Thesis for the Degree of Master of Science

A Prediction Algorithm for Coexistence Problem in Multiple WBANs Environment

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by

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Supervised by

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Prof. Intae Ryoo, Ph.D………………..…..

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Prof. Jinsung Cho, Ph.D…………………

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Abstract

A Prediction Algorithm for Coexistence Problem in Multiple WBANs Environment

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Supervised by Prof. Jin Sung Cho

Coexistence problem occurs when a single WBAN(Wireless Body Area Network) locates in multiple WBANs environment. In that case, WBANs are suffered from serious channel interferences which may degrade the performance of each WBAN due to failure of data transmission. Because WBAN handles physical signal or emergency data affecting human life, WBAN requires the prediction of coexistence condition to guarantee reliable communication continuously for each sensor node of WBAN. In this paper, we present a prediction algorithm to detect coexistence problem efficiently in multiple WBANs environment. The algorithm measures *PRR*(Packet Reception Ratio) and *SINR*(Signal to Interference and Noise Ratio) to detect interference reliably. In order to handle coexistence problem efficiently, the algorithm employs the naive Bayesian classifier which is one of machine learning techniques to classify the coexistence condition into four states. We conduct extensive simulations for coexistence prediction with various packet transmit rates of sender node and speeds of main mobile WBAN by using Castalia 3.2 simulator based on OMNet++ platform. Consequently, we demonstrate that the proposed algorithm provides more reliable and accurate performance than existing studies to detect coexistence in multiple WBANs environment.

Thesis Supervisor: Jinsung Cho
Title: Professor

Chapter 1

Introduction

WBAN is a special kind of network that provides intercommunication between devices, which exist in/on/around a human body, connected wirelessly from each other. Since 2007, IEEE 802.15 Working Group organized IEEE 802.15 Tasking Group 6 to establish the standardization for WBAN. They have been working on the communication standard for WBAN and aim to provide services for medical and entertainment fields simultaneously [1].

WBAN features from limited frequency band, so that coexistence problem declining the performance of each WBAN occurs when multiple users occupy the same channel concurrently. For example, data fails to be transmitted accurately under packet collision when more than one device uses the same frequency simultaneously. As well, channel capacity falls under the threshold or received signal strength decreases, by interference of channels, when more than one devices share a channel. Consequently, it increases PER(Packet Error Rate) and decreases *PRR*(Packet Reception Ratio). PER is the number of incorrectly transferred data packets divided by the number of transferred packets and a packet is assumed to be incorrect if at least one bit is incorrect. *PRR* is the ratio for the number of received packets based on a given number of packets transmission. Therefore, coexistence problem causes declining of channel utilization rate by arising data retransmission and increasing transmission delay. Thus in WBAN, the importance of study for prediction of coexistence environment beforehand and avoidance of coexistence problem is emphasized highly.

In this paper, we propose a system model of prediction for coexistence condition and detection of interference from other WBANs in multiple WBANs environment. The proposed algorithm applies *PRR* and *SINR* which is commonly used in wireless communication as a way to measure the quality of wireless connections, measured at a coordinator node from other sensor nodes composing a WBAN, to the naive Bayesian classifier. The naive Bayesian classifier is one of machine learning technique to classify the coexistence condition into four states, such as *static*, *semi-dynamic*, *dynamic* and *none*, according to the holding time of interference.

We conduct extensive simulations for coexistence prediction with various packet transmit rates of sender node and speeds of main mobile WBAN. The prospective results of coexistence from a single *PRR* or a single *SINR* are compared with results of coexistence from naive Bayesian classifier applied *PRR*, $SINR_{holding-time}$ and *previous state* to evaluate the performance of the proposed algorithm. Consequently, we demonstrate that the proposed algorithm provides more reliable and accurate performance than existing studies to detect coexistence in multiple WBANs environment.

The rest of this paper is organized as follows. We account for detection and solution for coexistence of other standards working at the ISM(Industrial Scientific and Medical) band as related work and naive Bayesian classifier as a background in Section2. Next, we propose a prediction algorithm in Section3. In Section4, we conduct extensive simulations to evaluate performance of the proposed algorithm. After a brief discussion on the future work, we conclude the paper in Section5.

Chapter 2

Related Work and Background

2.1 Related Work

According to the interest increasing in coexistence problem in WBAN which requires high transmission reliability, diverse studies about the coexistence problem are proceeding actively. Studies about analysis of performance degradation of respective WBANs in multiple WBANs environment or measures to solve the performance degradation caused by occurrence of coexistence condition are in process [2, 3]. However, these studies do not indicate measures to detect or predict coexistence condition but measures to improve performance after that interference is occurred only.

Meanwhile, there are studies about detection or prediction of coexistence problem based on wireless transmission technologies, such as WLAN(Wireless Local Area Networks), WPAN(Wireless Personal Area Networks)(e.g., Blutooth, ZigBee) and Ad-hoc, using ISM band . These existing studies are divided into several layers.

