An Intelligent Multi-stage Channel Acquisition Model for CR-WBANs: A Context Aware Approach

by

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I hereby declare that I am the sole author of this thesis. This is a true copy of the thesis, including any required final revisions, as accepted by my examiners.

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Abstract

Cognitive Radio (CR) came as a solution to mitigate challenges that wireless body area networks (WBANs) suffer from. CR is an intelligence-based technology that senses, observes, and learns from its operating environment to access licensed bands in the spectrum when they are not being utilized by primary users. Deploying a CR technology in WBANs applications, enhances spectrum scalability, increases system robustness, and decreases latency. Accordingly, CR-WBANs help in building a more efficient and reliable ubiquitous healthcare system than conventional WBANs do. However, CR-WBANs are still evolving, and many challenges need to be investigated, in particular, is how to acquire a channel and prioritize data streams among multiple CR-users (i.e., multiple patients) based on the severity of their health status, in a manner to decrease network latency and increase network scalability. To address this challenge, this work proposes a novel intelligent channel acquisition model for multiple CR-WBANs within ubiquitous healthcare system, whereby contextual data, namely, channel properties, intra-node characteristics, and patients profile information, is integrated in channel acquisition decision process. The proposed work is a multi-stage fusion system that is composed of local and global decisions units. A fuzzy logic system is utilized to make decisions in the local unit, which are sensing the channel availability and assessing the severity of patients' health status. Moreover, a neural network is employed as a global sensing decision center, whereby local sensing decisions,

channel properties, and intra-node characteristics are augmented in the decision process. Furthermore, a cluster-based heuristic algorithm is formulated, in the global decision unit, to prioritize data streams among CR-users based on the criticality of their health conditions (i.e., acute, urgent, and normal). Patients' local health assessments and avatars (e.g., age, medical history, etc.) are exploited in the prioritization process.

The proposed model has improved spectrum sensing accuracy and channel acquisition probability, for all CR-users in the network, under the consideration of the severity of their health status. Thus, network latency has reduced and network scalability has increased, and so more lives can be saved. The proposed work has gone through extensive experimental simulations to evaluate its performance. The results have shown that the channel acquisition model is robust, scalable, accurate, and reliable in acquiring a channel and prioritizing data streams among patients based on their health conditions.

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All praise is to Allah for giving me the ability and knowledge to accomplish this thesis.

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Thanks to all my friends and UW staff members who helped me directly or indirectly during my study.

Dedication

I would like to dedicate this thesis to my beloved parents, who were always there for me whenever I needed them; to my dear husband, Mohamed Ben Zeglam, who was the most helpful and supporting person I found throughout my graduate studies; to my sons and sisters, who motivated and inspired me all the time.

Table of Contents

List of Tables

List of Figures

Chapter 1

Introduction

Wireless body area networks (WBANs) have revolutionized the healthcare system by assisting patients with life-threatening situations and facilitating the continuous monitoring of patients while enabling their mobility [7]. WBANs comprise tiny wearable and implantable body sensors that collect and analyze patients vital signs, such as, heart rate, respiratory rate, brain activities, and temperature. These sensors also provide real-time feedback about patients health status. All these body sensors are connected to a centralized node called body controller unit (BCU). Each BCU is responsible for managing a WBAN and recognizing all sensors that are connected to its network. It is also responsible for transmitting vital-data to different medical locations (e.g., hospital systems, specialists, and pharmacists) via an access point.

However, the demand for deploying wireless technologies in healthcare programs is increasing rapidly. In fact, the international data corporation (IDC) has announced that the total number of health monitoring wearables to be shipped worldwide during a five-year period is expected to reach 155.7 million units in 2019, as depicted 1.1 [5]. All these demands result in new challenges in the network, such as, interference with other electronic devices, spectrum scarcity, and transmission failure, all of which may put patients lives at risk.

Cognitive Radio (CR) came as a technology to mitigate these challenges. It is an intelligent based technology that allows its users to sense, observe, and learn from its operating environment to opportunistically access licensed bands in the spectrum when they are not being utilized by primary users (PUs). Deploying the CR technology in medical services, increases system's robustness and scalability, reduces interference, and decreases latency [8].

However, CR-WBANs are still in its infancy stage, so various challenges need to be tackled, to apply the network in real-life applications. Channel acquisition is a crucial issue in CR-WBANs. Since the transmitted data in the network is associated with saving lives, acquiring a channel in the network must be accurate and reliable based on the severity level of patients health status. Different parameters can be included in designing an appropriate channel acquisition model in CR-WBANs: spectrum sensing and data prioritization are main parameters. Spectrum sensing is a major channel acquisition mechanism in CR networks. It is the first function that a CR-user performs and has a fundamental role in enabling efficient spectrum utilization. Spectrum sensing enables CR-users, or secondary users (SUs), to detect primary users (PUs) activities and makes a decision to utilize vacant channels in the spectrum. Data prioritization has a main function in saving patients with life-threatening situations. An appropriate prioritization mechanism must be applied to prioritize data transmission among body sensors and a BCU, or among multiple WBANs and an access point.

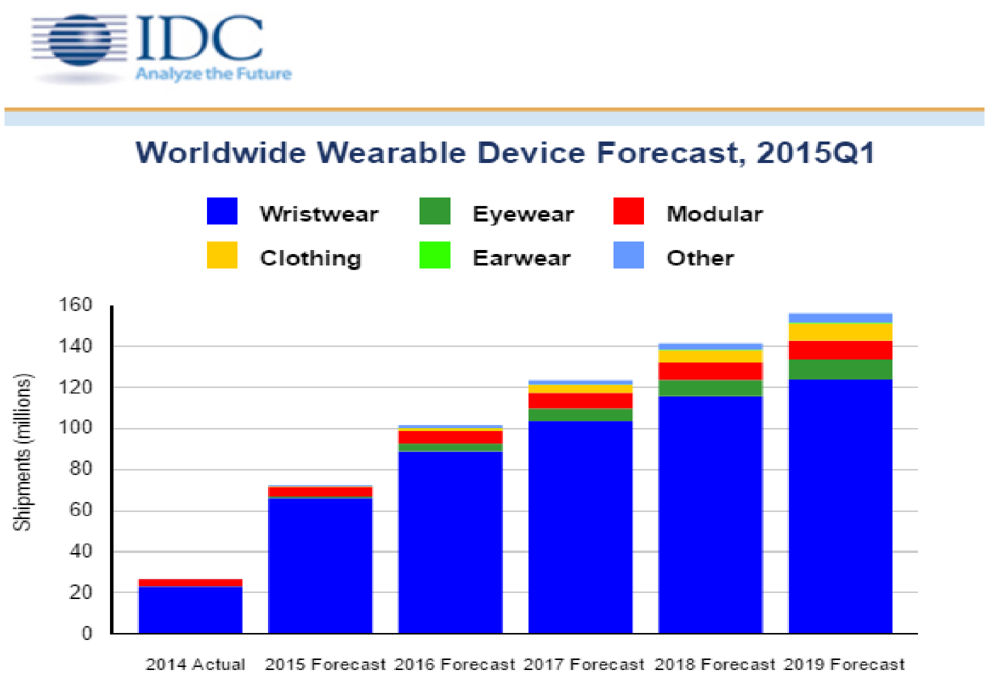


Figure 1.1: IDC world wearable devices forecast from 2014 until 2019[5]

1.1 Thesis motivation

Recently, demands of individuals with needs in the healthcare system have been rising significantly. In fact, according to Statistics Canada, in 2014/2015, the growth rate of the population over 64 is almost four times higher than the growth rate of the total population [9]. Additionally, due to the increasing cost of hospitalizations and specialist organizations [10], designing an intelligent ubiquitous healthcare system can assist healthcare professionals to overcome previous challenges and save more lives. WBANs are the first step in building an intelligent ubiquitous healthcare system. However, due to the increasing usage of WBANs in healthcare services, different challenges have faced the network, such as transmission failure, interference, and channels scarcity. all that may put lives' at risk.

CR-WBANs came as a solution to overcome different challenges that conventional WBANs suffer from. Moreover, building a high performing ubiquitous healthcare system with multiple CR-WBANs to serve the increasing number of patients requires designing an appropriate channel acquisition model. However, most of the state-of-the-art research is focused on acquiring a channel to transmit vital data among a BCU and body sensors. Ignoring that acquiring a channel effectively to send and prioritize data among multiple patients, based on their health status, can increase system robustness and scalability, and reduce system latency.

1.2 Research contributions

This research proposes a novel multi-stage intelligent channel acquisition model for CR-WBANs within ubiquitous healthcare system, whereby patients' contextual data, namely, intra-node characteristics, environmental properties, and patients' profile information, is augmented to acquire a channel for a patient with the highest priority level based on that patient health status. Main contributions of this work are:

- Building an intelligent channel acquisition model for multiple CR-WBANs within ubiquitous healthcare system, whereby patients with acute health status have the highest priority in acquiring a channel.
- Designing an architecture for the proposed intelligent channel acquisition model for CR-WBANs. The architecture is composed of 1) local decisions unit, where the intelligence is embedded in BCUs; and 2) global decisions unit, where the intelligence is encapsulated in access points.
- Designing an intelligent spectrum sensing model with high spectrum sensing accuracy for the channel acquisition model, whereby intra-node characteristics and environmental properties are included in spectrum sensing process.
- Utilizing fuzzy logic system and neural network, in local and global units, to sense

channel availability.

- Designing data prioritization model based on the criticality of patients health status (e.g., acute, urgent, and normal).
- Exploiting fuzzy logic system, again, in the local unit, to appraise the severity of patients' health according to their real-time vital signs measurements
- A cluster-based heuristic algorithm is formulated, in the global unit, to prioritize data transmission based on patients' local health assessment and patients' avatars (e.g., age, body mass index, etc.).

1.3 Thesis organization

This dissertation is composed of six chapters: Chapter 1 provides a brief introduction to the research area, research motivations and contributions.

Chapter 2 introduces a comprehensive overview of wireless body area networks (WBANs), its architecture, design requirements and challenges. Furthermore, this chapter provides an overview of cognitive radio (CR) and defines spectrum sensing and its techniques. It also presents a survey of state-of-the-art applications for CR-WBANs. Challenges that confront CR-WBANs are discussed briefly, to promote research in this area.

The architecture of the proposed intelligent channel acquisition model for CR-WBANs within ubiquitous healthcare system is presented in chapter 3. It is composed of two units, namely: the local and global decision units. Each unit consists of two modules: 1) the local decision unit consists of local sensing and health assessment decisions. 2) the global decision unit consists of global sensing and data prioritization decisions.

Chapter 4 describes design details of the proposed intelligent hybrid cooperative spectrum sensing model, which brings together the local sensing and global sensing decision modules. The chapter also presents extensive experimental simulations that are conducted to validate the model's performance regarding the probability of detection and spectrum sensing accuracy, for different number of CR-users.

Chapter 5 describes the proposed design details of the intelligent data prioritization model, which includes the local health assessment and global data prioritization decision modules. Patients' contextual information is utilized in the prioritization process. Experimental simulations are conducted to validate model's performance in terms of the probability of channel acquisition, network scalability and latency.

Finally, chapter 6 concludes this work and presents future recommendations

Chapter 2

Background and Literature Review

2.1 Introduction

WBANs positively affect the healthcare system by providing real-time monitoring, facilitating patient mobility, and reducing the cost of long-term treatment in hospitals [7]. It also provides remote monitoring for the elderly and individuals with chronic diseases which assist them for proceeding with their regular activities [11]. However, the increasing demands for employing WBANs in the healthcare system have brought new challenges to the network, such as interference with other electronic devices, spectrum scarcity, transmission delay, and transmission failure [11]. All of these challenges may put patients lives at risk. Cognitive radio technology came as a solution to mitigate previous issues and enhance network performance.

Cognitive radio (CR) technology is an emerging paradigm that provides more flexible and efficient usage of the radio spectrum. It allows illegitimate users to opportunistically access the spectrum without causing any harmful interference to legitimate users (i.e., primary users (PUs)). The CR technology adds cognition as an intelligent component in the radio spectrum, to detect a candidate channel that unlicensed users (secondary users (SUs)) can occupy in a manner to maximize spectrum utilization. The CR network can make a decision intelligently, learn to consider future goals, provide data prioritization, and be aware of the surrounding environment[12]. Hence, deploying CR in WBANs will improve system performance and overcome the pre-mentioned challenges.

This chapter provides a broad discussion on WBANs; overviews of CR technology; presents a novel categorization for the limited state-of-the-art applications for CR-WBANs; and discusses open issues to promote future research direction..

2.2 Wireless body area networks (WBANs)

WBANs are composed of small size, low power, low cost, and lightweight physiological sensors. These sensors can monitor several functions for different organs and vital signs in, on or around the human body, and collect and analyze the data in tests, such as blood rate, electrocardiogram (ECG), electroencephalography (EEG), pressure, and temperature [8][13]. The collected data is transmitted wirelessly to different healthcare services (e.g. hospitals, emergency rooms (ERs), specialists, or ambulances) depending on the purpose for collecting the data.

WBANs can be used in different areas, such as the military to track soldiers locations, entertainment in interactive gaming, and healthcare systems whether in medical or non-medical fields. In medical fields, WBANs can be used for diagnostics, therapeutic monitoring, acute situations, and remote monitoring for the elderly and patients in need at home. Also, for non-medical fields, WBANs can be deployed in sports to monitor fitness performance indicators, such as speed, distance, and heart rate. WBANs can also be utilized in wearables, such as, smart watches, Google glasses, and ear wears.

2.2.1 WBANs architecture

The general architecture of WBANs is divided into three tiers: the intra-BAN, the inter-BAN, and the Beyond-BAN [14], as shown in Figure 2.1. The intra-BAN is responsible for the communication between sensors and the body controller unit (BCU), sometimes called the central node or the personal server. According to the literature, there are four types of nodes within the intra-WBAN: 1) Core sensors, which collect and process data and then transmit it to the BCU; 2) Actuators, which do not gather any information by themselves, but work in sensor management where they act depending on the data they receive from core sensors, or by collaborating with patients [15]; 3) Relay sensors, whose task is to relay data from one node to another and which can be applied in hopping networks; and 4) the BCU which manages the network, where it communicates with sensors through different technologies, such as ZigBee and low power Bluetooth. The BCU is also responsible for gathering data, and organizing channel sharing and synchronization between sensors. Moreover, the BCU communicates nodes in a WBAN with a reachable network (e.g., WLANs, WANs, and the Internet) through an access point that exists in the second tier.

The intre-BAN tier is composed of an access point (i.e., gateway) and the cloud (i.e., the internet). The gateway is responsible for transferring data to the third tier, which is the beyond-BAN that includes different services, such as system hospitals, ambulances, and pharmacists, or any other healthcare providers, or with family members in cases of emergency.

2.2.2 WBANs requirements

The primary role of WBANs is enhancing individuals lives by facilitating their mobility. To accomplish that, certain requirements need to be taken into consideration:

- Sensor characteristics: Sensors must have low weight, small size, low power consumption, low cost, an adjustment that is tolerable for each patient, intact manufactured materials, avoid the use wired connections, be self-organized, and allow data registration in periodic and real times.

- Data transmission: transmission must be reliable with high throughput, secure, low latency, and prioritized.

- Network design: good design requires an acceptable quality of service (QoS) performance, interoperability among different body networks, traffic heterogeneity, minimum energy consumption, and scalability features.

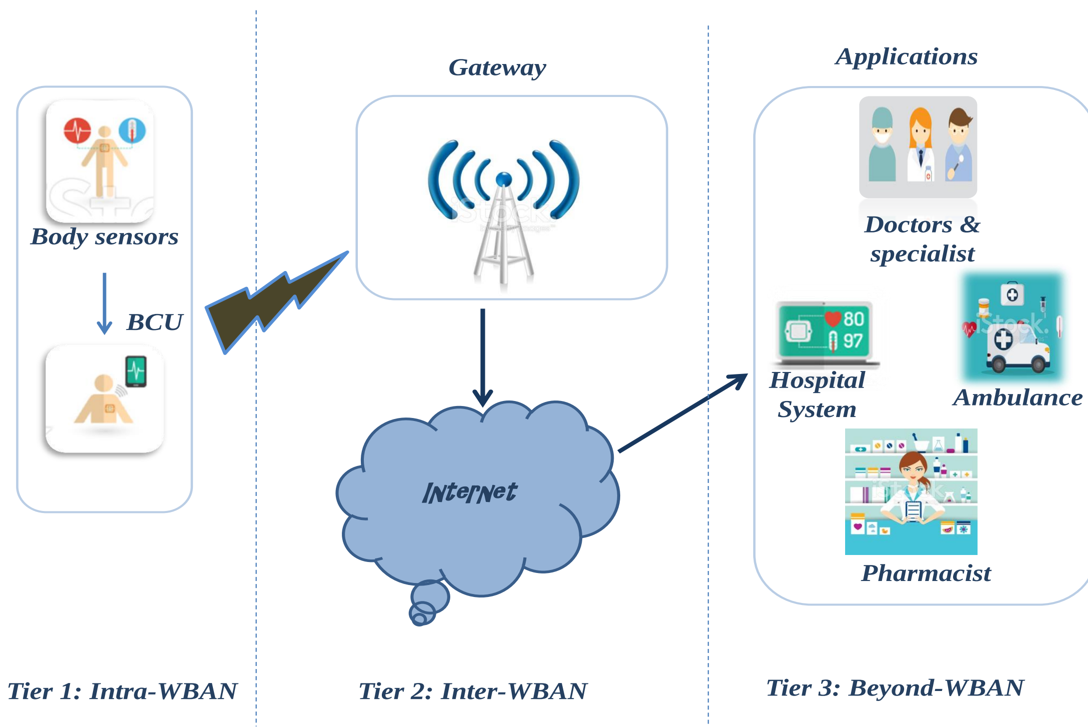


Figure 2.1: The general architecture of WBAN.

