $\hat{h} = 7$, then we get $\mathbf{b}_1 = [1, 1, 1, 0, ...,0]$. Therefore, only targets with indices 1, 2 and 3 of category 1 are present within the surveillance region. The total number of targets of category 1 being present N_1 is 3. Repeatedly implementing this step, for i = 3, if $\hat{h} = 3$, we obtain $\mathbf{b}_3 = [1, 1, 0, 0, ..., 0]$. So, targets with indices 1 and 2 of category 3 are present. The total number of targets of category 3 being present N_3 is 2.

The total number of targets K in the surveillance region is finally given by:

$$K = \sum_{i=1}^{M} N_i = \sum_{i=1}^{M}\sum_{j=1}^{N} b_{ij} \qquad (3.30)$$

In the example, the total number of targets within the surveillance region K is 5.

3.4 Simulation Results

We perform simulations to illustrate the performance of the proposed JMIC algorithm. An encounter of unknown K targets in the region of query was simulated. A set of R cognitive radar sensors was deployed. A cognitive radar sensor may detect more than one target at any given time. Therefore, a more accurate estimation about target categories and the total number of targets being present in each category can be obtained by fusion of several radar sensors. The maximum number of categories $M = 3$ and the maximum number of targets in each category $N = 4$ were assumed in the region of interest.

An example using JMIC for $K = 7$ targets in the region of interest is given in Table 3.2. We use JMIC algorithm to obtain $\hat{k} = 7$ which specifies that categories 1, 2, 3 are present and thus $N_c = 3$. The number of targets of category 1 is 2 (target index $\sharp 2$ and $\sharp 4$) corresponding to $\hat{h} = 10$. The number of targets of category 2 is 3 (target index

Table 3.2: Classification and Identification Example

	Index 1	Index 2	Index 3	Index 4
Category 1	0	1	0	1
Category 2	1	1	0	1
Category 3	1	1	0	0

$\sharp 1$, $\sharp 2$, and $\sharp 4$) corresponding to $\hat{h} = 11$. The total number of targets of category 3 is 2 (target index $\sharp 1$ and $\sharp 2$) corresponding to $\hat{h} = 3$.

To evaluate the performance of the proposed JMIC algorithm, we conduct a Monte-Carlo simulation of 10^5 runs. The probability of error of the proposed JMIC algorithm given in the form of function of signal-to-noise power ratio is shown in Fig. 3.2, Fig. 3.4, and Fig. 3.6. The total number of cognitive radar sensors $R = 3$, 5 and 10 were used in the simulations.
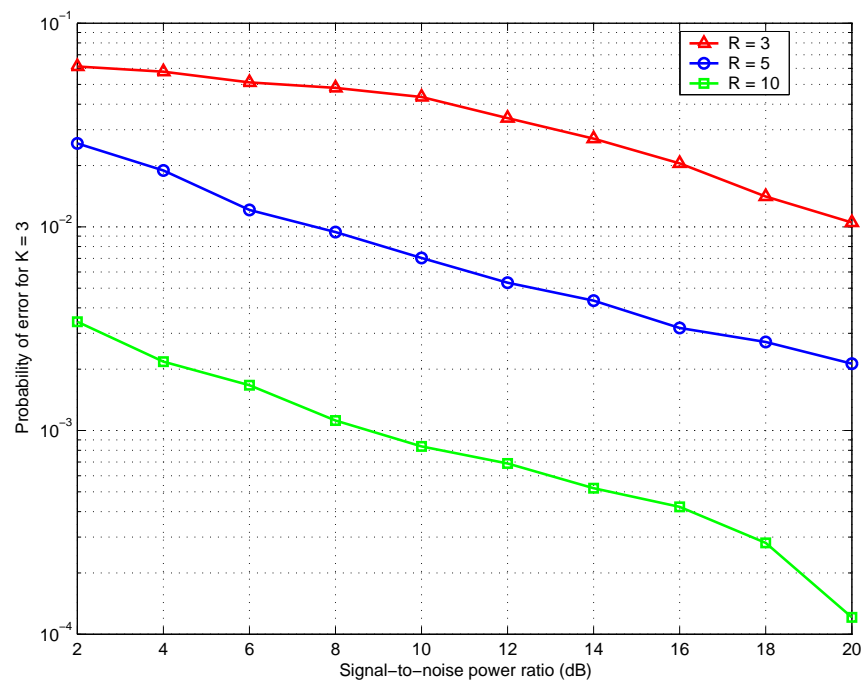
Figure 3.2: Probability of error using JMIC algorithm for K = 3