First, at the PHY(Physical) layer, interference is detected with three measures. Prior to the beginning of transmission, it is the most accurate way to check physical signal on the channel to ensure whether or not the channel is occupied by other user. Nevertheless, to check signal power is not appropriate for WBAN , which requires low power, because it may result in high energy consumption [4]. The major standards use the way measuring difference of *SINR* or BER(Bit Error Rate) [5,6]. However, we cannot make reliable judgement with only a single *SINR* value because it has fault entailing a systemic error sometimes. RSSI(Received Signal Strength Indicator) exceeding the threshold is another measurement to check if interference exists. It is useful for detecting interference between different kinds of devices, such as Bluetooth and WLAN, which have a wide difference of signal power [7]. Second, at the MAC(Media Access Control) layer, PER(Packet Error Ratio) is the criteria for detecting interference [8]. Finally, PDR(Packet Delivery Rate) is used at the NET(Network) layer.

However, it is a problem that the coexistence predicted with each measured single value at the MAC or NET layers is not highly reliable. Therefore, a reliable coexistence prediction model considering elements of interference measurement at each layer complexly is required for WBAN.

Despite of the uncertainty of SINR value by systemic error, it is used to interference modeling as a parameter usually [9, 10]. Interference modeling is crucial for the performance of numerous WSN protocols such as congestion control, link/channel scheduling, and reliable routing, because it is important to understand the complex wireless interference among sensor nodes. Recent studies suggest that PRR-SINR model is significantly more accurate than existing interference models. The PRR-SINR model offers significantly improved realism by accounting for the impact of various dynamics (e.g., environmental noise and concurrent transmissions). These studies support that usage of SINR value as a parameter to detect inference in this paper enhances accuracy of the proposed algorithm’s performance.

2.2 Naive Bayesian Classifier

Recently, the machine learning is recommended as one of efficient and practical solutions to solve several learning issues. Supervised and unsupervised learning methods are particular cases which perform learning tasks with labeled and unlabeled data, respectively. Due to the huge algorithm complexity and low estimation accuracy, the unsupervised learning method cannot deal with estimation task feasibly in wireless networks. Therefore, supervised learning algorithms are widely applied in wireless technology to estimate and predict the variance of wireless resources and network environment [11,12].

The naive Bayesian classifier which is based on the Bayes rule is widely exploited in posterior probability calculation with priori information which is a kind of supervised learning method. Based on existing attribute values $\{w_1, w_2, ..., w_n\}$, the Bayes theorem can estimate the most possible hypothesis c_{MAP} as follow:

$$\begin{aligned} c_{MAP} &= \underset{c_j \in C}{\arg\max} \frac{P(w_1, w_2, ..., w_n | c_j) P(c_j)}{P(w_1, w_2, ..., w_n)} \\ &= \underset{c_j \in C}{\arg\max} P(w_1, w_2, ..., w_n | c_j) P(c_j) \end{aligned} \tag{1}$$

When we make an assumption that the attribute values are conditionally independent, the item in Eq. (1) can be calculated as: $P(w_1, w_2, ..., w_n | c_j) P(c_j) = \prod_i P(w_i | c_j)$. Substituting this into Eq. (1), we can obtain the naive Bayes classifier as follow.

$$\underset{c_j \in C}{\arg\max} P(c_j) \prod_i P(w_i | c_j) \tag{2}$$

The naive Bayesian classifier is a classification model that has several advantages [13] : it is easy to learn and understand, it is very efficient, it is in general robust and has a high accuracy. So, some of the studies use naive Bayesian classifier to classify information accurately. For example, there is a study that aims at classifying moods of songs based on lyrics by using naive Bayesian classifier [14].