2.2.3 WBANs challenges

Designing WBANs that satisfy different requirements mentioned previously ,has many challenges: Increased energy consumption, latency, interference, and degradation in spectral efficiency. All these challenges need to be carefully addressed during network design to achieve satisfactory Quality of services (QoS) performance.

- Interference: WBAN's performance is influenced by the interference that may result from communication through a human body, nodes that are close to each other, and nodes that are nearby electronic equipment [15]. Interference decreases system reliability, since it increases packet loss and transmission delay.

- Security: the transmitted data in WBANs is personal and private since it contains information related to patients health and personal lives. Thus, appropriate security models need to be incorporated in the network design to protect patients rights.

- Power consumption: sensors in WBANs are power constraint devices, meaning that some sensors have a five-year battery lifetime and others have a 12-hour battery lifetime, depending on the required application. Thus, different actions, such as idle listening and increasing the number of retransmissions, will cause depletion in sensors power. Accordingly, designing a network with high power efficient model is required

- Latency: it is considered a main challenge in WBANs, since the transmitted data helps to save lives. Fading and collisions are two important factors that increase packet retransmissions, hence latency will increase also. Thus, designing a network with low latency, especially for patients with acute status, helps to save more lives.

- Data prioritization: since the transmitted data is related to saving individuals with life-threatening situations, it is crucial to design a network that prioritizes transmission based on the severity of patients conditions.

- Spectral efficiency: The demand for using WBANs is increasing, and bands in the spectrum are fully allocated for different applications, but not fully utilized. This case will degrade system performance by increasing collisions, packets retransmissions, and latency; as a result, it will decrease QoS performance. Efficient technologies need to be incorporated with WBANs to enhance spectrum utilization. Cognitive radio is one paradigm that can be employed to improve spectrum utilization.

2.3 An overview of cognitive radio (CR) technology

The term cognitive radio was first coined by Dr. Mitola in the late 90s [16]. Cognitive radio (CR) is an emerging paradigm that has built based on software defined radio. CR can be described as an intelligent radio that employs different methodologies to recognize its surrounding environment by observing, learning and then adopting its parameters based on its previous knowledge [16] [17]. Applying the idea of cognition to the radio spectrum enhances spectrum efficiency, provides smoothness to the interoperability process between different wireless communication systems and provides reliable transmission between radio services. Main goals for CR-network are the following: provide decent communication when it needs, and increase the usage of unoccupied spectrum bands.

A CR-user has two essential characteristics: capability is the ability to sense and understand the surrounding environment, to detect the empty spaces in the spectrum. Configurability is the ability to allow a CR-user to change transmission channel as soon as it senses the presence of a PU. Moreover, the CR implements four main functions: spectrum sensing, spectrum management, spectrum sharing, and spectrum mobility. Spectrum sensing is considered a chief component of cognitive radio technology, which helps SUs to sense and learn about white spaces in the spectrum, and makes sure that these spaces are empty. Spectrum management is responsible for choosing the best candidate channel in the spectrum. Spectrum sharing allows SUs to share the band seamlessly without harming a PU. Spectrum mobility assists an SU in evacuating the channel when a PU presents again to reuse the licensed band and resuming transmission from another available channel. To understand the concept of CR technology, it is crucial to understand the cognitive cycle, which is shown in Figure 2.2.

Cognitive cycle: a CR user starts to observe and learn about its surrounding environment by becoming aware of the environment characteristics (i.e., modulation scheme, transmission power, and bit rate) of empty bands in the spectrum using spectrum sensing capabilities. A CR user will analyze its observations and learn from previous experiences to make an intelligent decision, by choosing the best candidate band corresponding to its requirements and characteristics then adopting the decision and moving to the selected band in the spectrum.

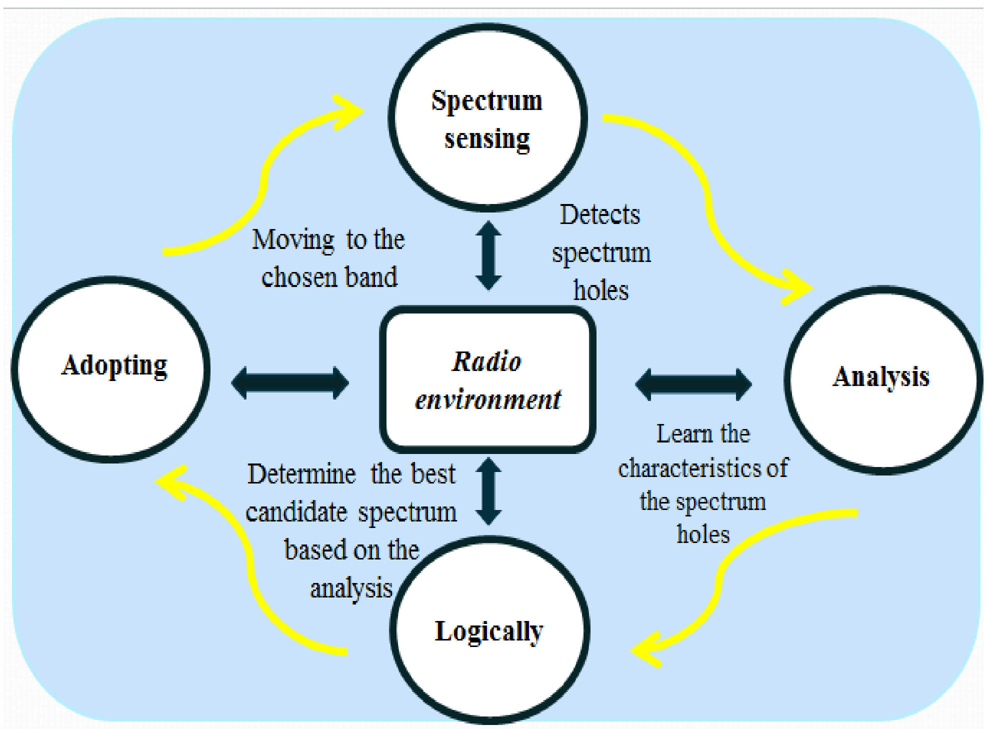


Figure 2.2: A cognitive user cycle.

2.3.1 Spectrum sensing (SS)

Spectrum sensing is the main component between the four functions in the cognitive cycle, where all next CR functionalities (i.e., spectrum management, spectrum sharing, and spectrum mobility) depend on spectrum sensing [18]. In spectrum sensing (SS) process, the cognitive user will start sensing for empty holes in the spectrum, to occupy them opportunistically. The major challenge in SS is to detect the PU signal accurately. There are different SS techniques exist in the literature. The general classification for SS is divided into three broad categories:

- Non-cooperative spectrum sensing:

  It also is known as local spectrum sensing techniques, which is based on extracting some features from a PU signal to calculate the decision statistic, and then comparing it with a predefined threshold or a certain reference level [18]. Furthermore, local sensing is classified from different aspects: coherent and non-coherent spectrum sensing. Coherent sensing requires previous knowledge of the PU activities to compare its features with the received ones. Non-coherent spectrum sensing, on the other hand, does not demand any prior knowledge of a PU signal, where it compares the received signal with a predefined threshold. Local spectrum sensing employs the pre-mentioned classifications under three different methods:

- Energy detection (ED):

  It is a non-coherent energy detection method [19], where it does not need any prior knowledge of a PU signal. It considers the most common local spectrum sensing technique due to its simplicity and its relatively small sensing time for high decision accuracy [18].

- Matched filter (MF):

  Unlike ED, MF is considered as a coherent detector, where it requires a prior knowledge about PU activities. MF correlates the received signal based on the known characteristics of a PU signal (i.e., modulation type, carrier frequency, data rate), then compares it with a predetermined threshold to decide the presence or absent of a PU. MF performs accurately in the white Gaussian channel if the information about a PU signal is available, which is not always the case. MF also maximizes the SNR at the output of the detector to increase sensing accuracy. However, for MF to achieve a highly accurate decision, each CR user needs a dedicated receiver for every PU signal to extract its characteristics [17].

- Cyclostationary feature detection (CFD):

  Basically, CFD extracts periodic features of a received signal (i.e., mean and auto-correlation) to detect a PU signal, by using characteristics that exist in the signal that are not presented in the noise. The main advantage of CDF is the ability to detect a PU at very low SNR, which makes CDF robust against noise uncertainty problem that the ED technique suffers from. However, the main drawback in CFD is its designing complexity; it requires high cost and higher observation time.

- Cooperative spectrum sensing:

  The pre-mentioned local sensing techniques may be affected by multipath fading and shadowing, and hidden nodes problem. Cooperative spectrum sensing comes as a solution to mitigate these challenges. In cooperative sensing, all nodes in the network share their sensing information or decision about the desired channel and augment sensing outcomes via a fusion rule center to make sensing decision, locally or globally. Moreover, cooperative sensing can be schemed based on how nodes cooperate: centralized, decentralized, and hybrid cooperative sensing schemes. Also, cooperative sensing can be divided depending on the type of the fused information: hard and soft fusion schemes.

  - Scheme one: based on type of cooperation

    1. Centralized cooperative sensing: in this method, all nodes make their local decisions, then transmit their decisions to a central unit where all received data is fused using one of the fusion techniques to conclude an optimal

(global) decision.

2. Decentralized cooperative sensing: in this technique there is no central unit. All nodes share their sensing information among each other until they reach an optimal decision; however, each node makes its own final decision. Decentralized sensing has the superiority in terms of complexity, since it does not need extra infrastructure for a central unit, but at same time the communication between nodes consumes more power.

3. Hybrid cooperative sensing: This approach is a combination between centralized cooperative sensing and decentralized cooperative sensing. This means that nodes share their sensing information among each other and with a centralized unit.

– Scheme two: based on the type of the fused information

1. Hard fusion: all SUs share their final local decisions, and the decision is made, locally or globally. The main benefit of this scheme is only requires one bit transmission, which means less overhead [6].

2. Soft fusion: SUs do not make any local decisions; instead, they share their sensed information, and based on these information, a decision is made via fusion rule center, locally or globally. Soft fusion provides better sensing performance than the hard fusion; however, it requires more transmission

overhead [6]. Recently, soft computation has gripped significant attention in designing decision fusion models instead of hard computation, because of soft computing high efficiency in dealing with uncertainties and nonlinearities.

2.4 Cognitive radio based wireless body area networks (CR−WBANs)

This section provides an overview of CR-WBANs, discusses state-of-the-art applications, introduces challenges in this research area, and makes suggestions for future investigation.

2.4.1 An overview of CR−WBANs

The main concept in CR-WBANs is merging two important technologies (i.e., CR and WBAN) to provide more flexible and efficient ubiquitous healthcare system. CR-WBANs help to overcome issues that conventional WBANs experience. Deploying CR in WBANs reduces Interference, energy consumption, and latency. It also increases spectrum scalability, and system robustness.

The architecture of CR-WBAN is very similar to conventional WBAN except for the intelligent components that are embedded in the network. As discussed, WBAN consists of three tiers: Intra-BAN, inter-BAN, and beyond-BAN. It would not be practical to add cognition to the core or actuator sensors that exist in the first tier, since such sensors would consume power and cause harmful electromagnetic fields to patients bodies. Additionally, the need for frequent battery replacement would be problematic, especially for sensors implanted inside patients' body.

It is more convenient to add cognition to BCUs, since they have longer battery life and higher processing capacity. BCUs are also responsible for communication between the two tiers (i.e., inter and intra-BAN), so adding intelligence to BCUs helps to organize spectrum accessing between nodes, with more efficiently and reliability. Moreover, in the second tier (the inter-BAN) cognitive capabilities can be integrated into an access point (gateway), whose primary function is providing communication between patients, through BCUs, and different healthcare services. Therefore, making communication between BCUs and the gateway more intelligent enhances network performance in terms of prioritizing data, avoiding collisions and retransmissions, reducing latency, and increasing spectrum efficiency [14].

2.4.2 CR−WBANs applications: the−state−of−the−art

Although there is extensive research related to applications in WBANs, only limited literature is specifically concerned with CR-WBANs. This section presents state-of-the-art applications for CR-WBANs to promote more research in this field and provides different categorizations for these applications regarding their main goals, metric performance, and layers.

Figure 2.3 provides analysis of the state-of-the-art CR-WBAN applications with respect to: system's goals, metric performance, and applied layers. Most of the-state-of-the-art applications are focused on deploying CR technology in the physical layer and media access control (MAC) sublayer. Moreover, most of the research is focused on reducing latency and energy consumption, and increasing throughput.

In [20], the authors introduce an infrastructure based on CR that is composed of a cognitive base station (CBS) and health care station (H-station). H-station has two interfaces; one collects the healthcare data from sensors through WBAN or WPAN, and the second one communicates with the CBSs. Each CBS is covering a certain area (C-cell) and each area is containing a number of H-stations. This article prioritizes data with low latency by presenting two sensing methods, periodic and triggered based on the traffic level (periodic or urgent). In periodic sensing, the CBS senses the spectrum periodically and only sends the data (periodic traffic) during certain period. On the other hand, triggered sensing, it senses the spectrum all the time and once the CBS is lost the channel it switches immediately to the another channel and continuous sending the data (urgent traffic). However, the proposed system still requires another prioritizing mechanism to help prioritizing urgent traffic that may come from different H-stations and so to avoid collisions and enhance throughput.

Prioritizing data with low delay is presented again in [21], traffic is divided into two levels: critical and non-critical. These two levels are done by sending critical data with high power and non-critical data with low power. However, the results of this proposal show that critical data experience collisions when two or more packets are transmitted at the same time. Also, increasing the power for sensors that have critical data will increase power consumption which is not practical for WBAN, since it is a power constraint network.

In [22] the authors, proposed a technique for prioritizing data and choosing the optimum access point for transmitting the urgent data with minimum delay and cost. The article constructs a queuing system in the coordinator node with three priority levels and chooses the optimum access point to reduce latency based on three parameters: the speed of CR-users, access point delay, and connection cost. However, this article does not explain how the coordinator prioritizes data. In [23], Dong et al. propose a CR-based mobile ad hoc network for WBAN, with architecture and design of a healthcare automation system to collect and document patients' information with lower cost than the typical network (i.e., WiFi). The system shows better transmission performance in interference environments and higher channel utilization.

The authors in [24] and [25] suggest applying cognition and cooperation concepts in WBAN to enhance transmission reliability and decrease energy consumption. In [24] au-

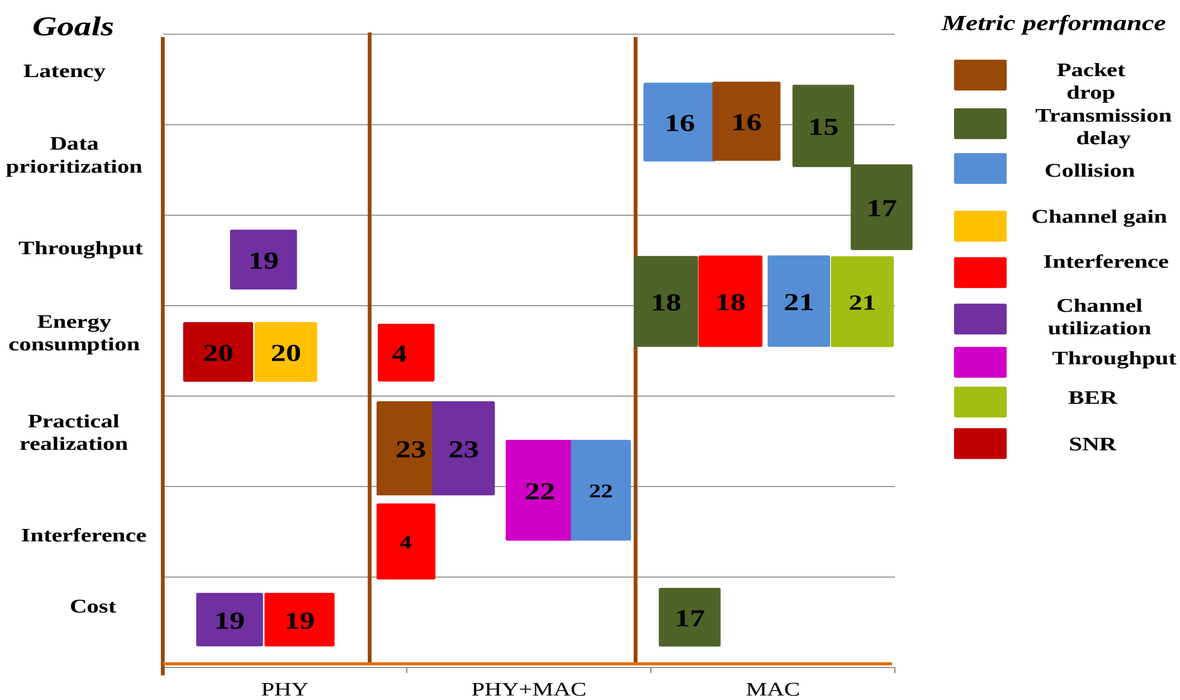


Figure 2.3: Analysis of the-state-of-the-art applications

thors suggest using transceivers as relay nodes, by sharing a part of their band. The game theory approach is proposed as a cooperative mechanism, where each BAN (i.e., communications between BNC and sensor) is considered to be a player, and a fixed bandwidth is allocated to each sensor. Each sensor can play as a relay node and share a part of its allocated bandwidth with another user, to send sensors vital data. The article also introduces an optimal frequency allocation for finding the best bandwidth set from all relay nodes based on different parameters: SNR, channel gain, and battery level. However, the proposed system does not consider the cognitive model particularly, only the intelligent reuse of the bandwidth gives a cognition aspect.