Figure 3.3: Surveillance scenario of K = 3
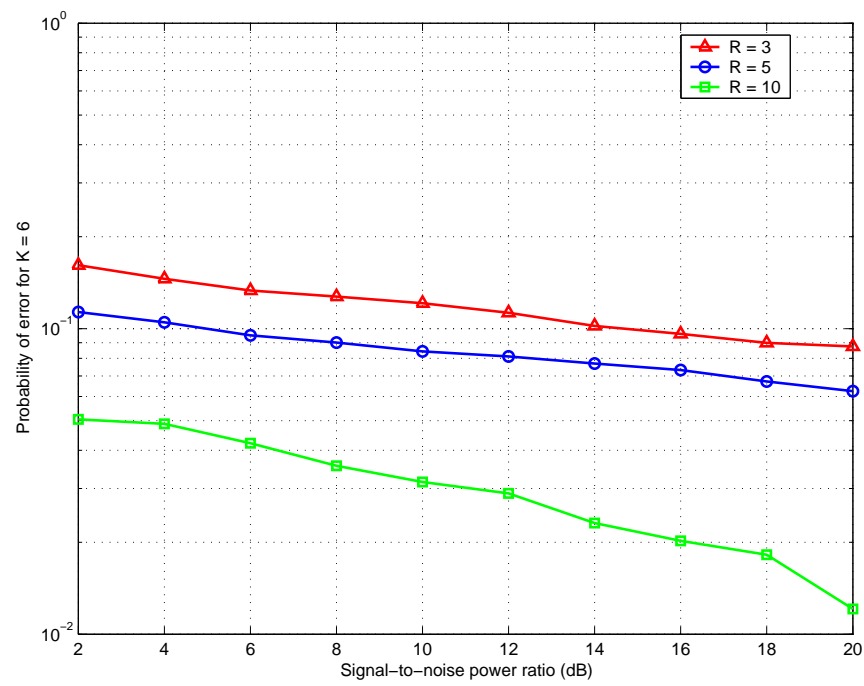
Figure 3.4: Probability of error using JMIC algorithm for K = 6
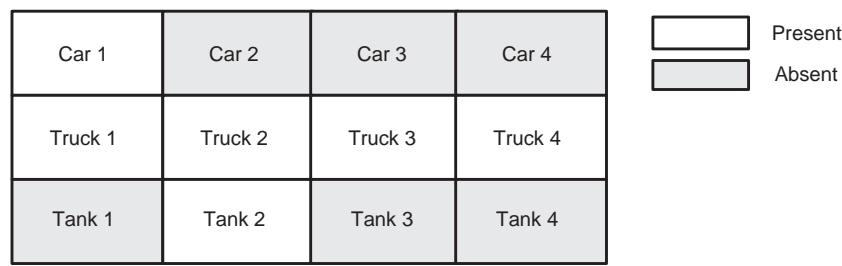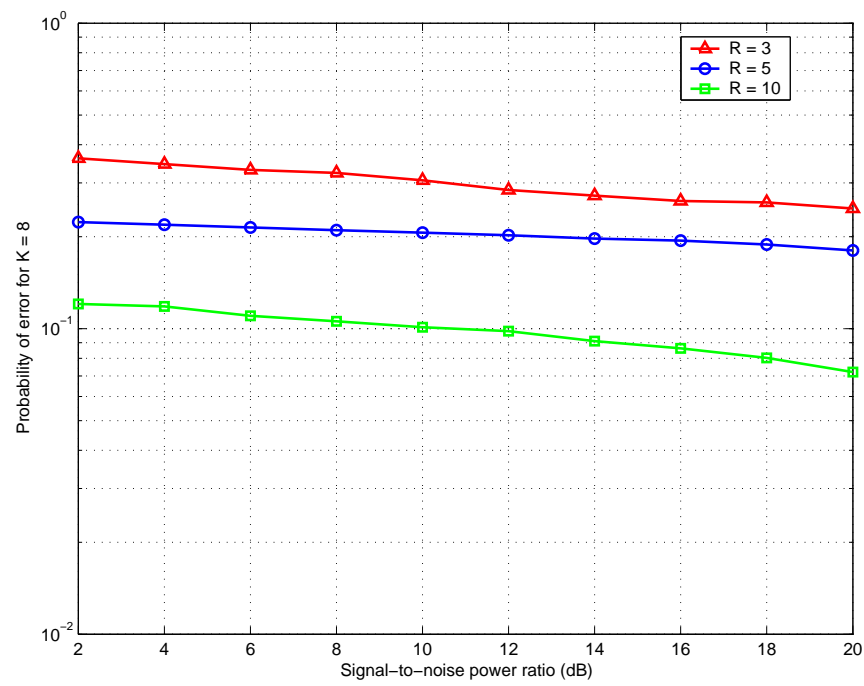