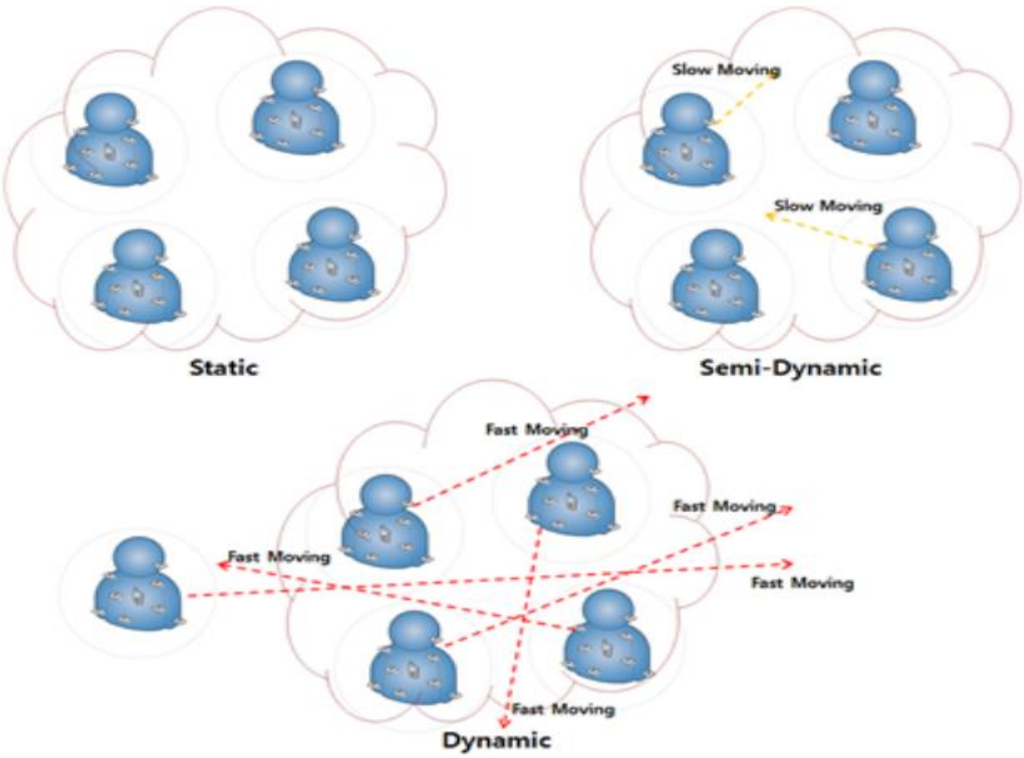
Chapter 3

Proposed Algorithm

3.1 System Model and Problem Description

WBAN aims to provide services for medical and entertainment fields simultaneously through sensor devices existing in/on/ around a human body. Many different type of devices, which have different features according to the specific service type, are required to offer various services concurrently [15]. Also, WBAN which is proposed to medical service mainly could exist in a small space, such as the hospital or medical clinic center, with multiple WBANs simultaneously. There are densely concentrated area more than three WBANs existing close or rarely concentrated area more than one WBAN existing. Fig. 1 shows each WBAN moves in different speed to other WBANs, and it has an influence on the duration time of coexistence problem to other WBANs.

IEEE Std. 802.15.6 classifies coexistence environment according to the mobility level as shown in Table 1. There is no figure which indicates a clear distinction among *static*, *semi-dynamic* and *dynamic*. In this paper, we focus on the holding time of interference to define *static*, *semi-dynamic* and *dynamic*.



[Figure 1.] Multiple WBANs environment

[Table 1.] Coexistence environment

Static	A single BAN in a residential environment or a hospital with a single patient node and a fixed bedside hub
Semi-dynamic	Slowly moving ambulatory patients in an elder care facility
Dynamic	Fast moving ambulatory patients in a hospital with a large number of BANs

In this paper, we propose a prediction algorithm for coexistence problem in multiple WBANs environment. In addition, we classify the coexistence condition into four states, such as *static*, *semi-dynamic*, *dynamic* and *none*, according to the holding time of interference. *Static* indicates that WBAN is influenced by interference from other WBANs for a long time consistently without any mobility, *semi-dynamic* indicates that WBAN is influenced by interference from other WBANs for a normal time consistently with slow mobility, *dynamic* indicates that WBAN is influenced by interference from other WBANs temporarily with fast mobility and *none* indicates that there is no interference around.

We configure a single WBAN with four sensor nodes and one coordinator node on the human body. *PRR* and *SINR* are utilized as the parameter for interference detection, and coordinator node calculates average *PRR* and *SINR* of received values from four sensor nodes. We measure holding time of *SINR* under the threshold, called $SINR_{holding-time}$, instead of *SINR* itself to classify coexistence condition for the holding time of interference. Furthermore, we consider *previous state* having an influence on the current state besides these parameters such as *PRR* and $SINR_{holding-time}$. Ultimately, we aim to detect coexistence problem in multiple WBANs environment by applying three measured vales, which are *PRR*, $SINR_{holding-time}$ and *previous state*, to naive Bayesian classifier and classify coexistence condition into four states according to the holding time of the interference. Fig 2 shows the overall flow of the proposed system model.

Algorithm on Coordinator

```
PRR ← Input about PRR; PRR_a ← Average of PRR
PRR_th ← Threshold of PRR
SINR ← Input about SINR; SINR_a ← Average of SINR
SINR_th ← Threshold of SINR
SINR_h ← Holding-time of SINR
Pre ← Input about pre-state
P_st ← Pre-state; C_st ← Coexistence-state
PRR() ← Calculate average PRR from 4nodes
SINR() ← Calculate average SINR from 4nodes
P_st() ← Get previous state
NB_Classifier() ← Naive Bayesian classifier

loop
  PRR_a = PRR(); SINR_a = SINR(); P_st = P_st();
  if(PRR_a >= PRR_th)
    PRR = 0
  else
    PRR = 1
  end of if

  if(SINR_a >= SINR_th)
    SINR = 0
  else
    if(0 < SINR_h && SINR_h <   )
      SINR = 1
    else if(α <= SINR_h && SINR_h < β)
      SINR = 2
    else if(β <= SINR_h)
      SINR = 3
    end of if
  end of if

  if(P_st == None)
    Pre = 0;
  else if(P_st == Static)
    Pre = 1;
  else if(P_st == Semi-d)
    Pre = 2;
  else if(P_st == Dynamic)
    Pre = 3;
  end of if
  C_St = NB_Classifier(PRR,SINR,Pre)
end of loop
```