In [25], on the other hand, the authors use an intelligent mobile device (i.e., a coordinator) that acts as a common relay for all sensors in BAN. The mobile device also behaves as a gateway that transmits data collected from sensors to a hospital server via the Internet. Two cooperative schemes are proposed: energy-conserved cooperative transmission, which is applied to transmit data when the power of the sensors or mobile device is low. Reliability-driven cooperative communication which is applied when the data that needs to be sent is critical.

Also in [11], CR is employed with ultra wide band (UWB) technology to decrease power consumption, provide more reliable data transmission, and more data security. The cognition is implemented on BCUs using two UWB modalities: impulse radio (IR) and multiband orthogonal frequency-division multiplexing (MB-OFDM). The impulse radio (IR)-UWB radio interface is implemented between a BCU and body sensors in the first tier. The MB-OFDM-UWB is performed between a BCU and gateway to reduce interference. The proposed architecture enhances interference avoidance through two main features: frequency agility, which assists sensor nodes to, rapidly, change their frequency band to an unoccupied one; spectrum shaping which is used to protect the nearby electronic devices. However; the proposed work does not use any simulation to validate the approach.

The authors in [26] and [27] propose the CR-WBAN platform to realize practical situations, by augmenting the hardware and software components. In [26], hybrid cognitive validation platform (HCVP) is proposed which uses CC2510 SoC for the hardware part to guarantee low power consumption and easy configuration. For the software part, the CR-MAC algorithm is adopted to reduce interference and collision rate. On the other hand, an adaptive cognitive enhanced platform for WBAN (ACEP) is suggested. As in [27] a CC2510 SoC is used, for the hardware part. For the software part, fast dynamic cognitive radio (FDCR) algorithm is implemented to improve the performance of ACEP by alleviating the effect of interference due to the coexistence with another network on the same band, and this is done by reducing the packets drop rate and increasing channel utilization.

2.4.3 Open issues and future research direction in CR−WBANs

Deploying CR in WBAN improves overall system performance; however, it brings new challenges to the network. Many issues need to be discussed and tackled. This section provides an overview of some important problems in CR-WBAN and provides some directions for future work.

- Power consumption: consuming power in sensor networks was and is still an open issue that needs to be considered. It is known that sensors in WBANs are power constraint devices; thus, implementing cognitive functionalities will consume power.

Various techniques can be applied to avoid power consumption:

1. Designing energy efficient algorithms that minimize the wasted power caused by collisions, retransmissions, and idle listening.

2. Deploying artificial intelligence tools helps to enhance the performance of cognitive radio networks [28]. However, there is a lack of the proposed literature, as far as research knowledge, in deploying artificial intelligence in CR-WBANs.

3. Energy harvesting has a significant role in future research, especially for implanted devices, whereby energy can be collected from external sources and stored in autonomous devices. In the healthcare field, the human body and its organs are external energy sources, and they are called enzymatic biofuel cells. These environmentally friendly cells convert chemical energy to a fuel source.

- Security and confidentiality: deploying CR in WBANs adds more security issues to the network, such as PU emulation attack. CR-WBANs face many security challenges that put patients information at risk more than a conventional WBAN, due to the nature of its operating environment (i.e., sensing, learning, and adopting). Although there are few security algorithm proposals in the literature, this area of research needs more investigation.

- QoS performance: the QoS performance of the network must be high, by increasing data transmission. On the other hand, QoS performance of a PU should not be affected. Thus, an SU (i.e., a BCU) should accurately sense the presence of a PU. This can be done by designing sensing mechanisms that can highly detect the presence of a PU.

- Channel acquisition: to provide CR-WBANs with appropriate services, acquiring a channel with high accuracy and reliability is a major factor. Designing a channel acquisition model can include various parameters such as sensing performance and data prioritization. Even though channel acquisition is an influential element in the performance of CR-WBANs, there is a lack of the literature in designing such models.

- Data prioritization: the main goal in CR-WBANs is saving patients with life-threatening situations; prioritizing data based on patients health status is a primary concern. State-of-the-art research has proposed different algorithms to tackle this issue, especially, in the first tier (i.e., between body sensors and a BCU). However, prioritizing data in the second tier (i.e., between a BCU and an access point) and third tier (i.e., between an access point and healthcare services) have not been discussed heavily.

- Communication among multiple body controller units (multiple CR-users): it has a significant role in building an adequate ubiquitous healthcare system with efficient and reliable performance. A Few research is focused on communications among multiple BCUs on the same network. Thus, this area is still a real challenge and needs more investigation, to build a robust pervasive healthcare system.

2.5 Summary

A discussion about WBANs, its architecture, requirements, and challenges are presented in this chapter. Moreover, the chapter presents an overview of CR technology and proposes the concept of spectrum sensing techniques. A comprehensive survey is presented about state-of-the-art applications for CR-WBANs. Last, a brief discussion of open issues that CR-WBANs may confront to design a network with high performance is reviewed. CR-WBANs are a rich area for new research and innovation, since CR-WBANs overcome challenges that WBANs suffer from, CR-WBANs can help to build more efficient and reliable intelligent ubiquitous healthcare system that will facilitate patients lives, save individuals from life-threatening situations, and reduce the cost of long-term treatment in hospitals. This intelligent ubiquitous healthcare system could include multiple intelligent entities (e.g., CR-WBANs, intelligent-BCUs and -access points).

Chapter 3

The Architecture of The Proposed Channel Acquisition Model

Demands for utilizing healthcare services, not only at hospitals but also at homes for the elderly and patients with chronic diseases are growing rapidly [29]. Moreover, increasing the cost of long-term treatments in hospitals and the shortness of medical staff members [30], have made building an intelligent ubiquitous healthcare system an essential solution.

In order for a ubiquitous healthcare system to perform efficiently, it requires an accurate and reliable communication among multiple CR-WBANs with least latency. Thus, to achieve these requirements, system foundations have to be designed carefully. Channel acquisition is a major foundation in building an intelligent ubiquitous healthcare system. One of the main challenges is how CR-users can accurately sense a channel and transmit their data, according to the severity of their health status, whereby patients with acute conditions have the preference in transmission. Spectrum sensing and data prioritization are key factors in designing an appropriate channel acquisition model with high spectrum sensing accuracy and channel acquisition probability.

Hence, this chapter describes the architecture of the proposed intelligent channel acquisition model. The architecture is a multi-stage fusion model that is composed of local and global decision units; each unit has two modules. The local unit is comprised of: local sensing and health assessment decisions. The global unit is composed of: global sensing and data prioritization decisions.

3.1 The architecture of the proposed channel acquisition model for CR−WBANs

This research proposes an intelligent multi-stage channel acquisition model for multiple CR-WBANs within ubiquitous healthcare system, whereby patients contextual data, particularly, intra-node characteristics, environmental properties, and patients profile information, are augmented to acquire a channel based on the severity of patients health.

Demands for acquiring a channel, intelligently, are sensing a channel and prioritizing data streams among multiple CR-users (i.e., multiple patients) based on the criticality of their health status, as expressed in Equation 3.1. Mainly, the first stage, which is the local unit, helps to make preliminary decisions about sensing the channel and assessing patients' health. The second stage will make the intensive processing to decide channel availability and then prioritize data transmission among patients with respect to their local decisions and avatars. Designing a multi-stage model aims to increase system's accuracy and reliability in acquiring a channel among patients, by taking patients' contextual data (i.e., environmental properties, node characteristics, and patients' avatars) into consideration. Hence, the proposed model can help in saving more individuals with life-threatening situations. The model comprises two models: the hybrid cooperative spectrum sensing model and the data prioritization model. The architecture of the proposed channel acquisition model is shown in Figure 3.1, which consists of the following components:

$$CH_{acq} = CH_{idle} \cap PS_{highest}; \tag{3.1}$$

where CH_{acq}: represents the condition for acquiring a channel successfully by a CR-user, CH_{idle}: represents that the channel must be idle(the PU is not present), and $PS_{highest}$: represents that a CR-user (i.e., patient) has the highest severity health status among all users in the network.

3.1.1 Body controller units (BCUs):

A BCU, or a CR-user, is the component that has intelligence capabilities, where all local decisions are made there. A BCU is responsible for sensing the spectrum to make local sensing decisions and collecting data from body sensors to make local health assessment

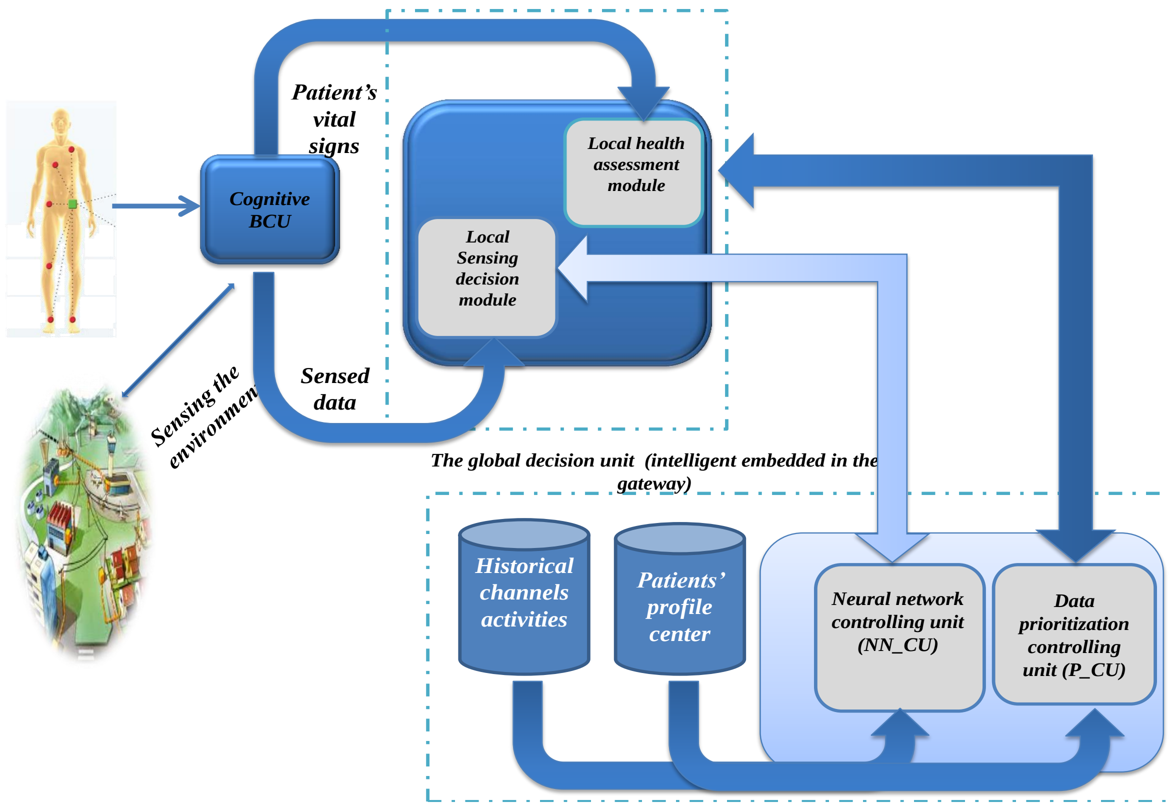


Figure 3.1: the architecture of the proposed intelligent channel acquisition model.

decisions. The intelligence in each BCU is embedded in the local decision unit which is composed of two modules:

- The local sensing decision: it is made by integrating intra-node characteristics and environmental properties in the decision-making process. Fuzzy logic system is utilized as a decision fusion center.

- The local health assessment decision: each BCU aggregates patients vital signs data from that patient's body sensors to make an assessment about patients health status (i.e., a patient has acute, urgent, or normal health status). Fuzzy logic system is utilized, again, to fuse vital signs data to indicate the criticality of that patient condition.

3.1.2 Access points (gateways):

All BCUs in the network aggregate their local decisions within an access point, which by itself transmit BCUs' data to different healthcare services via reachable networks. In the proposed architecture, the intelligence is also embedded in the gateway, whereby the global decision unit is built within the gateway. The global unit comprises two modules:

- The global sensing decision: in this module, a neural network is utilized as a global controlling unit that augments local sensing decisions, intra-node characteristics, and channel properties for all CR-users (i.e., BCUs) in the network to optimize a global sensing decision.

- The global prioritization decision: in this module, the data prioritization controlling unit (PCU) is the unit that is responsible for making global prioritization decisions. The PCU is built based on a cluster-based heuristic algorithm that is designed to prioritize transmission among multiple patients in the network, according to the severity of patients health status, and patients' contextual data (i.e., patients' avatars). Patients' avatars are updated and stored in the patients' profile center, within the global decision unit.

3.2 An overview of the process for acquiring a channel among multiple CR-users

Each CR-user is considered to be mobile to include users mobility in a decision-making process. If N-CR-users have data to transmit, the model will perform the following procedures:

- Each BCU (i.e., CR-user) senses PU-activities in the channel, by utilizing local sensing decision module, and makes a local sensing decision. Simultaneously, each BCU collects vital signs measurements from patient's body sensors, to makes a local assessment of patients health status; this is done via the local health assessment module.
- Both local decisions (sensing and patients health assessment decisions) are transmitted to the global decision unit. The information about node characteristics and channel environmental properties are also sent, to be utilized in the global sensing decision module.
- The global sensing module will make a sensing decision, according to the received data

from N-BCUs. At the same time, the global data prioritization module will prioritize transmission among patients based on their local health assessment decisions and contextual information (i.e., patients avatars).

- Successively, all BCUs will transmit their data, to the required healthcare service, as soon as the sensing unit has sensed a new idle channel; whereby patients with the acute health status have the highest priority in transmission.

All previous steps will be repeated each time there is a patient who has data to transmit. However, using a multi-stage prediction model increases the network complexity, regarding communication overhead between the local and global units which may increase the consumed power. Hence, there is a trade-off between increasing the spectrum sensing accuracy and decreasing power consumption. In this design, different considerations have been taken to reduce the consumed power and keep high performance:

- If the global sensing decision shows that a PU occupies the sensed channel, then data the PCU will store the prioritized data until spectrum sensing model senses an empty channel. Hence, the local health assessment modules do not need to retransmit their data all over again.

- During the waiting for an idle channel, only BCUs with updated local health assessment information will retransmit their recent data to the global prioritization module, which itself will rearrange prioritization based on the updated severity levels.

- For the local sensing decision, each BCU (i.e., SU) will exchange the data with the two nearest neighbors only to reduce the overheads resulting from the communication in the local unit.

- All BCUs that do not have any updated vital signs data to transmit will go to inactive mode, and they will not make any local sensing decisions or participate in the global sensing decision.

3.3 Summary

To design CR-WBANs with high sensing accuracy and reliability, this chapter proposes an intelligent multi-stage architecture for the channel acquisition model for CR-WBANs within ubiquitous healthcare system. The architecture is composed of Local decision unit that comprises: 1) local sensing and health assessment decision modules. 2) Global decision unit also comprises global sensing and data prioritization decision modules.

Details design of the sensing model, which brings together both local and global sensing modules, and the data prioritization model, which, also, brings together both local health assessment and global prioritization modules, are presented in depth, in chapters 4 and 5, respectively.

Chapter 4

The Intelligent Hybrid Cooperative Spectrum Sensing Model

Cooperative spectrum sensing is a powerful sensing approach which is based on sharing information about channel activities among secondary users (SUs). Cooperative spectrum sensing aims to overcome hidden node problem and shadowing and fading problems, and it also enhances sensing accuracy. However, sensing accuracy may degrade due to various reasons: if the detect PU-signal is low due to poor environmental conditions or intra-node characteristics are continuously altering. Recently, soft computation has brought significant attention in designing decision fusion models instead of hard computation, because of soft computing high efficiency in dealing with uncertainties and nonlinearities. Different methods from artificial intelligence are deployed in soft fusion computation, such as hidden Markov model, Bayesian inference, neural networks, and fuzzy logic [21].

Fuzzy logic and neural network have been recently introduced in the literature as CR-fusion centers to control sensing decisions. Although various papers have proposed fuzzy logic as a local or global fusion center, [31] [32] [2] [3], these papers have not taken into consideration the impact of, both, intra-node characteristics and channel properties in the decision-making process. Furthermore, most of the proposed research has not considered a multi-stage sensing model, where the sensing decision is made locally and then is optimized in an NN based-global fusion center. Optimizing the sensing decision, globally, helps to improve the spectrum sensing accuracy. Providing spectrum sensing models with high accuracy is important in healthcare applications, such as CR-WBANs, since the transmitted data can save individuals with life-threatening situations.