Figure 3.5: Surveillance scenario of K = 6

Figure 3.6: Probability of error using JMIC algorithm for K = 8

Figure 3.7: Surveillance scenario of K = 8

From Fig. 3.2, we realize that a sufficiently low probability of error can be obtained with a small number of cognitive radar sensors $R = 5$ in the surveillance scenario of $K = 3$ targets as shown in Fig. 3.3. Comparison of probability of error for the different number of cognitive radar sensors in the scenario of $K = 3$ targets was shown in Fig. 3.2. The simulation results demonstrate our algorithm in the surveillance scenarios of $K = 6$ as described in Fig. 3.5 and K =8 as in Fig. 3.7 are, correspondingly, given in Fig. 3.4 and Fig. 3.6. From Fig. 3.2, Fig. 3.4 and Fig. 3.6, we also observe that for a given number of targets K in the surveillance region, the performance of JMIC using $R = 5$ or $R = 10$ radar sensors is better than that using $R = 3$ radar sensors. Besides, for a given number of R radar sensors, the identification and classification performance is reduced when we notice an increasing number of targets in the surveillance region. The probability of JMIC error is inversely proportional to signal-to-noise power ratio. At high SNR, the probability of error is rather small. The simulation results validate the robustness and effectiveness of our proposed JMIC algorithm.

3.5 Conclusion

We have demonstrated that K targets in a query region can be classified and identified reliably by a network of R cognitive radar sensors using our JMIC algorithm. A computer simulation with simulated radar data was used to investigate the accuracy of classification and identification algorithm in the variations of the target signals in the network. Using JMIC algorithm, we show that a sufficiently low probability of error can be achieved with a fairly small number of radar sensors for a given common number of targets. The unprecedented desire of knowing not only the number of categories, but also the total number of targets belonging to each category in a surveillance region is making JMIC algorithm an attractive choice in practice for military applications.

CHAPTER 4

CONCLUSION AND FUTURE WORKS

4.1 Contributions

Cognitive radio has been considered as an efficient approach to opportunistic spectrum sharing between primary (licensed) users and cognitive radio users. However, in order to have such opportunistic spectrum sharing, cognitive radio must be able to intelligently adapt to the behavior of primary user (PU). Under the constraint that no excessive interference to the PUs is generated, TPC decision-making for SUs is still a daunting task when efficient communications of PUs as well as SUs are taken into consideration. Studies on TPC are progressing to investigate the best scheme for a workable SU system. In this thesis, we have discussed the transmit power control problem in cognitive radio networks. To address the problem, a novel power control design using the fuzzy logic system to opportunistically control the transmit power of a cognitive radio in the case this cognitive radio has a desire for coexistence with primary user has been proposed.

- We have received acceptable decisions on transmit power control for cognitive radios by obtaining the linguistic knowledge of transmit power control based on three antecedents from a group of network experts.

- Our studies show that, using the proposed scheme, we have achieved lower average outage probability and lower average transmit power increase compared to the fixed-step power control scheme, thereby improving the performance and decreasing power consumption of the whole network.

Moreover, our proposed scheme is an efficient solution not only to reduce the spectrum handoff duration for cognitive radios since cognitive radios can continue their transmissions while looking for new spectrum bands, but also to improve the performance of

cognitive radios by allowing cognitive radios to use reclaimed band and other unused bands for multi-band transmissions.

Multiple target identification and classification have become major concerns in radar surveillance applications. In this thesis, we have also discussed the problem of jointly classifying and identifying multiple targets in radar sensor networks where the maximum number of categories and the maximum number of targets in each category are obtained a priori based on statistical data. However, the actual number of targets in each category and the actual number of target categories being present at any given time are unknown. We considered the scenario wherein the total number of targets is unknown in a region of interest and a query regarding the classification of these targets and the identification of the targets in each category is inquired.

- We have demonstrated that multiple targets in a surveillance region can be classified and identified reliably by a network of cognitive radar sensors using our JMIC algorithm.

- A computer simulation with simulated radar data was used to investigate the accuracy of classification and identification algorithm in the variations of the target signals in the network. Using JMIC algorithm, we have proved that a sufficiently low probability of error can be achieved with a fairly small number of radar sensors for a given common number of targets.

The unprecedented desire of knowing not only the number of categories, but also the total number of targets belonging to each category in a surveillance region is making JMIC algorithm an attractive choice in practice for military applications.

4.2 Future Works

Our future research ideas include the following works:

- Develop an efficient cross-layer design between the physical (PHY) layer and the MAC layer for spectrum sensing algorithms in cognitive radio networks.

- Investigate adaptive channel-coding algorithms in cognitive radio networks to optimize transmission data throughput and reduce error rate.

- Apply Independent Component Analysis (ICA) to cognitive radars to facilitate multiple target identification in military applications. A mixture of different sounds will be extracted to identify each individual target noise (for example, aircraft noise or tank noise).

- Design cognitive waveform for cognitive radios and cognitive radars.

- Develop novel non-interference methods for dynamic spectrum access.

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