[Figure 2.] Pshudo code for overall flow

3.2 Training Data and Prior Probability

In the naive Bayesian classifier, the classification algorithm is trained with a set of training data. In general, the training data can be obtained from an intuitive knowledge or accumulation of experiential information. In this paper, we perform a set of experiment in various WBAN environments to get the labeled training data, and we show them in Table 2.

The experiment is performed based on ZigbeXⅡ motes which is equipped with CC2420 radio. The sensor modules carry a micro embedded system-KHIX which is developed by our laboratory [16]. A single WBAN consists of one coordinator node and four sensor nodes besides the interference node that belongs to the other WBAN and causes the interference for the existing WBAN's communication.

We assume that coordinator node knows the number of transmitted packets by receiving beacon node from four sensor nodes before beginning the transmission. An average *PRR* is calculated by received packets number from four sensor nodes at the coordinator node. And we calculate an average *SINR* based on measurements taken directly from four sensor nodes at the coordinator node with applying values to the Eq. (3) as below:

$$SINR_{dB} = 10\log_{10}\frac{10^{RSS_{dBm}/10} - 10^{N_{dBm}/10}}{10^{RIS_{dBm}/10}} \tag{3}$$

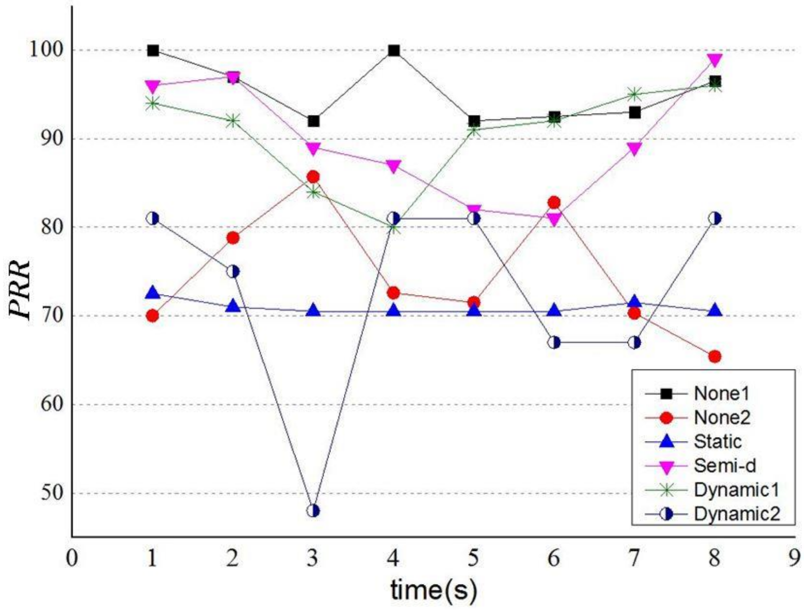
where *RSS*(Received Signal Strength) and *RIS*(Received Interference Strength) are for concurrent transmission and *N* is noise level measured at the coordinator node. In detail, *RSS* is average received signal strength from four sensor nodes and *RIS* is received interference signal strength from other WBAN. We obtain $SINR_{holding-time}$ using calculated *SINR* value.