Thereby, this chapter proposes a unique intelligent multi-stage hybrid cooperative spectrum sensing approach based on integrating the effect of environmental properties and intra-node characteristics in the decision making process. The first stage utilizes a fuzzy logic system for local fusion center, whereby SU-mobility and its signal-to-noise ratio (SNR), and its neighbors SNRs are included in the local sensing decision process. The second stage proposes a neural network, based on feed forward backpropagation learning algorithm, for global fusion center. All SUs transmit their sensing information, local decisions, and their mobility levels to be augmented for an optimized global sensing decision. A neural network is trained based on a real-world measured power dataset. Main contributions in this chapter are:

- Providing an intelligent pervasive cooperative spectrum sensing algorithm that can be utilized in various applications (e.g., WBAN).
- Designing a hybrid multi-stage spectrum sensing model.
- Including the effect of neighbors environmental properties in each SUs local decision.
- Maintaining system robustness against unpredictable changes in node characteristics.
- Reducing the effect of shadowing and fading by including SNRs in the decision process.

The remainder of this chapter is arranged as follows: section 2 provides an overview on deploying artificial intelligence in spectrum sensing process. Section 3 presents an overview of the related work in deploying fuzzy logic and neural network in spectrum prediction. Section 4 explains design details of the multi-stage cooperative spectrum sensing model. Section 5 discusses simulation results of the proposed model and illustrates the merits of the proposed model over the state-of-the-art work. Section 6 concludes this chapter.

4.1 Background

Different techniques have been proposed in the literature to design an efficient classifier with high observing and learning capabilities. Artificial intelligence tools have been proposed as classifiers to predict PU activities. The merits of deploying artificial intelligence in prediction models are their ability to model humans intelligence to deal with uncertainty and imprecision situations which bring robustness to the decision making process. Neural network (NN) and fuzzy logic system (FLS) have gripped considerable attention in the literature of spectrum sensing techniques. Fuzzy logic and neural network are branches from soft computing techniques. This section provides a brief overview of NN and FLS.

FLS was first introduced by Zadeh in 1965 [33]. FLS is a set of linguistic rules that represent actions or vague situations and convert these rules into a mathematical representation based on using fuzzy membership functions instead of crisp membership functions. Fuzzy inference system is preferable to be used in the decision-making process in CR networks, and it is composed of: fuzzification, inference engine, set of rules, and defuzzification as shown in Figure 4.1. FLS also uses the fuzzy set theory for its representation, and a fuzzy set theory is a set that does not have precise boundaries whereby unprecise membership functions can symbolize entity of situations (input) (e.g., cold, cool, warm, hot, etc.,) [34]. Each membership function represents a specific ambiguous situation for the input, and the same for the output. There are different representations for membership functions such as triangular, trapezoidal, and Gaussian functions [34].

On the other hand, the origin of NN was in early 40s when W. McCulloch and W. Pitts attempted to mimic the functionality of the humans neural network using electrical

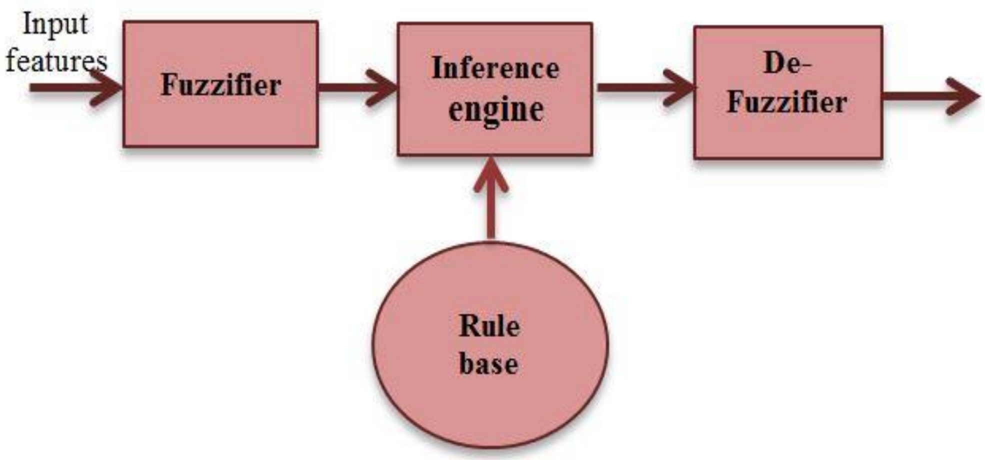


Figure 4.1: the fuzzy inference system

circuits [19]. Mainly, NN recognizes the pattern of a data and gathers information to build its knowledge. It consists of hundreds or thousands of components (i.e., neurons). The significance of an NN comes from an interconnecting group of neurons in parallel into one network, and because of this structure, it considers as a promising modeling technique for nonlinear systems [6]. NN can tackle advanced problems without having knowledge of the input data. However, since NN consists of a large number of weights which need to be estimated, it requires greater amount of dataset to be trained from, where the bigger the trained dataset the better the learning was. Figure 4.2 illustrates NN-neuron model.

NN can be classified from different aspects [6]. First, based on types of connections between neurons: feedforward connection, it does not have any feedback to the input of

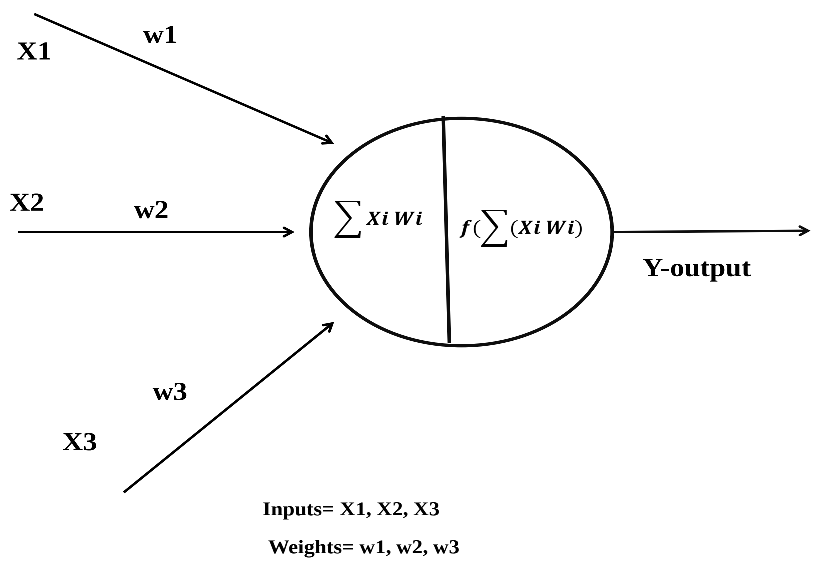


Figure 4.2: Model of the NN-neuron [6]

the neuron. Multi-layered perceptron (MLP) neural network is one of the most popular connections in feedforward NNs. Feedback connection has a feedback route to the input of the neuron and makes the next state becomes depending on the input and the current state. Hopfield network is the mostly employed in feedback NNs. Second, NN has two types in terms of learning rules: Backpropagation (BP), and delta rules. Third, NN also classified based on different training models: Supervised and unsupervised models. The most common NN is supervised with backpropagation learning rule. This method has the superiority in tasks that require prediction and classification.

4.2 Related work

Fuzzy logic has been recently introduced in the literature as a CR fusion center to control sensing decisions. However, most of the-state-of-the-art research focuses on fusing the sensed power to make a sensing decision, ignoring the impact of channel properties and intra-node characteristics on the decision process. The work in [31] has proposed a fuzzy logic based cooperative spectrum model at the global fusion center. The fuzzy logic is utilized to make a global decision if a PU is present or absent. Each SU senses energy level in a channel using energy detection technique and sends the local information to the fusion center to make a global decision, where multiple thresholds are entered, and majority rule is applied to obtain the final decision. However, the impact of node characteristics, such as node mobility, and environmental properties to overcome Shadowing and fading problem, did not be considered in the decision process.

Authors in [32] have, again, proposed a fuzzy logic system at the global fusion center to overcome the fading problems using 27 different combination rules. Where local decisions are made based on hopping sequence module that randomly selects three SUs to sense the channel and collects the local information by implementing two different schemes: Random hopping and sequential hopping. The local sensing information is then transmitted to the global fusion center to make a global decision. Still, the work in [32] did not include users' mobility or any other node characteristics in the decision process.

[2] has proposed a distinct work, wherein a fuzzy logic based cooperative spectrum sensing system has been presented for a local fusion. The work includes the received energy of the two nearest neighbors, and the energy and SNR of the desired node to make its local sensing decision. The advantage in this work is including the effect of SNR that reduces the impact of neighbors who are under fading or shadowing problems. However, the use of dependent resources at the fuzzy input (i.e., sensed energy and SNR level of the node of interest) could bias the sensing decision. Moreover, the impact of node characteristics, also, did not be considered in the channel sensing decision.

Neural network (NN) has been employed in spectrum sensing to optimize the detection decision by utilizing a prior sensing experience. Feed forward neural network with back propagation algorithm (MLP-BP) is one of the most popular techniques in NN-spectrum prediction, due to its high performance in classifying very complicated nonlinear problems, and its high learning capabilities. In [3], the authors have introduced neural network based sensing algorithm, whereby the SNR, the sensed energy, and the probability of false alarm have been used to train the feed forward neural network. The proposed model has achieved prediction accuracy up to 94% at -5dB SNR level. However, the impact of users' mobility has not been included; also, the work in [3] did not use real-world dataset to train its neural network.

On the other hand, authors in [4] have proposed an improved feed forward back propagation algorithm to detect vacant channels, by using momentum and genetic algorithms in the training stage. The channel state is used instead of using power values in the training stage. The proposed system has achieved prediction accuracy up to 91.1%. However, Neither the influence of node characteristics nor environmental properties are included in the decision process.

In [35] the author has proposed NN based cooperative spectrum sensing to detect PU activities, whereby context information and local decision for each SU are fused to optimize a global sensing decision for N-users in the network. However, the impact of node characteristics is not included in the decision process; also, a simulated data is used to train the network instead of real-world power measurements dataset.

In [36] authors have introduced two local decision fusion stages; namely, fuzzy logic and neural network. In the fuzzy logic stage, the channel access decision is made based on the SUs intra-node characteristics. The neural network, as second stage, is deployed to optimize the local sensing decision. However, the work in [36] did not consider any channel properties in the decision process, locally and globally.

4.3 The proposed intelligent hybrid cooperative spectrum sensing model

The architecture of the proposed model of the intelligent hybrid cooperative spectrum sensing, as discussed in chapter 3 encapsulates local and global sensing decision modules, as shown in Figure 4.3. The proposed model is based on deploying fuzzy logic for local decision and neural network to optimize a global decision. It is considered that N mobile-SUs surround a single PU, each SU estimates its SNR. Different techniques have been suggested in the literature to determine the SNR levels in CR networks, such the one proposed in [37],

In this work, a real-world power measurements dataset from [38] is utilized to calculate SNR values. The used dataset is collected by using netBravo app that can be downloaded in any smart phone and will automatically record the characteristics of the signal from different mobile networks and WiFi at various locations (e.g., city, urban areas, etc.). For privacy reasons, the collected data, by the netBravo app, is anonymised and will not store any personal information about the data collectors. The data is generated monthly and published by the European Commission, open data portal (ODP). The measured data is signal strength, in dBm, for cellular networks 2G, 3G, and 4G at different locations. The measurements are taken over 100m and 1Km geospatial grid. for this work, the collected data for 1Km is used to train the NN.

It is also considered that Gaussian noise and Rayleigh fading affect the received signal from a PU. Equation 4.1 is deployed to calculate SNR values. At the same time, all SUs can estimate their mobility using different techniques proposed in the literature, such as the one in [39].

$$SNR(dB) = P(dBm) - Noise(dBm) \tag{4.1}$$

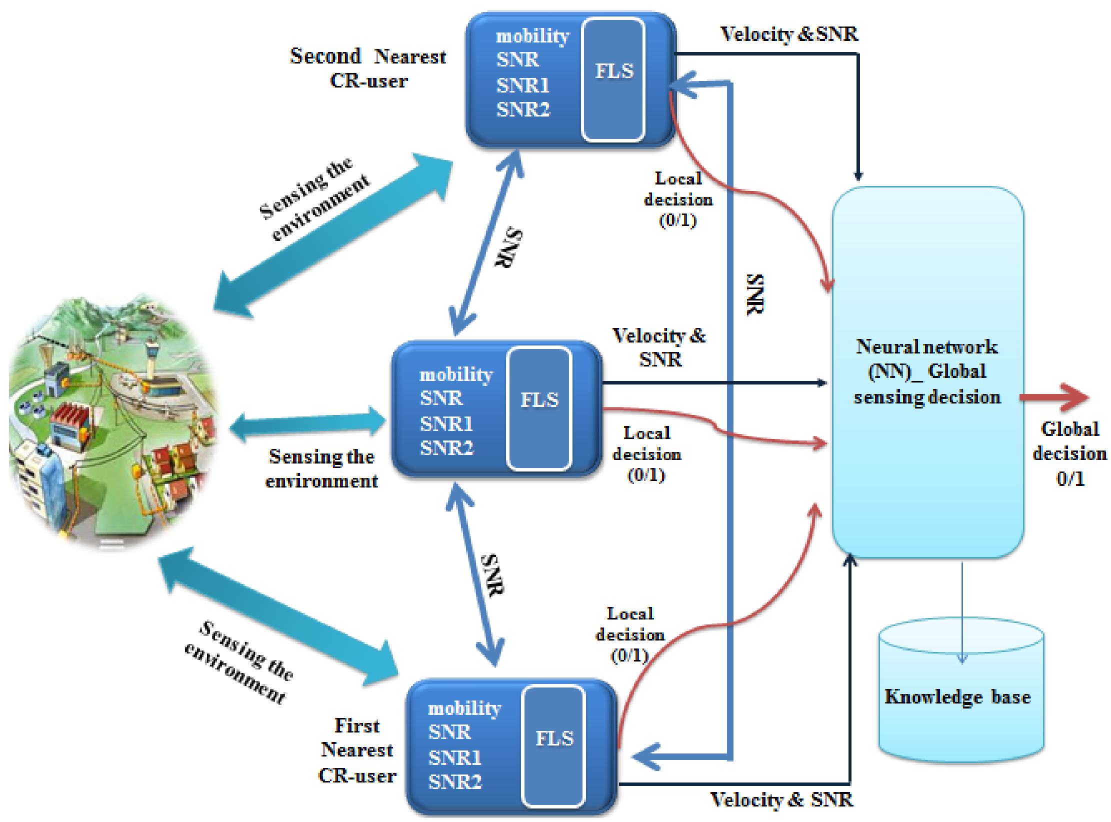


Figure 4.3: The architecture of the proposed spectrum sensing model.

4.3.1 Stage one: the intelligent fuzzy logic-local fusion model [1]

This work proposes an intelligent cooperative spectrum sensing model based on utilizing fuzzy logic for local fusion center, by including the influence of environmental properties and intra-node characteristics in sensing decision. Integrating these parameters in the prediction model increases detection probability under poor environmental conditions, and stabilizes system performance at unpredictable changes in intra-node characteristics. This approach aggregates the SNR of an SU and its corresponding mobility, and the SNR of an SU's nearest two neighbors as inputs for the fuzzy logic system.

The Mamdani model is deployed to design the fuzzy logic system as follows: the fuzzifier maps SU parameters (i.e., SNR and SU-mobility) to fuzzy inputs, using Gaussian function method. The set of rules represents different knowledge base for various access spectrum options. The inference engine is used to aggregate the real-time measured features at the input with different rules to estimate the presence or absence of the PU activity.

Furthermore, to reduce communication overheads and power consumption resulting from sharing sensing information among users, it is considered that SU exchanges data with one-hop neighbors using Route Discovery protocol. In this work, SUs will exchange information, only, with their two nearest one-hop neighbors, which will be chosen based on their proximity. Moreover, each SU and its nearest neighbors are communicating to exchange environmental properties information, by considering local consensus among users. Various consensus algorithms for wireless ad hoc networks have been introduced in the literature, such as the one proposed in [40]. All previous features (i.e., SU-SNR, SU-velocity, and the SNR of the nearest SU-neighbors) are gathered at the fuzzy logic system to predict channel status based on the knowledge base.

The system has four inputs: SNR of the desired node and its velocity, and SNRs from the first and the second nearest neighbors. Each input is represented in the fuzzification model with three membership function levels. SNRs membership functions are defined by: Low (L), Moderate (M), and High (H). Velocity membership functions are defined by: Slow (S), Normal (N), and Fast (F). The representation of membership functions for SNR and velocity are shown in Figure 4.4.

To include the impact of user's mobility on the decision making process, the fuzzy inference rule set is built according to the following conditions:

- If the velocity of an SU is Fast (F), then the weights between,user's measurements (i.e., the SNR of the SU) and its neighbors (the SNR of the two nearest neighbors) are normally distributed.
- If the velocity of an SU is low/normal, then user's measurements get the heaviest weight in the decision making.

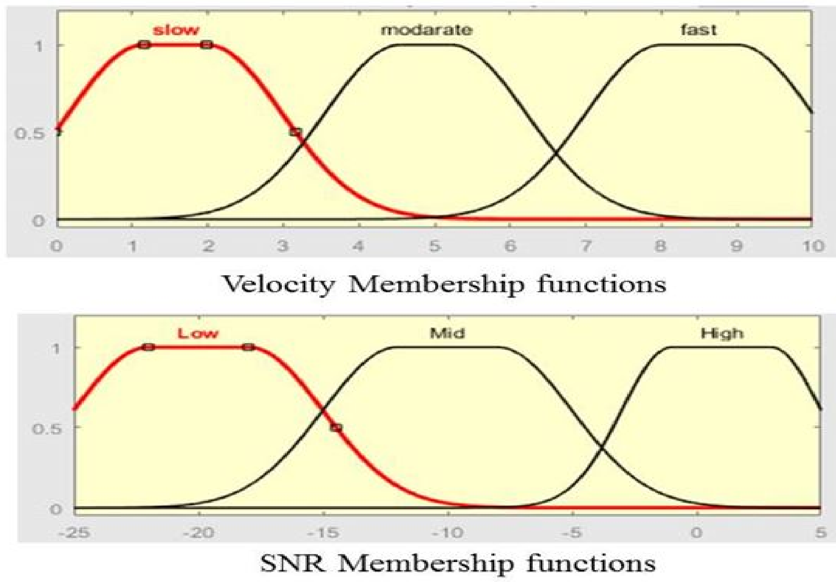


Figure 4.4: Input membership functions.

The output is considered to represent the probability that a PU is present, and three crisp membership functions define it: Low (low probability that the PU is present, Good (good probability that PU is present), or High (high probability that PU is present).

4.3.2 Stage two: the intelligent neural network (NN)-global fusion model

The second stage proposes a neural network (NN) for global decision fusion center, whereby environmental properties, intra-node characteristics, and local decision for each SU are augmented as input features for NN- fusion center. Employing NN as global fusion unit optimizes the local decision of all SUs in the network; hence, the network prediction accuracy will increase. A real-world power dataset is adopted from [38] to formulate the training dataset for NN. Moreover, a feed forward multi-layer perceptron with back propagation learning algorithm (MLP NN- BPL) is chosen to be employed to predict channel activities. The proposed model is designed based on following steps:

- Training step: it is important for networks with supervised learning to be provided by appropriate dataset with different features and targets. This work uses real-world dataset power measurements from [38] to train the network. The extracted features for the training are: SU-SNR, SU-mobility, and SU-local decision. Targets represent the real status of a PU-channel [1 PU is active and 0 PU is inactive].

- Testing step: after each SU makes its local decision based on the proposed local sensing model. Each SU transmits its three features: SU-local decision, SU-SNR level, and SU-mobility to the NN-global fusion center. According to the extensive knowledge that the NN gained from the prior training step an transmitted features, the network can make an accurate spectrum sensing decision.

Pseudocode for the proposed multi-stage hybrid cooperative spectrum sensing model is presented in Table 4.1.

Table 4.1: pseudocode of the proposed multi-stage hybrid cooperative sensing model

Fuzzy inputs	SU-SNR, SU-velocity, SNR1, SNR2
Fuzzy outputs	1/0, PU is present or absent
NN-inputs	SU-SNR, SU-velocity, SU-local fuzzy output
NN-output	1/0 , PU is present or absent
Entre parameters	N-users, 1-hidden layer, N-hidden nodes

Stage one: Local decision
1- Each SU senses the power of the desired channel.
2- Simultaneously, each SU estimates
- Its SNR value:
$SNR(dB) = Power(dBm) - Noise(dBm)$
- Its velocity
4- Each SU, Receives SNR1, SNR2 from its nearest two neighbors
5- Insert SU-SNR, SU-velocity, SNR1, SNR2 at the fuzzy input.
6- Apply the rule base:
- IF the SU-velocity is F THEN
Normally distributes the weights between SU and its neighbors
- IF the SU-velocity is N/L THEN
the SU measurement gets the heaviest weight
Stage two: Global decision
7-Train the NN based on the collected features and corresponding targets that formulated from [38]:
- Features [SU-SNR, SU-velocity,] and SU-local detection probability”
- Targets [1 PU is present/ 0 PU is absent]
8- Each SU transmits its parameters for NN-fusion center
9- NN classifies the data and determines channel status

4.4 Simulation results and discussion

The simulation considers N mobile-SUs surround a single PU. It is also assumed that the received signal of a PU is affected by white Gaussian noise and Rayleigh fading. A real-world measured power dataset from [38] is used to formulate the trained data. The work is tested at different SNR values ranging from [-25 dB to 5 dB]. The velocity of mobile objects in this simulation is the average speed for humans. Accordingly, velocity levels have been selected based on uniform distribution and are ranged from [1 Km/h (human is moving slowly) to 10 Km/h (human is moving fast)]. Various sizes of training dataset for the NN are tested, and different numbers of hidden nodes are inserted. The model performance is evaluated through the probability of detection, spectrum sensing accuracy, and F1-score.

4.4.1 Stage one: results of the intelligent fuzzy logic local fusion model

For this stage, Monte-Carlo simulation is carried out to analyze the probability of detection with 10^5 iterations. The results of the proposed approach are compared with those presented in [2]. Figure 4.5 shows the detection probability (Pd) for the local sensing fusion center, for a single SU. The mobility levels for an SU are uniformly distributed during the experiment at different SNR values. The system has maintained a robust performance during unpredictable changes in SU-mobility levels, whereby the Pd improves when the SNR improves.

Figure 4.6 illustrates the probability of detection (Pd) for different SNR values, for a single SU, at each speed level. The system shows high accuracy in predicting PU activities, particularly, when the SU has low to normal speeds; however, the probability of detection

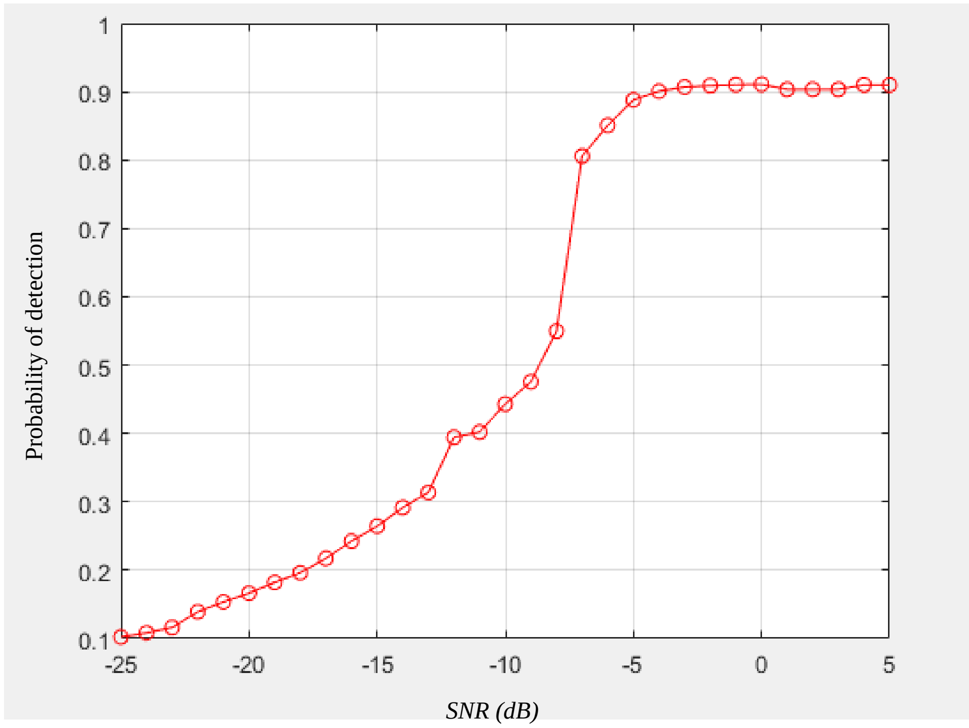


Figure 4.5: probability of detection (Pd) at different SNR values, with unpredicted changes in SU speed levels

decreases when the SU has high speed, which proves that node mobility has a significant impact on sensing performance.

Table 4.2 compares the probability of detection, at different SNR levels, of the proposed work and the work presented in [2]. The results show that the proposed work performs approximately twice better than the work in [2] at -5dB at all speed levels; however, the probability of detection decreases at fast speed, which confirms the impact of SU mobility on sensing performance.

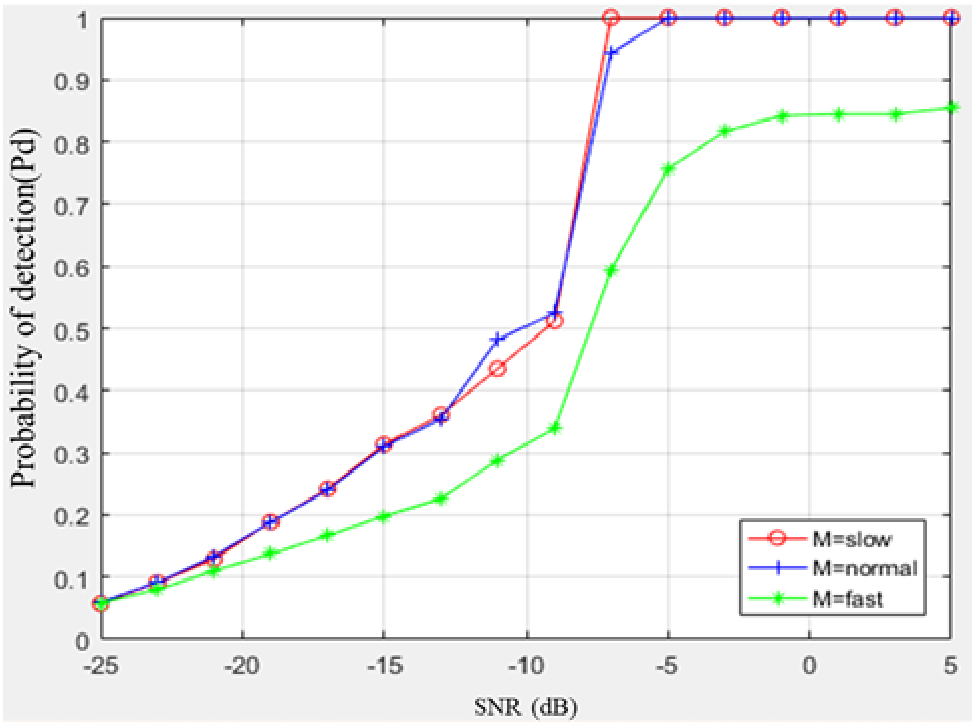


Figure 4.6: Probability of detection(Pd) at different SNRs values when SU-mobility has constant speed level (slow, normal, or fast)

Table 4.2: A comparison in terms of probability of detection(Pd) between the work done in [2] and the proposed local sensing model at different SNR levels

Pd at	-15dB	-10dB	-5dB
The work proposed in [2]	0.28(stationary)	0.38(stationary)	0.43(stationary)
The proposed local sensing model	0.3(stationary) 0.3(slow) 0.3(normal) 0.22(fast)	0.48(stationary) 0.48(slow) 0.5(normal) 0.33(fast)	1(stationary) 1(slow) 1(normal) 0.7(fast)

4.4.2 Stage two: results of the intelligent neural network (NN) global fusion model

In this stage, all SUs have made their local sensing decision. Each SU transmits its three features: SU-local decision, SU-SNR level, and SU-mobility to the NN-global fusion center. The first step is training; the neural network is trained by various training dataset sizes to investigate how the training size affects the prediction accuracy. The number of hidden layers is set to one since a single layer can provide less complexity regarding network design. The number of users is varied between 100 to 200 to test the model scalability. The setup division of data for training (tr), validation (va), and testing (t) are set 70%, 15%, and 15%, respectively. Parameters for NN-simulation are listed in Table 4.3.

Table 4.3: simulation parameters for the global sesning module

Network Parameters	Feed forward multi-layer perceptron
N-Users	100, 200
Training algorithm	Backpropagation
Training function	trainscg
Training dataset size	vary [1000-3000]
Number of hidden layers	1
Number of hidden nodes	1,3,10
Data division: tr, va, test	70% ,15%, 15%

Table 4.4 shows calculations of spectrum sensing accuracy and F1-socre for different experiments. Results show that the performance of the detection model improves when the size of the training dataset is enlarged. Furthermore, results prove that when the

size of the training dataset is small, the performance can be enhanced by increasing the number of hidden nodes. However, when the dataset size reaches 3000, the detection model can achieve satisfying performance with three hidden nodes. Thus, using small dataset size to train the network comes with the cost of increasing the number of hidden nodes; accordingly, the system complexity. Moreover, Figure 4.7 illustrates the performance of the spectrum sensing model by varying dataset size and number of hidden nodes. Results show that by training the NN with larger dataset size, the spectrum sensing accuracy of the proposed model increases with less number of hidden nodes.

Table 4.4: calculations of the accuracy and F1-score of thespectrum sensing model with different parameters

Test 1 (N-users=100, training dataset size=1000)			
N-hidden nodes	1	3	10
Accuracy%	95.3	96	96.7
$Model_{sensitivity}$%	93.5	93.8	96
$Model_{precision}$%	95.1	97.9	96
$F1_{score}$	94.32	95.8	96
Test 2 (N-users=200, training dataset size=2000)			
N-hidden nodes	1	3	10
Accuracy%	96.7	97	97.3
$Model_{sensitivity}$%	94.1	94.6	94.8
$Model_{precision}$%	98.5	99.2	99.2
$F1_{score}$	96	96.8	97
Test 3 (N-users=200, training dataset size=3000)			
N-hidden nodes	1	3	10
Accuracy%	98.2	98.9	99
$Model_{sensitivity}$%	97.2	97.6	98
$Model_{precision}$%	99.6	100	100
$F1_{score}$	98.2	98.5	98.9

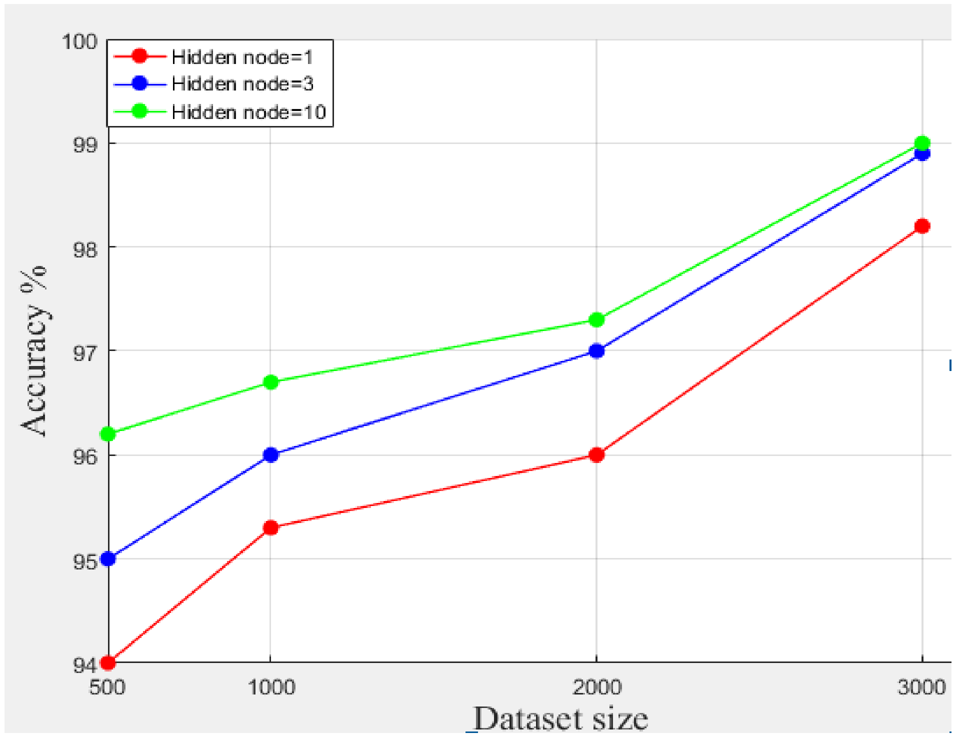


Figure 4.7: performance in terms of spectrum sensing accuracy with various N-hidden nodes and dataset sizes

Furthermore, Table 4.5 compares calculations of spectrum sensing accuracy of: 1) the proposed intelligent multi-stage hybrid cooperative spectrum sensing model, where the intelligence is embedded in local and global decision units; 2) the multi-stage hybrid co-operative spectrum sensing model, where the intelligence is only embedded in the local decision unit and the global decision is designed by applying the majority rule; 3) and the single stage cooperative spectrum sensing, where the intelligence is embedded in the local unit and no global decision is made. The results show that the proposed intelligent multi-stage hybrid cooperative spectrum sensing model outperforms the other models dramatically.