[Table 2.] Training data

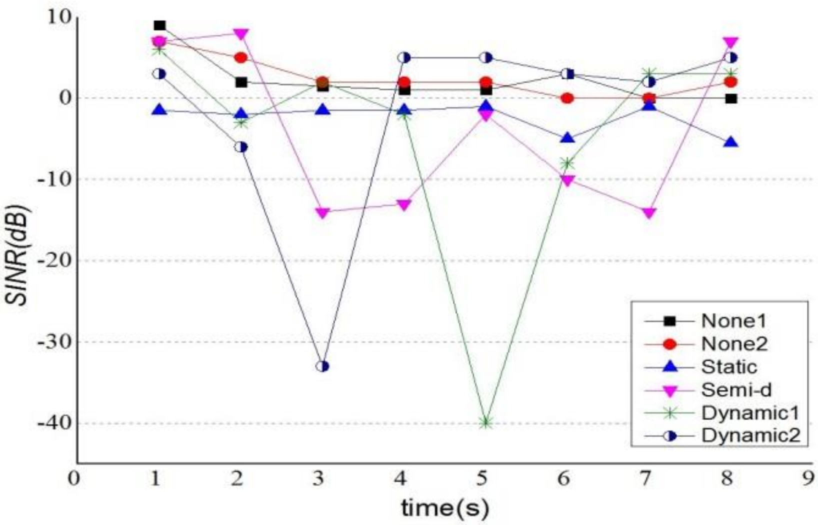
PRR	***SINR***	***Pre-state***	**State**
$PRR \geq PRR_{threshold}$	$SINR_{holding-time} = 0$	*None*	*None*
		Static	
		Semi-dynamic	
		Dynamic	
	$0 < SINR_{holding-time} < \alpha$	*None*	*Dynamic*
		Semi-dynamic	
		Dynamic	
	$\alpha \leq SINR_{holding-time} < \beta$	*None*	*Dynamic*
		Semi-dynamic	
		Dynamic	
	$\beta \leq SINR_{holding-time}$	*None*	*None*
		Static	
		Semi-dynamic	
		Dynamic	
$PRR < PRR_{threshold}$	$SINR_{holding-time} = 0$	*None*	*None*
		Static	
		Semi-dynamic	
		Dynamic	
	$0 < SINR_{holding-time} < \alpha$	*None*	*Dynamic*
		Semi-dynamic	
		Dynamic	
	$\alpha \leq SINR_{holding-time} < \beta$	*None*	*Semi-dynamic*
		Semi-dynamic	
		Dynamic	
	$\beta \leq SINR_{holding-time}$	*None*	*Static*
		Static	
		Semi-dynamic	
		Dynamic	

Our experiment consists of four types of interference cases. In *case1*, we do not set any interference node. In *case2*, we set fixed interference node having an influence on the WBAN's communication consistently. In *case3* and *case4*, interference node moves slowly with 0.5m/s and moves fast with 1.5m/s, respectively.

We experiment each cases for 5 times and obtain average *PRR* and *SINR* at every a second during 8 seconds. The results are shown in the Fig. 3. It is the result from the experiment for different coexistence conditions. None1 and None2 are experimented in *case1* and packet transmission rate of None2 is like two times higher than None1's. We set this difference to get *PRR* value under the $PRR_{threshold}$ without any interference around. Also, Dynamic1 and Dynamic2 are experimented in *case4* and interference node of Dynamic2 is closer to WBAN's nodes than Dynamic1's. Mostly, calculated values indicate the similar result with intuitive knowledge. Furthermore, we found that result state can be different according to *PRR* during $\alpha \le SINR_{holding-time} < \beta$ and it is hard to obtain by intuitive knowledge only. Consequently, we gained the training data Table 2 by analyzing *PRR* and *SINR* values on the Fig. 3.



(a) *PRR*



(b) *SINR*

[Figure 3.] *PRR* and *SINR* value according to the coexistence condition

3.3 Naive Bayesian Classifier Application

Inputs of naive Bayesian classifier are *PRR*, $SINR_{holding-time}$ and *previous state*. Attribute of *PRR* is divided into two cases like case1 with higher value than threshold and case2 with lower value than threshold. And, attribute of *SINR* is divided into four cases, case1 taking $SINR_{holding-time}$ equal to 0, in other words, *SINR* value is always higher than threshold, case2 taking $SINR_{holding-time}$ between 0 to α seconds, case3 taking $SINR_{holding-time}$ between α to β seconds, case4 taking $SINR_{holding-time}$ longer than β seconds. Also, *previous state*'s attributes are *none*, *static*, *semi-dynamic* and *dynamic*.

The prior probability can be derived from the training data in Table 2, and the results are shown in Table 3. We detect the coexistence condition by substituting prior probability value of input into the Eq. (2). For example, when $PRR \geq PRR_{threshold}$, $0 < SINR_{holding-time} < \alpha$, and *previous state*=*none*, the most probable state(*dynamic*) can be derived by the proposed prediction algorithm as follows:

- $P(s)P(PRR \geq PRR_{threshold}|s)P\left(0 < SINR_{holding-time} < \alpha|s\right)P(n|s) = 0$
- $P(s-d)P(PRR \geq PRR_{threshold}|s-d)P\left(0 < SINR_{holding-time} < \alpha|s-d\right)P(n|s-d) = 0$
- $P(d)P(PRR \geq PRR_{threshold}|d)P\left(0 < SINR_{holding-time} < \alpha|d\right)P(n|d) = \frac{3}{64}$
- $P(n)P(PRR \geq PRR_{threshold}|n)P\left(0 < SINR_{holding-time} < \alpha|n\right)P(n|n) = 0$

[Table 3.] Prior probability

Instance	**Attribute**	***None***	***Static***	***Semi-dynamic***	***Dynamic***
PRR	$PRR \geq PRR_{threshold}$	$\frac{2}{4}$	0	0	$\frac{2}{4}$
	$PRR < PRR_{threshold}$	$\frac{1}{4}$	$\frac{1}{4}$	$\frac{1}{4}$	$\frac{1}{4}$
SINR	$SINR_{holding-time} = 0$	1	0	0	0
	$0 < SINR_{holding-time} < \alpha$	0	0	0	1
	$\alpha \leq SINR_{holding-time} < \beta$	0	0	$\frac{1}{2}$	$\frac{1}{2}$
	$\beta \leq SINR_{holding-time}$	$\frac{1}{2}$	$\frac{1}{2}$	0	0
Pre-state	*None*	$\frac{3}{8}$	$\frac{1}{8}$	$\frac{1}{8}$	$\frac{3}{8}$
	Static	$\frac{3}{4}$	$\frac{1}{4}$	0	0
	Semi-dynamic	$\frac{3}{8}$	$\frac{1}{8}$	$\frac{1}{8}$	$\frac{3}{8}$
	Dynamic	$\frac{3}{8}$	$\frac{1}{8}$	$\frac{1}{8}$	$\frac{3}{8}$

Chapter 4

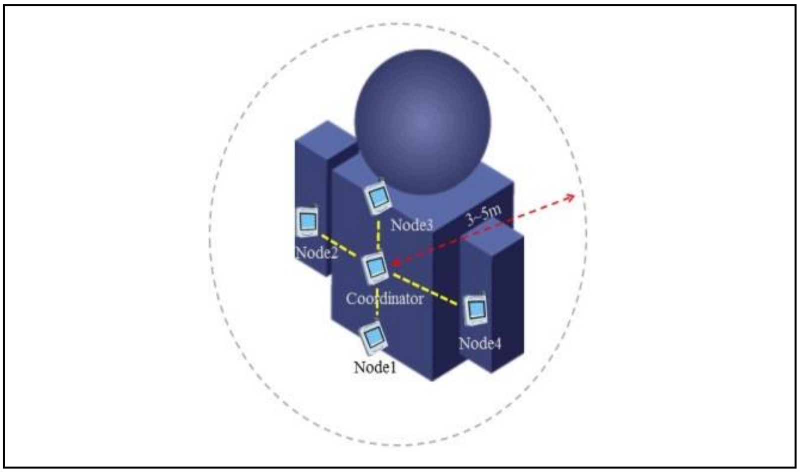
Performance Evaluation

4.1 Simulation Model

In this paper, we perform a set of simulations based on the OMNeT++ platform which is a modular simulation library primarily for building wired and wireless communication network simulator to evaluate the performance of the proposed algorithm. A single WBAN consists of one coordinator node and four sensor nodes(i.e. Node1, Node2, Node3, and Node4) which exist 1m apart from coordinator node with maintaining square shape like Fig. 4.

PRR is calculated with received average packets number from four sensor nodes at the coordinator node and we calculate *SINR* based on measurements taken directly from four sensor nodes at the coordinator node with applying values to the Eq. (3) as described in the Section3.2. We measure $SINR_{holding-time}$ using the calculated *SINR* value.

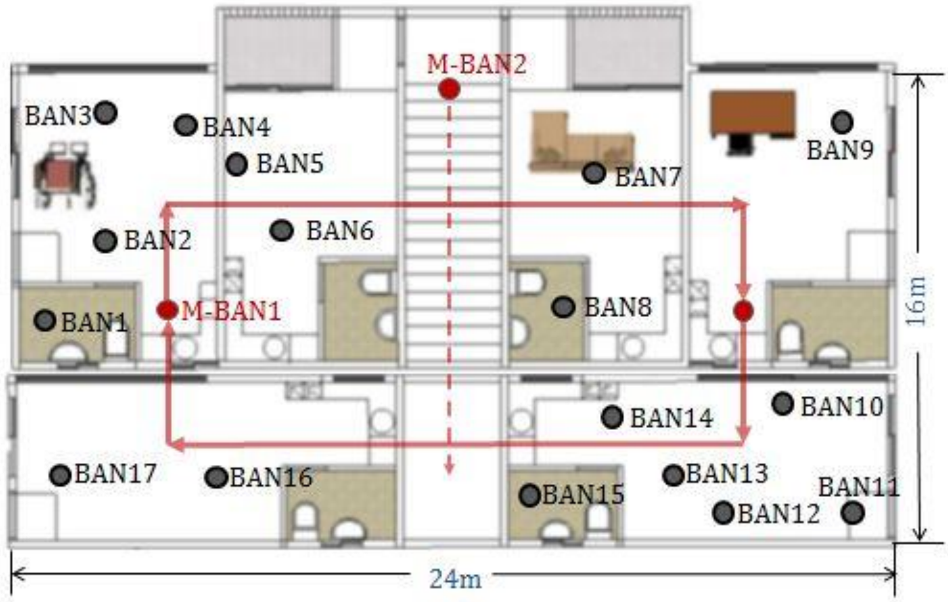
All nodes use CC2420 radio transceiver which occupies 2.4GHz frequency band and transmit power of sender nodes is fixed to -3dBm. We set packet transmit rate to 10pts/s and 5pts/s to get a result of influence on packet transmit rate and threshold value to 0.9 and 0dB for



[Figure 4.] A single WBAN

PRR and *SINR* respectively to guarantee superior quality of communication. And we designate α=3 and β=19 of the Table 2 and Table 3 taking the speed of main mobile WBAN into account.