Table 4.5: Compares calculations of spectrum sensing accuracy for intelligent multi-stage, multi-stage (intelligent is embedded in local unit only), and single-stage (no global unit) cooperative spectrum sensing model

	Description	Number of users	Iterations	Accuracy %
Multi-stage model	The intelligence is embedded locally and globally	100	1000 training dataset size	96
		200	3000 training dataset size	99
Multi-stage model	The intelligence is only embedded locally, and majority rule is used for global decision	100	1000 (500 PU is present)	25
		200	3000 (1500 PU is present)	70
Single-stage model	The intelligence is embedded locally. No global decision unit	100	1000 (500 PU is present)	Average value 55
		200	3000 (1500 PU is present)	Average value 64

Table 4.6 compares the spectrum sensing accuracy of the proposed multi-stage hybrid cooperative spectrum sensing with the state-of-the-art research proposed in [3] and [4]. Like the proposed work, both proposals [3] and [4], have employed the MLP-BP NN as a single-stage prediction model; The simulated data is used to train the NN in both proposals. Thus, this yields a better detection performance for the proposed multi-stage spectrum sensing than the other works proposed in [3] and [4].

Thus, this confirms that utilizing intelligence in, both, global and local units improves spectrum sensing accuracy. Although multi-stage cooperative spectrum sensing model increases the system complexity it certainly increases the system accuracy which is a fundamental necessity in CR-WBANs.

Table 4.6: Compares the proposed work with the state-of-the-art research presented in [3] and [4]

	N-users tested	Number of hidden layers	Number,of hidden nodes	Features used in training NN	User - mobility	Accuracy %
The proposed multi-stage hybrid cooperative sensing model	100-200	1	Vary,(1-10)	SNR, SU-mobility, and local sensing, decision (based on fuzzy logic model)	Mobile	99
Proposed work in [3], 2016	20	2	Vary,(5-10)	SNR, Probability of false alarm, & fixed threshold	Stationary	94
Proposed work in [4], 2015		1	10	Dynamic threshold	Stationary	91.1

4.5 Summary

This chapter has proposed an intelligent multi-stage hybrid cooperative spectrum sensing model, by considering the effect of, both, environmental properties and intra-node characteristics in the decision process. The first stage is a fuzzy logic that is utilized as a local fusion center. In the second stage, a neural network is deployed as a global fusion center to optimize local sensing decisions for all SUs in the network. Real-world power measurements dataset is utilized to train the NN.

Results of the proposed model have shown high robustness against unpredictable changes in SU-mobility levels. Moreover, the work has shown its superiority compared with the state-of-the-art research, at low SNRs and different SU-mobility levels, with spectrum sensing accuracy reaches up to 99%. Furthermore, the results have clarified that the intelligent multi-stage prediction model outperforms single-stage (i.e., intelligence is embedded in local stage and no global unit exists) and multi-stage prediction models (i.e., intelligence is only embedded in the local stage, and majority rule is applied in the global unit).

Acquiring a channel with high spectrum sensing accuracy is an imperative factor, in applications such as CR-WBANs, when the transmitted data is related with saving lives. However, building an efficient and reliable channel acquisition models is not only relay upon spectrum sensing accuracy, but also upon in prioritizing data transmission among patients according to the severity of their health status. Accordingly, the next chapter proposes an intelligent data prioritization model.

Chapter 5

The Intelligent Data Transmission Prioritization Model

Prioritizing data among multiple CR-WBANs within an ubiquitous healthcare system is a crucial function, since doing so reduces network latency and saves more patients with life-threatening situations [41]. In fact, adding more cognition to intelligent components, develops components' capabilities in terms of more reliable prioritization process based on patients' health [41]. The concept of context awareness has been introduced in the literature in attempts to design more reliable and efficient data prioritization models [29]. The concept is based on integrating intelligence within the data prioritization process. Integrating more intelligence is done by building a knowledge base of parameters that help to distinguish patients states at a particular time, such as, channel status, patients activities and vital signs, patients' geolocations, environmental conditions, and patients' avatars (i.e., a contextual data that indicates each patient's medical history, such as, age, gender, and medical record). Even without context awareness, CR-WBANs overcome various challenges that exist in conventional WBANs. Thus, augmenting context awareness will certainly improve data prioritization in the network, and so save more individual with critical conditions

However, most of the state-of-the-art research, which has deployed context awareness to prioritize data among multiple BCUs [29] [42] [43] and [44], did not consider the effect of the local health assessment of the patient in prioritizing data transmission in the global unit. Local assessment helps to reduce processing time at the global unit and gives an indication of the criticality level of patient's health (i.e., is a range from normal to acute). Although, different research has augmented different contextual data (e.g., patients location, patients activities, etc.) in the global prioritization process the contribution of including patients avatars as a contextual data has not been introduced yet. Thus, this chapter proposes a novel multi-stage data prioritization model, whereby the effect of patients real-time vital signs data and patients' avatars are utilized in prioritization decisions. The first stage is deploying fuzzy logic, as an intelligent component, for the local assessment about patient's health status based on the collected vital signs data. The second stage proposes a cluster-based heuristic algorithm that prioritizes transmitted data among multiple patients. The prioritization is based on clustering the transmitted data, according to the severity of patients health status, into one of the three levels: acute, urgent, or normal. Patients avatars and local health status decisions made for these patients are augmented in the prioritization controlling unit (PCU), to make global prioritization decision among multiple patients (i.e., BCUs). Main contributions in this chapter are:

- Designing a local health status model that provides a preliminary assessment about patients health condition according to that patient real-time vital signs measurements.
- Including patients' contextual data (i.e., patients' avatars) and local health assessment in the prioritization process.
- Building a cluster-based heuristic algorithm that prioritizes transmission according to the severity of patients' health condition, whereby patients with acute status have the highest priority in transmission.

The remainder of this chapter is organized into four sections: section 2 introduces the related work in deploying context awareness in WBANs and remarks the absence of studies on deploying contextual data in CR-WBANs. Section 3 explains the design and implementation of the proposed intelligent data prioritization approach for multiple CR-WBANs. Section 4 discusses simulation results for the proposed model, the chapter concludes with a summary in section 5.

5.1 Related work

This section introduces the related work in deploying context awareness in WBANs and remarks the absence of studies on deploying contextual data in CR-WBANs. Most of state-of-the-art applications, [42] [43] [29] [44], have added more awareness to WBANs, by including contextual data related to patients states (e.g., patients' environment, location, vital signs, etc.) and did not consider the effect of patients' avatars (e.g., age, gender, etc.) in the prioritization process. Moreover, the research has focused on deploying this concept in the first tier in the network (i.e., between body sensors and a body controller unit (BCU)), and did not consider that augmenting contextual data in the second tier (i.e., between multiple BCUs and the access point) helps to prioritize data transmission among patients based on the state indicated by their context.

In [42], the authors have proposed remote monitoring for patients, wherein nodes with abnormal data have a higher transmission probability. In [10], the authors have proposed an aware WBAN protocol, whereby slot allocations among body sensors are dynamically changing based on the priority of data. The authors in [43] has used a hybrid access scheme combining contention-based and time division multiple access (TDMA)-based schemes to enhance transmission reliability and efficiency. All previous proposals have focused on prioritizing data within the first tier. On the other hand, in [29] the authors have proposed ubiquitous healthcare system, whereby different wireless communication tools have deployed in a wirelessly connected local mobile computing grid, which consists of multiple wireless components (e.g., a laptop, computer, etc.,). The authors have proposed a prioritization model that can prioritize data among BCUs; the network is divided into clusters, and each cluster has a central node that fuses data of all BCUs in the cluster. The model uses a distributed cluster head mechanism to select a node with higher capabilities to act as a gateway that fuses the data for transmission to the most appropriate base station. The base station will then transmit data for preprocessing in the computing grid. In [44], the author has proposed a cloud-based context-aware system for assisted living. This context-aware cloud is designed to gather different data from sensor nodes in the network, and then fuses the data to conclude the type of context from the collected data. The contextual data can be a user activity, heart rate signal, temperature, environmental conditions, etc..

5.2 The proposed intelligent data transmission prioritization model

The architecture of the proposed intelligent data transmission prioritization model is shown in Figure 5.1. This work considers a homogeneous network, where all patients have body sensors with same functionalities. A fuzzy logic system is utilized to fuse vital signs measurements, locally, to assess patients health status. A prioritization controlling unit (PCU) has been constructed to prioritize data among multiple BCUs (i.e., patients). Moreover, a cluster-based heuristic algorithm is designed within the PCU to prioritize transmissions according to the severity of patients health status. The proposed algorithm integrates different parameters that influence data prioritization which are: the patient local health assessment, patient avatar, and patient health status factor (i.e., the cluster factor). The patient avatar is the collected contextual data of that particular patient that is likely to influence the assessment of that patients health status (e.g., age, medical record, body mass index (BMI), etc.). Each patient in the network will have his/her patient avatar, which is updated and stored in the patient profile center.

5.2.1 Local health assessment decision module

It is assumed that there are N-patients in the system. Each patient has an intelligent BCU that deploys a fuzzy logic system for local decision making to assess patients health condition. The fuzzy logic system fuses measurements of four vital sign sensors: blood pressure, temperature, pulse rate, and respiratory rate. These vital signs are the most common tools in monitoring patients health. The proposed fuzzy logic system is designed as follows: the fuzzifier maps vital signs that body sensors measure to fuzzy inputs, using membership functions that are represented by high (patient's vital data is up normal), normal (patient's vital data is regular), and low (patient's vital data is below the normal).

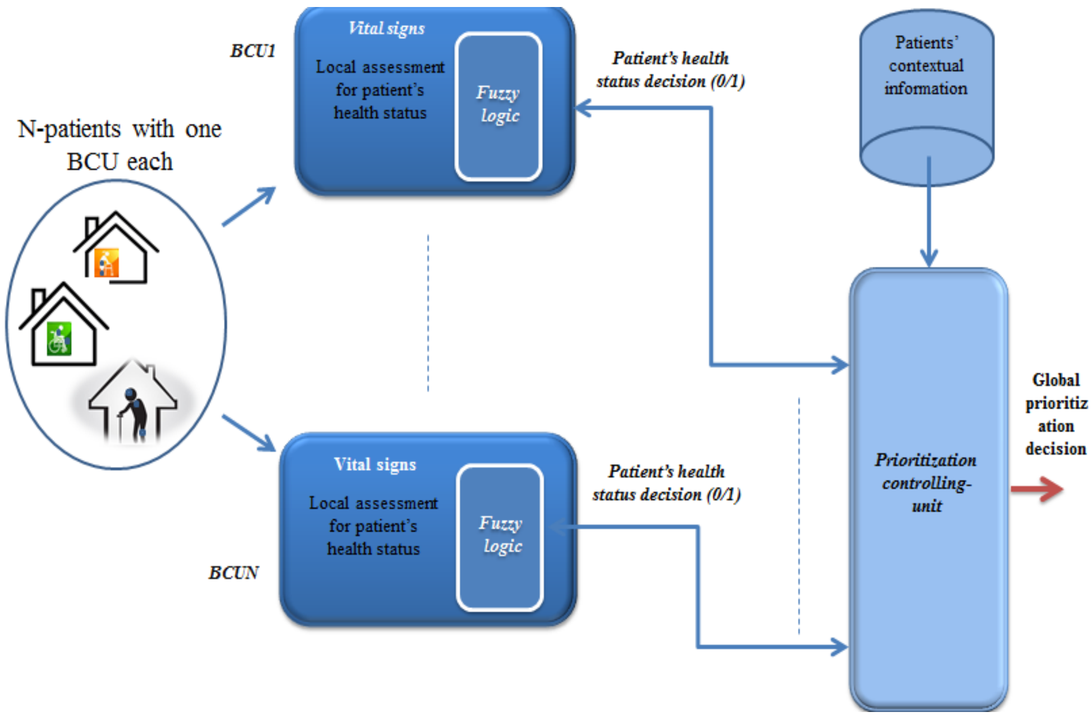


Figure 5.1: the architecture of the proposed data prioritization model for multiple CR-WBANs

The set of rules represents knowledge for different health status and is built with the help of a medical expert. The inference engine is used to aggregate the real-time measured vital sign data at the input with different rules, to evaluate patient health status which is represented with a certain probability. The defuzzifier is used to convert the fuzzy output to a crisp one using membership functions.

The fuzzy logic system has three inputs with three membership functions, and the fourth input has two membership functions. In the defuzzification model, one output is considered which represents the critical level of patients health status, and it is defined by three membership functions, namely, normal (patient has stable vital signs measurement), urgent (patient has demanding vital signs measurements), and acute (patient has dangerous vital signs measurements).

5.2.2 Global prioritization decision module

The global prioritization module comprises the patients' profile center and the prioritization controlling unit (PCU). Mainly, the PCU receives decisions about patients' health status from all BCUs (i.e., local health assessment modules) in the network. The PCU requests patients' avatars from patients profile center, where a common ID identifies each patient in all components in the prioritization model. In this subsection, the description and process for each element of the global prioritization module is discussed in details:

- **The patient profile center**

  It gathers patients avatars that distinguish each patients state at a particular time. Each patients avatar is characterized with the following parameters:

  – Patient age: can be divided into different groups, whereby each group can be monitored differently.

  – Patient medical record: it includes patients medical history, such as, heart and kidney diseases, diabetes mellitus, or asthma disease.

  - Patient body mass index (BMI): indicates whether a ptatient has an obesity or below the normal weight.
  - Experts' health evaluation index: it represents the opinions of specialists about monitoring patients' health. The experts regularly update the index based on the last assessment of the patient health.

A patient avatar can include other parameters, such as patient's gender, location, etc.. In this design, only, the mentioned parameters are chosen as patients' contextual data.

- **The prioritization controlling unit (PCU)**

The PCU aggregates the following information: cluster factor, patient's avatar, and local health assessment for each patient in the network. The PCU receives the local health assessment from the local module and the patient's avatar from the patient profile center. The cluster factor is generated within the PCU. The PCU utilizes a cluster-based heuristic algorithm to aggregates all the previous information to eventually calculate the probability of acquiring a channel P_{ca} for each patient. Hence, the data that need transmission will align based on the predetermined channel acquisition probability of each patient (i.e., from the highest to the lowest probability).

- The cluster factor: the PCU categorizes the transmitted data into three clusters: acute, urgent, and normal. Each group is defined by a certain weight (i.e., cluster factor) that describes its priority level. Cluster factor varies between 1 to 0 based on the required severity for each cluster.

- The cluster-based heuristic algorithm: it aggregates the influential factors of each patient, namely, patients local decision, cluster factor, and patient's avatar. Then, allocates an appropriate weight for each influential factor. Integrating all these weighted factors defines the probability of channel acquisition$P_{ca}/patient$ as expressed in Equation 5.1.

$$P_{ca}/patient = L_{assess} * w_1 + Pa_{avatar} * w_2 + C_{factor} * w_3; \tag{5.1}$$

where $P_{ca}/patient$: the probability of channel acquisition model for each patient; L_{assess}: the local health assessment for each patient; Pa_{avatar}: patient avatar; C_{factor}: the cluster factor; and w_1,w_2, and w_3 are the allocated weights for each influential factor. The allocated weight w_2 is distributed among different information that a patient's avatar includes. For example, patients with acute status have the highest cluster factor; hence, have top priority in transmission (i.e., patients with Acute status transmit before patients with urgent and normal health status). Additionally, patients within the acute cluster will be prioritized based on their contextual data (i.e., patients' avatar), from the highest severity condition to the lowest one. The same prioritization process is applied in each cluster.

The value of the allocated weights is flexible based on the application requirements.

The pseudocode for the proposed intelligent data transmission prioritization Model is shown in Table 5.1

Table 5.1: pseudocode for the proposed Intelligent Data Transmission Prioritization Model

Fuzzy input	blood pressure, temperature, pulse rate, and respiratory rate
fuzzy output	Local health assessment (normal, urgent, or acute)
Pcu-input	Fuzzy output and patients avatars
Pcu-output	Patients prioritized according to their health status

Stage one: local decision
    1.Each BCU fuses its vital data using fuzzy system
    2.The fuzzy system evaluates patients health condition:
      Acute, Urgent, and Normal
    3.The local health assessment is made and transmitted
  Stage two: global decision
    4.Patients profile center (i.e., patients avatars) is updated and stored
    5.Cluster factor is distributed among patients based on their health status:
      Acute, Urgent, and Normal
    6.Prioritization controlling unit (PCU) aggregates all influential factors:
      Patients local decision, Cluster factor, Patient avatar
    7.The PCU distributes weights among the influential factors to produce the $P_{ca}/patient$:
      $L_{assess} * w_1 + Pa_{avatar} * w_2 + C_{factor} * w_3$
    8.The global prioritization units Aligns data transmission according to Pca of each patient.