There are patients who are required to regular hospital visit and rehabilitation treatment. So, we set the simulation environment that reflects the situations of multiple WBANs existing in the same space. The simulation of this paper is conducted on a field 24m×16m. Then, we set 19 WBANs at the field to make a multiple WBANs environment. A main WBAN which gathers information and calculates *PRR*, $\mathrm{SINR}_{\text{holding-time}}$ and *previous state* have mobility and 18 WBANs are interferential WBANs. Speed feeling each other is relative so that we set 17 interferential WBANs to be fixed. In other words, we wanted to describe the distance between main mobile WBAN and interferential WBANs when main mobile WBAN locates a specific spot. To generate crossing environment between main mobile WBAN and interferential WBAN for more general experiment environment, we gave a specific interferential WBAN mobility. In order to apply the most real environment, we classify the field into dense interference area, sparse interference area and no interference existing area. In Fig. 5, M-BAN1 and M-BAN2



[Figure 5.] Simulation field

with red dot mean the main mobile WBAN and interferential mobile WBAN respectively and red line means route. Black dots distributed in the field mean interferential WBANs. The main mobile WBAN measuring *PRR* and *SINR* difference value moves with changing speed to 0m/s, 0.2m/s or 0.4m/s at an interval of 4m. On the other hand, interferential WBAN have fixed location without any mobility except M-BAN2. M-BAN2 moves with 0.4m/s speed at an interval of 4m.

The coexistence condition is predictable according to the speed of main mobile WBAN and density of interferential WBANs in around. For example, speed of the main mobile WBAN has an influence on the coexistence condition when there is dense or sparse interference around the main mobile WBAN. On the other hand, when there is no existing interference, result of coexistence state is always *none* regardless of the speed of the main mobile WBAN.

In this paper, we demonstrate reliability and accuracy of the proposed algorithm by comparing the predicted coexistence state according to the speed of the main mobile WBAN with the result of naive Bayesian classifier applying *PRR*, $SINR_{holding-time}$ and *previous state* gained from simulation progress. We set 4 simulation cases depending on changes of speed of the main mobile WBAN and the interference environment. Case 1 and Case 2 have 17 fixed interferential WBANs and Case 3 and Case 4 have 17 fixed interferential WBANs and one mobile interferential WBAN. As shown in Table 4, coexistence condition is predictable to *static, semi-dynamic*, *dynamic* or *none* according to the speed of main mobile WBAN for each interval.

Zhou *et al*., set the jammer node to introduce interference to the communication between receiver and sender node [17]. If jammer node comes to receiver node, it uses the *PRR* difference value that occurs depending on the distance between jammer and receiver node to detect interference from circumjacent node. Likewise, *PRR* reflecting the link quality of the communication is appropriate parameter to check whether or not interference existed. However, *PRR* falls under the influence of packet transmit rate as well as link quality of the communication [18, 19]. If there is interference, e.g., the more packet transmit rate increases, the more *PRR* declines. Also, this outcome occurs even there is no interference around.

In [20], RSSI(Received Signal Strength Indicator) is employed to detect interference in the environment that WLAN coexists with ZigBee network as interference factor. It is a simple method to detect interferential existence by using RSSI difference value when ZigBee network providing low power communication is affected by WLAN having high power to communicate relatively. But, it is hard to determine that ZigBee network is going through interference from WLAN by analyzing just RSSI value because RSSI of IEEE 802.15.4 frames existing within the 0.3m is around 250dBm as high as the maximum 255dBm. Furthermore, systemic error region that is due to inaccuracies in the RSSI values arises for a fleeting moment randomly. For these reasons, we cannot entirely depend on a single RSSI vale to detect interference [21].

[Table 4.] Predicted coexistence state per speed

<table>
<tr><th rowspan="2"></th><th colspan="2">Case 1</th><th colspan="2">Case 2</th></tr>
<tr><th>Speed (m/s)</th><th>Coexistence-state</th><th>Speed (m/s)</th><th>Coexistence-state</th></tr>
<tr><td rowspan="2">section 1</td><td rowspan="2">0.2</td><td rowspan="2">Semi-dynamic</td><td rowspan="2">0.4</td><td>Dynamic</td></tr>
<tr><td>Dynamic</td></tr>
<tr><td>section 2</td><td>0.2</td><td>Semi-dynamic</td><td>0.2</td><td>None</td></tr>
<tr><td rowspan="2">section 3</td><td rowspan="2">0</td><td rowspan="2">Static</td><td rowspan="2">0.4</td><td>None</td></tr>
<tr><td>Dynamic</td></tr>
<tr><td>section 4</td><td>0.4</td><td>None</td><td>0.2</td><td>None</td></tr>
<tr><td rowspan="2">section 5</td><td rowspan="2">0.4</td><td>Dynamic</td><td rowspan="2">-</td><td rowspan="2">-</td></tr>
<tr><td>None</td></tr>
</table>