5.3 Simulation results and discussion

This simulation is conducted for assisted living system of multiple CR-WBANs, whereby all patients have four vital sensors for their health monitoring. The following steps show the model design for this simulation:

- The local stage: Table 5.2 represents input membership functions for all vital signs, whereby ranges are considered according to the elderly vital signs:

Table 5.2: input membership functions and their ranges for four vital signs

	Level-1	Level-2	Level-3
Temperature (F°)	High (>99)	Normal (96-99)	Low (<96)
Heart rate (BPM)	High (>130)	Normal (90-130)	According to the experts opinion, it is not a usual case for the elderly.
Blood pressure rate	High (>144/90)	Normal (131/86)	Low(<118/82)
Respiratory rate	High(>20)	Normal(12-20)	Low (0-12)

- The global stage:
  - Parameters of patients profile center, which constitutes N-patients avatars, are considered as shown in Table 5.3.
  - The weights for each cluster are generated in the PCU, based on the local health assessment levels as illustrated in Table 5.4.
  - The probability of channel acquisition P_{ca} for each patient is calculated by determining the weights for each influential factor. Different weights have been

Table 5.3: contextual data of each patient avatar

patient avatar	Description	Normalized value
patient's age	Vary [65-100]	(Patient age - 65)/(100-65)
Patient medical record	It considers the most illness that the elderly has: - Kideny diseases. - Heart attack. - Stroke. - Diabetes.	- 1: patient has a disease. - 0: patient dose not have any diseases
BMI	Normal BMI is ranged [25 to 30]	- 0: BMI is normal - 1: BMI is not normal.
Expert's health evaluation index	Ranges [1 to 0]	- 1: patient requires special monitoring - 0: patient dose not require any special monitoring

Table 5.4: the distributed weights for each cluster

cluster factor	Weight
patients with acute conditions	1
patients with urgent conditions	0.7
patients with normal conditions	0.3

tested, and the best results performance is yielded when $w_1 = 0.4$, $w_2 = 0.4$,and $w_3 = 0.2$, for the given scenario. It can be noted that cluster factor and local health assessment have the highest weights, this is to strengthen the condition that patients with highest severity health status in the network will always have the priority in transmission. This means that patients with acute conditions will not be dragged down to lower severity health level (i.e., urgent and normal). Equation 5.2 demonstrates the probability that each patient has to acquire a channel based on his/her given influential factors.

$$P_{ca}/patient = L_{assess} * 0.4 + Pa_{avatar} * 0.2 + C_{factor} * 0.4 \tag{5.2}$$

Scalability results:

Figure 5.2 shows the probability of channel acquisition for 100 patients in terms of patients local and global severities. The results demonstrate that patients with acute health status have the highest P_{ca} compared with patients that have urgent and normal health status. Moreover, the results indicate how patients in the same cluster have different P_{ca} values, due to the integration of patients avatars in the prioritization process. Furthermore, the outcomes of the proposed model can guarantee system scalability, whereby the number of patients can vary from 1 to N and maintains the same performance in terms of prioritizing transmission among different clusters and within each cluster, as it appears in Figure 5.3. The figure shows data prioritization among 500 patients regarding their local and global severities.

The effect of patients' avatars on the prioritization decision:

These results clarify how the contextual data affects the prioritization decision as it will be discussed. Figure 5.4 shows the P_{ca} of 10 patients, at three different scenarios, versus transmission priority:

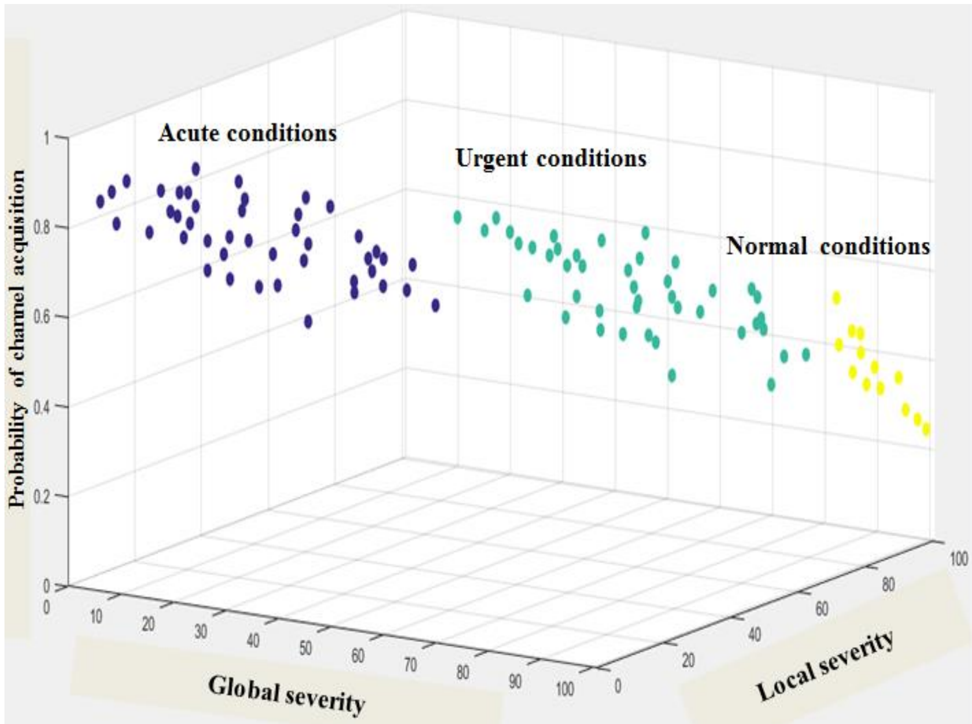


Figure 5.2: the probability of channel acquisition for 100 patients in terms of global and local severities

1. In the first scenario (i.e., the green line), data is prioritized without integrating any intelligence, locally or globally. As is shown in Figure 5.4, the P_{ca} is equally distributed among patients, regardless of patients' health status. Thus, the chances for patients with acute status will be reduced, due to the inefficient allocation of data transmission.

2. In the second scenario (i.e., the blue line), intelligence is integrated, locally, to make a local health assessment for each patient. The data will be prioritized and transmitted

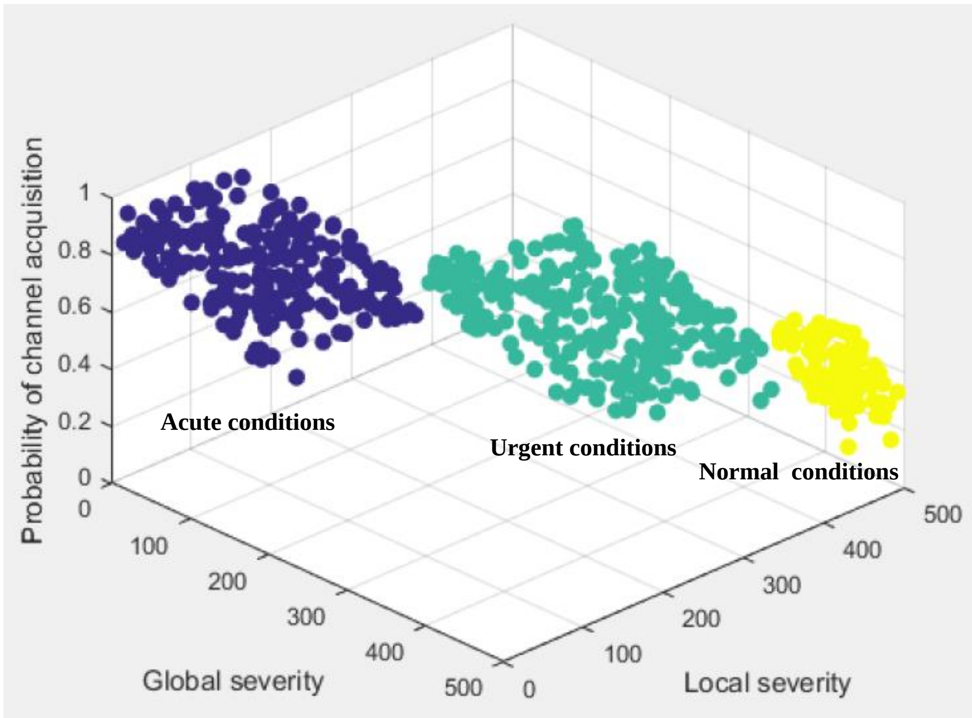


Figure 5.3: the probability of channel acquisition for 500 patients in terms of global and local severities.

based on the local assessment only, without considering patients contextual data.

3. In the third scenario (i.e., the red line), the intelligence is integrated locally by making local health assessment, and globally by considering patients avatars in the prioritization process.

The results show that the priority level of data transmission is adjusted based on the severity level of patient contextual data (i.e., patients' avatar). As shown in Figure 5.4, transmission priority of the patient (i.e., patient colored with blue) is changed from trans-

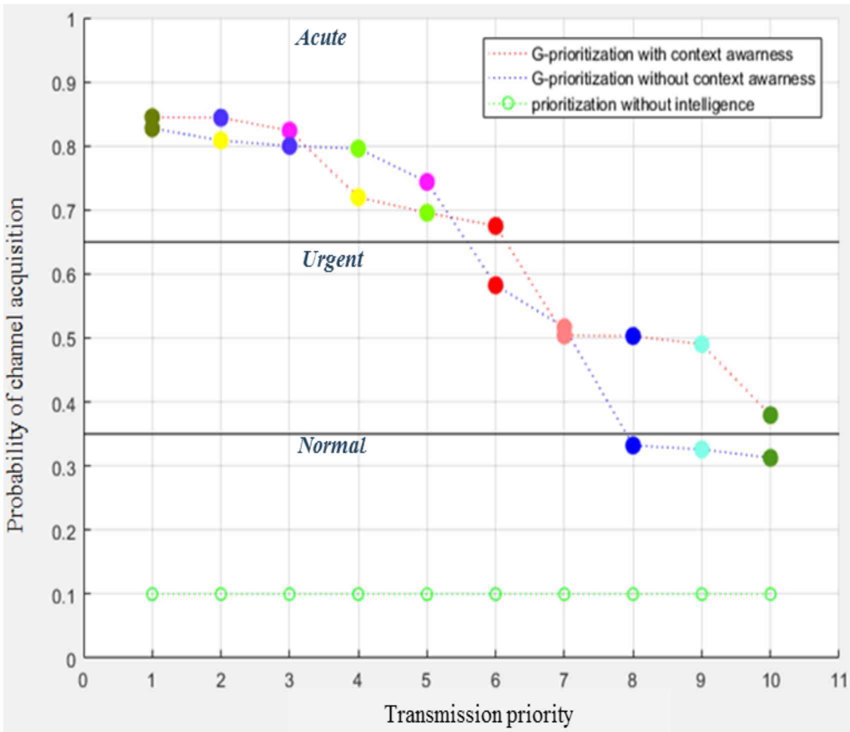
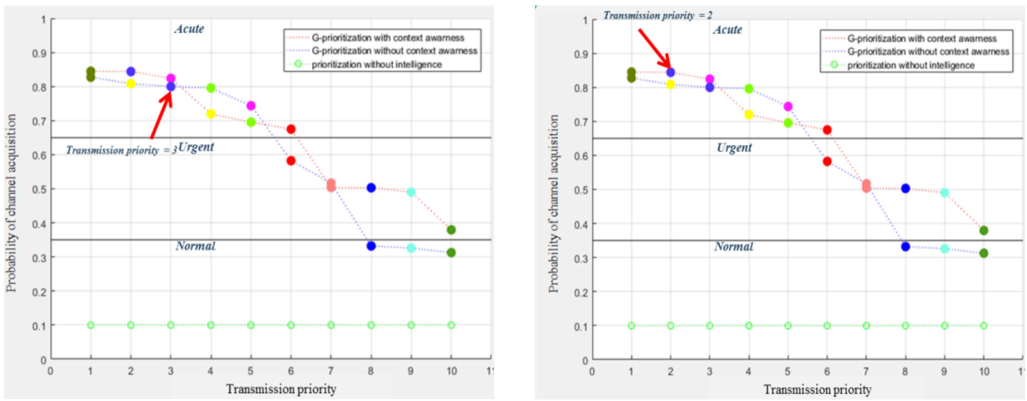


Figure 5.4: shows the Pca of 10 patients at three different scenarios in terms of transmission priority

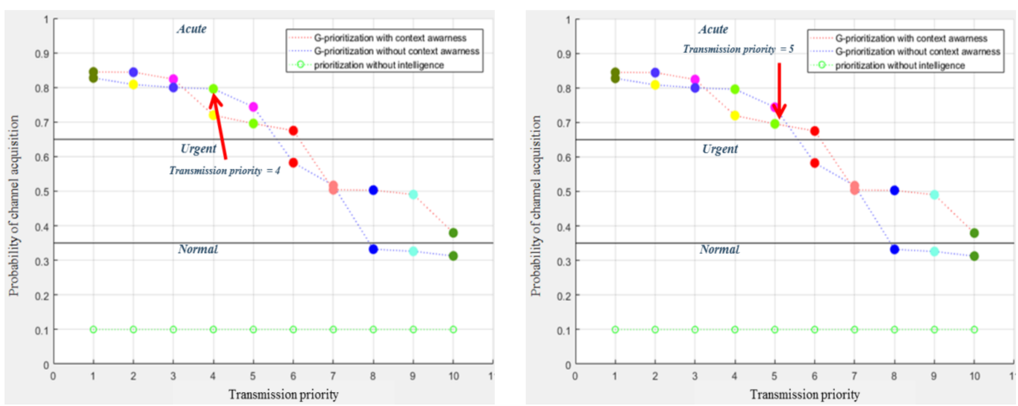
mission priority=3, see Figure 5.5a, to transmission priority=2, see Figure 5.5b. Moreover, the results in Figures 5.5 and 5.6 clarify that patients who are clustered within acute level will maintain the highest priority in transmission. Additionally, the results demonstrate that transmission priority within the cluster is prioritized, according to patients' avatars.

Moreover, patients clustered within urgent and normal levels may be dragged up into a cluster that has a higher severity level, according to their contextual data, as shown in Figure 5.7. The patient (i.e., colored with red) has an urgent local health assessment;



(a) transmission priority without contextual data=2 (b) transmission priority with contextual data=3

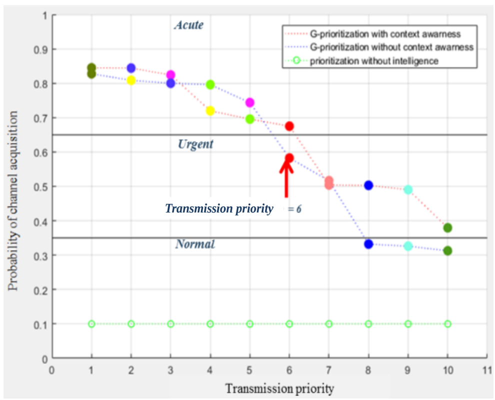
Figure 5.5: the effect of the contextual data on the transmission priority



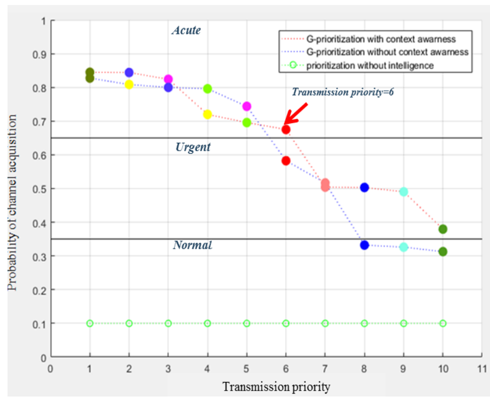
(a) transmission priority without contextual data=4 (b) transmission priority with contextual data=5

Figure 5.6: the effect of the contextual data on the transmission priority

however, by including the effect of his/her contextual data, the P_{ca} is increased to reach the acute level. Thus, the system shows high reliability in terms of considering both patient's real-time vital signs measurements and patients' avatars in the prioritization process. On the other hand, the model keeps the higher transmission priority for patients with acute health status.



(a) transmission priority without contextual data=6



(b) transmission priority with contextual data=6

Figure 5.7: the effect of the contextual data on the transmission priority

Average delay:

For more evaluation to the proposed system, the average delay for 10-patients is calculated. The algorithm is run 100 times, and each time the local health assessment for each patient is changing between the three severity levels (acute, urgent, and normal). The results in Figure 5.8 show the average delay, for one patient, versus the three severity levels. The results clarify that when the patient has an acute health status, the average transmission delay is the lowest among the three severity levels. Furthermore, the same experiment is repeated to calculate the average delay for 10-patients. The results in Figure 5.9 show that the 10-patients within the same cluster have different average delay value, which clearly proves the effect of contextual data on the prioritization process inside each cluster.

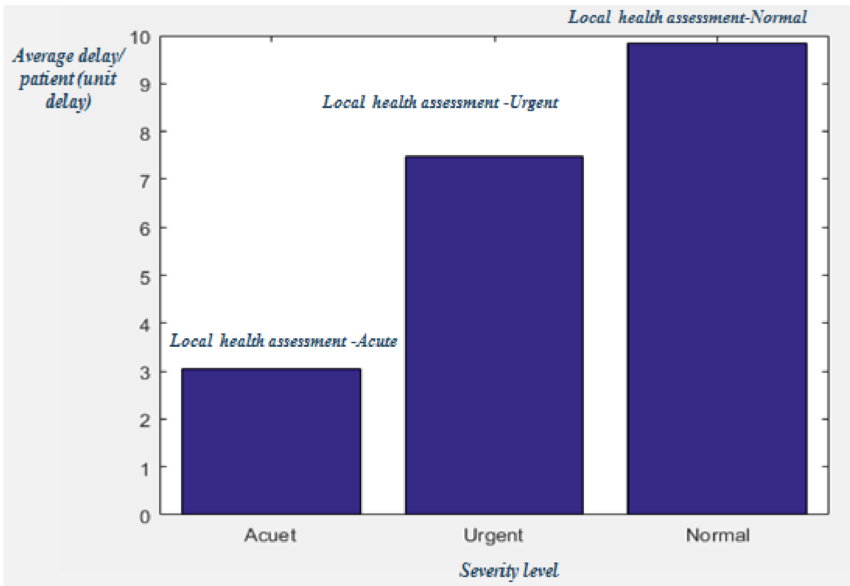


Figure 5.8: the average delay for single patient versus different severity levels

5.4 Summary

This chapter has proposed an intelligent multi-stage data prioritization model, whereby patients real-time vital signs measurements and patients' avatars (i.e., contextual data) are integrated into the prioritization process. Fuzzy logic is utilized to make a local assessment of patients health status. Prioritization controlling unit is designed to prioritize transmission among multiple BCUs in the global unit, whereby a cluster-based heuristic algorithm is utilized to make a prioritization decision.

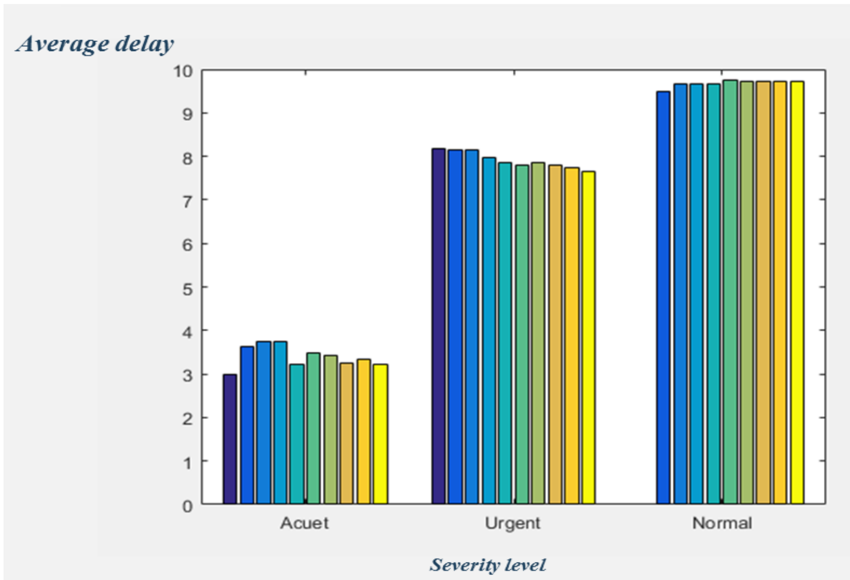


Figure 5.9: the average delay forten patients versus different severity levels

The results have shown high scalability, where it maintains its performance (i.e., transmitting data according to the severity of patients' health) with a different number of patients within the network. Furthermore, the results have demonstrated high reliability in prioritizing data transmission among multiple patients, while maintaining the highest transmission priority for patients with acute conditions. Additionally, the average transmission delay for patients are reduced, and patients with acute status have the lowest transmission delay.

Thus, in order to acquire a channel among candidates who have data to transmit, a channel needs to be sensed efficiently and then acquired by a user that has the highest health severity level.

Chapter 6

Conclusion and Future Work

6.1 Conclusion

This work has proposed an intelligent multi-stage channel acquisition model for multiple CR-WBANs in a ubiquitous healthcare system, whereby environmental properties, intra-node characteristics, and patients' contextual data are utilized in the decision process. The architecture of the proposed intelligent channel acquisition model has divided into two approaches: the first approach is an original multi-stage hybrid cooperative spectrum sensing, which brings together local and global sensing modules. Real-world power measurements are used to train the neural network. The second approach is an intelligent multi-stage data prioritization model, which, again, brings together local health assessment and global data prioritization modules. Real-time vital signs measurements and contextual data for patients are integrated in the prioritization process. A cluster-based heuristic algorithm is utilized to prioritize transmission among patients.

The proposed multi-stage hybrid cooperative spectrum sensing model has shown high performance in sensing the channel availability, where its accuracy has reached 99%. The model has compared with intelligent single-stage (no global decision) and multi-stage models (the intelligence is embedded only in the local unit, and the majority rule is used in the global unit), it has outperformed both models with 54% and 41%, respectively. Moreover, the model is also compared with state-of-the-art models, and it has shown its superiority with 5% better performance.

The proposed multi-stage data prioritization model has guaranteed scalability, whereby the number of patients can vary from 1 to N and maintains the same performance in terms of prioritizing transmission. Moreover, the proposed model has compared with a transmission model without any intelligence (i.e., first come first serve mechanism), and intelligent single-stage prioritization model (i.e., prioritization decision has not considered patients avatars). The proposed model has outperformed both other models, by clustering data transmission according to the severity of patients health status; and within each cluster, the prioritization of data transmission is adjusted based on patients avatars. Furthermore, the model has demonstrated that patients with acute conditions have the lowest average transmission delay compared with patients with urgent and normal conditions.

6.1.1 Benefits of the proposed intelligent channel acquisition model

The proposed intelligent channel acquisition model has shown high performance in

- Robustness: it maintains a robust performance against unpredictable changes in SU-mobility levels, whereby the probability of detection improves when the SNR levels improve, regardless of the changes in SU-speed levels;
- Accuracy: it predicts PU-activities with high accuracy under environmental conditions (i.e., low SNRs);
- Scalability: it meets ubiquitous healthcare requirements, by maintaining the prioritization process among multiple patients based on their local health assessments and contextual data (i.e., patients avatars);
- Reliability: it performs consistently, by clustering transmission based on the severity of patients health conditions (i.e., acute, urgent, and normal health conditions), and then prioritizing transmission, within each cluster, according to patients avatars.

6.2 Future work

Although the results of the channel acquisition model have demonstrated the effectiveness of the proposed approach, each model could further be developed in different ways:

- The hybrid cooperative spectrum sensing model:
  - Additional features can be included to train the NN, such as SU-distance and path loss, to enhance the sensing performance of the network.
  - The proposed model is designed, where only a single PU exists in the environment. Considering more than one PU in the network allows more than a single SU to transmit at the same time, which decreases network latency and increases network scalability. Hence, the enhanced model helps to saves more lives. For implementing this enhancement, different considerations need to be taken, such as calculations of the distance between SUs and PUs, to determine the shortest transmission path for each SU.
  - Since the proposed model has achieved very high prediction accuracy and so to avoid any overfitting, testing the proposed model using another dataset is considered.
  - Since preserving power is fundamental in sensor networks, it is preferable to investigate the power consumption of the proposed model.
- The Data transmission prioritization model:
  - Heterogeneous networks are more effective in real life than homogeneous networks. In designing a channel acquisition model, the consideration of different

users who have different vital signs sensors helps to simulate the real-world situation.

- Including more contextual data within each patient's avatar at the patients profile center, provides more information about the severity of patients health status.
- In the proposed model, each patient's avatar in the patient profile center is regularly updated by the specialists and doctors. However, for more efficient and reliable performance each patient's avatar should be updated automatically when the local health assessment module updates its data.

References

[1] Refga Elgadi, Allaa Hilal, and Otman Basir. A fuzzy logic approach for cooperative spectrum sensing in cognitive radio networks. In *IEEE 2017 Canadian Conference on Electrical and Electronic Engineering*. IEEE, 2017.

[2] Jaison Jacob, Babita R Jose, and Jimson Mathew. A fuzzy approach to decision fusion in cognitive radio. *Procedia Computer Science*, 46:425–431, 2015.

[3] Rahul Singh and Sarita Kansal. Performance evaluation of neural network based spectrum sensing in cognitive radio. In *Internet of Things and Applications (IOTA), International Conference on*, pages 368–372. IEEE, 2016.

[4] Suya Bai, Xin Zhou, and Fanjiang Xu. Spectrum prediction based on improved-back-propagation neural networks. In *Natural Computation (ICNC), 2015 11th International Conference on*, pages 1006–1011. IEEE, 2015.

[5] Idc home: the premier global market intelligence firm, Jan 2014.

[6] Nikhil Arora and Rita Mahajan. Cooperative spectrum sensing using hard decision fusion scheme. *Int. J. Eng. Res. General Sci.*, 2(4):36–43, 2014.

[7] Luis Filipe, Florentino Fdez-Riverola, Nuno Costa, and António Pereira. Wireless body area networks for healthcare applications: protocol stack review. *International Journal of Distributed Sensor Networks*, 2015.

[8] Raúl Chávez-Santiago and Ilangko Balasingham. Cognitive radio for medical wireless body area networks. In *Computer Aided Modeling and Design of Communication Links and Networks (CAMAD), 2011 IEEE 16th International Workshop on*, pages 148–152. IEEE, 2011.

[9] The daily canada's population estimates: age and sex, july 1, 2015, Jul 2015.

[10] Shafiullah Khan, Al-Sakib Khan Pathan, and Nabil Ali Alrajeh. *Wireless sensor networks: current status and future trends.* CRC Press, 2012.

[11] Raúl Chávez-Santiago, Keith E Nolan, Oliver Holland, Luca De Nardis, João M Ferro, Norberto Barroca, Luís M Borges, Fernando J Velez, Vania Goncalves, and Ilangko Balasingham. Cognitive radio for medical body area networks using ultra wideband. *IEEE Wireless Communications*, 19(4), 2012.

[12] Sabin Bhandari and Sangman Moh. A survey of mac protocols for cognitive radio body area networks. *Sensors*, 15(4):9189–9209, 2015.

[13] Sana Ullah, Henry Higgins, Bart Braem, Benoit Latre, Chris Blondia, Ingrid Moerman, Shahnaz Saleem, Ziaur Rahman, and Kyung Sup Kwak. A comprehensive survey of wireless body area networks. *Journal of Medical Systems*, 36(3):1065–1094, 2012.

[14] Aqeel Raza Syed and Kok-Lim Alvin Yau. On cognitive radio-based wireless body area networks for medical applications. In *Computational Intelligence in Healthcare and e-health (CICARE), 2013 IEEE Symposium on*, pages 51–57. IEEE, 2013.

[15] Dheeraj Rathee, Savita Rangi, SK Chakarvarti, and VR Singh. Recent trends in wireless body area network (wban) research and cognition based adaptive wban architecture for healthcare. *Health and Technology*, 4(3):239–244, 2014.

[16] Joseph Mitola and Gerald Q Maguire. Cognitive radio: making software radios more personal. *IEEE Personal Communications*, 6(4):13–18, 1999.

[17] Simon Haykin. Cognitive radio: brain-empowered wireless communications. *IEEE Journal on Selected Areas in Communications*, 23(2):201–220, 2005.

[18] Mansi Subhedar and Gajanan Birajdar. Spectrum sensing techniques in cognitive

radio networks: a survey. *International Journal of Next-Generation Networks*, 3(2):37–51, 2011.

[19] Harry Urkowitz. Energy detection of unknown deterministic signals. *Proceedings of The IEEE*, 55(4):523–531, 1967.

[20] Shan Feng, Zhongliang Liang, and Dongmei Zhao. Providing telemedicine services in an infrastructure-based cognitive radio network. *IEEE Wireless Communications*, 17(1), 2010.

[21] Khaled A Ali, Jahangir H Sarker, and Hussein T Mouftah. A mac protocol for cognitive wireless sensor body area networking. *Wireless Communications and Mobile Computing*, 10(12):1656–1671, 2010.

[22] E Seven and A Çalhan. Priority based wireless body area network with cognitive radio. 2015.

[23] Ziqian Dong, Shamik Sengupta, S Anand, Kai Hong, Rajarathnam Chandramouli, and KP Subbalakshmi. Cognitive radio mobile ad hoc networks in healthcare. In *Cognitive Radio Mobile Ad Hoc Networks*, pages 335–350. Springer, 2011.

[24] Mohsin Nazir and Aneeqa Sabah. Cooperative cognitive wban: from game theory to

population dynamism. In *Ultra Modern Telecommunications and Control Systems and Workshops (ICUMT), 2011 3rd International Congress on*, pages 1–6. IEEE, 2011.

[25] Rong Yu, Yan Zhang, Chen Gao, Chujia Huang, and Ruchao Gao. Energy-efficient and reliability-driven cooperative communications in cognitive body area networks. *Mobile Networks and Applications*, 16(6):733–744, 2011.

[26] Junchao Han, Jing Liu, Hui Yu, Chen Chen, and Zhichun Shen. Hcvp: A hybrid cognitive validation platform for wban. In *Wireless Communications & Signal Processing (WCSP), 2012 International Conference on*, pages 1–6. IEEE, 2012.

[27] Qiang Shen, Jing Liu, Hui Yu, Zhichao Ma, Ming Li, Zhichun Shen, and Chen Chen. Adaptive cognitive enhanced platform for wban. In *Communications in China (ICCC), 2013 IEEE/CIC International Conference on*, pages 739–744. IEEE, 2013.

[28] An He, Kyung Kyoon Bae, Timothy R Newman, Joseph Gaeddert, Kyouwoong Kim, Rekha Menon, Lizdabel Morales-Tirado, Youping Zhao, Jeffrey H Reed, William H Tranter, et al. A survey of artificial intelligence for cognitive radios. *IEEE Transactions on Vehicular Technology*, 59(4):1578–1592, 2010.

[29] Hariharasudhan Viswanathan, Baozhi Chen, and Dario Pompili. Research challenges in computation, communication, and context awareness for ubiquitous healthcare. *IEEE Communications Magazine*, 50(5), 2012.

[30] Chinmay Chakraborty, Bharat Gupta, and Soumya K Ghosh. A review on telemedicine-based wban framework for patient monitoring. *Telemedicine and e-Health*, 19(8):619–626, 2013.

[31] Sitadevi Bharatula, Meenakshi Murugappan, et al. An intelligent fuzzy based energy detection approach for cooperative spectrum sensing. *Circuits and Systems*, 7(06):1042, 2016.

[32] Ammar Abdul-Hamed Khader, Ahmed Hameed Reja, Arkan Ahmed Hussein, MT Beg, et al. Cooperative spectrum sensing improvement based on fuzzy logic system. *Procedia Computer Science*, 58:34–41, 2015.

[33] Warren S McCulloch and Walter Pitts. A logical calculus of the ideas immanent in nervous activity. *The Bulletin of Mathematical Biophysics*, 5(4):115–133, 1943.

[34] Amir Ghasemi and Elvino S Sousa. Collaborative spectrum sensing for opportunistic access in fading environments. In *New Frontiers in Dynamic Spectrum Access Networks, 2005. DySPAN 2005. 2005 First IEEE International Symposium on*, pages 131–136. IEEE, 2005.

[35] Nada Gohider. Context augmented spectrum sensing in cognitive radio networks. 2016.

[36] Chandrashekhar Choudhari and Varsha Jaink. An optimum decision making in cognitive radio via fuzzy neural network. *International Journal of Engineering Research & Technology*, 1(5):2278–0181, 2012.

[37] Mohsen Riahi Manesh, Adnan Quadri, Sriram Subramaniam, and Naima Kaabouch. An optimized snr estimation technique using particle swarm optimization algorithm. In *Computing and Communication Workshop and Conference (CCWC), 2017 IEEE 7th Annual*, pages 1–6. IEEE, 2017.

[38] Pravir CHAWDHRY. European cellular signal strength coverage. european commission, Jun, 2016.

[39] Omar Alfandi, Arne Bochem, Mehdi Akbari Gurabi, Alberto Rivera Díaz, Md Istiak Mehedi, and Dieter Hogrefe. Calculating the speed of vehicles using wireless sensor networks. In *Computer Science and Information Systems (FedCSIS), 2016 Federated Conference on*, pages 1043–1047. IEEE, 2016.

[40] Henrique Moniz, Nuno F Neves, and Miguel Correia. Byzantine fault-tolerant consensus in wireless ad hoc networks. *IEEE Transactions on Mobile Computing*, 12(12):2441–2454, 2013.

[41] Diana P Tobón, Tiago H Falk, and Martin Maier. Context awareness in wbans: a

survey on medical and non-medical applications. *IEEE Wireless Communications*, 20(4):30–37, 2013.

[42] Zhisheng Yan and Bin Liu. A context aware mac protocol for medical wireless body area network. In *Wireless Communications and Mobile Computing Conference (IWCMC), 2011 7th International*, pages 2133–2138. IEEE, 2011.

[43] Bin Liu, Zhisheng Yan, and Chang Wen Chen. Ca-mac: a hybrid context-aware mac protocol for wireless body area networks. In *e-Health Networking Applications and Services (Healthcom), 2011 13th IEEE International Conference on*, pages 213–216. IEEE, 2011.

[44] Abdur Rahim Mohammad Forkan. *A cloud-based, predictive and context-aware system for Ambient Assisted Living*. PhD thesis, RMIT University Melbourne, Australia, 2016.

[45] Refga Elgadi, Allaa Hilal, and Otman Basir. Intelligent hybrid cooperative spectrum sensing: a multi-stage decision fusion approach. In *IEEE International Conference on Systems, Man, and Cybernetics*. IEEE, 2017.

[46] Refga Elgadi, Allaa Hilal, and Otman Basir. An intelligent multi-stage channel acquisition model for cr-wbans: a context aware approach. In *IEEE Journal of Biomedical and Health Informatics*. IEEE, 2017.

[47] Nhat-Quang Nhan, Matthieu Gautier, and Olivier Berder. Asynchronous mac protocol for spectrum agility in wireless body area sensor networks. In *Cognitive Radio Oriented Wireless Networks and Communications (CROWNCOM), 2014 9th International Conference on*, pages 203–208. IEEE, 2014.

[48] Lotfi A Zadeh. Fuzzy sets. *Information and Control*, 8(3):338–353, 1965.

[49] L A. Zadeh. Fuzzy logic, neural networks, and soft computing. *Communications of The ACM*, 37(3):77–85, 1994.