(a) Case 1 and Case 2

<table>
<tr><th rowspan="2"></th><th colspan="2">Case 3</th><th colspan="2">Case 4</th></tr>
<tr><th>Speed (m/s)</th><th>Coexistence-state</th><th>Speed (m/s)</th><th>Coexistence-state</th></tr>
<tr><td>section 1</td><td>0.2</td><td>Semi-dynamic</td><td>0.2</td><td>Semi-dynamic</td></tr>
<tr><td rowspan="2">section 2</td><td rowspan="2">0</td><td rowspan="2">Static</td><td>0.4</td><td>Dynamic</td></tr>
<tr><td>0.4</td><td>Dynamic</td></tr>
<tr><td rowspan="2">section 3</td><td>0.4</td><td>Dynamic</td><td rowspan="2">0</td><td rowspan="2">Dynamic</td></tr>
<tr><td>0.4</td><td>Dynamic</td></tr>
<tr><td rowspan="2">section 4</td><td>0.4</td><td>Dynamic</td><td rowspan="2">0.2</td><td rowspan="2">Dynamic</td></tr>
<tr><td>0.4</td><td>Dynamic</td></tr>
<tr><td rowspan="2">section 5</td><td rowspan="2">0.2</td><td rowspan="2">None</td><td>0.4</td><td>Dynamic</td></tr>
<tr><td>0.4</td><td>None</td></tr>
</table>

(b) Case 3 and Case 4

So, in this paper, we measure two parameters, i.e., *PRR* and *SINR*, to improve weak points occurred in the case that user depends on just a single parameter for detecting existed interference. We check *PRR* value whether it is above or below the threshold value providing reliable communication and $SINR_{holding-time}$ difference value simultaneously.

4.2 Simulation Result

Table 5 shows measured average *PRR* and $SINR_{holding-time}$ for each interval in simulation Case 1, Case 2, Case 3 and Case 4. Contrary to *PRR*, $SINR_{holding-time}$ is same independent of transmit rate change.

In the results of *PRR* for packet with change of the transmit rate, there are sections that is able to predict coexistence state, while there are sections that is not possible to get a correct prediction. For instance, we can catch the influence of interference of *section 2* and *section 3*'s *PRR* values that are below threshold in Case 1. But, *PRR* values of *section 1* and *section 5* in Case 1 are relatively high even though there is interference existed. It is the same in Case 2 and we got to know that *PRR* value is measured relatively high when main mobile WBAN passes interferential WBAN fast by Case 2. And, the most *PRR* values are fairly high despite interference when packet transmit rate is low as 5pts/s. Consequently, we can confirm that packet transmit rate of sender and speed of main mobile WBAN have an substantial influence on the *PRR* value by analyzing results of simulation.

In Case 1, we can analogize coexistence condition with $SINR_{holding-time}$ precisely. In spite of fast move as 0.4m/s, however, $SINR_{holding-time}$ is maintained for a long time in *section 2* of Case 2.

In Case 3 and Case 4, we add interferential mobile WBAN to environment of Case1 and Case 2. Let's see the values of *section 3* in Case 3 and *section 2* in Case 4. According to the values of *PRR* and $SINR_{holding-time}$, the predictable coexistence states are *none* and *semi-dynamic* respectively but Fig. 5 shows that actual state is *dynamic* and result of proposed algorithm is exactly same with actual state. Also, values of *section 3* in Case 4 are influenced by interferential mobile WBAN. According to the values of *PRR* and $SINR_{holding-time}$, the

[Table 5.] *PRR* and $\boldsymbol{SINR_{holding-time}}$

	Case 1			**Case 2**		
	***PRR* (pts/s)**		$\boldsymbol{SINR_{holding-time}}$ **(s)**	***PRR* (pts/s)**		$\boldsymbol{SINR_{holding-time}}$ **(s)**
	Rate 5	**Rate 10**		**Rate 5**	**Rate 10**	
section 1	1	0.981	3	1	0.982	1
				0.96	0.982	4.5
section 2	0.95	0.868	18	1	0.95	0
section 3	0.918	0.807	20	1	1	0
				1	0.982	2
section 4	1	1	0	1	1	0
section 5	1	0.982	2	-	-	-
	1	1	0			

	Case 3			**Case 4**		
	***PRR* (pts/s)**		$\boldsymbol{SINR_{holding-time}}$ **(s)**	***PRR* (pts/s)**		$\boldsymbol{SINR_{holding-time}}$ **(s)**
	Rate 5	**Rate 10**		**Rate 5**	**Rate 10**	
section 1	0.894	0.869	3	0.894	0.869	3
section 2	0.857	0.857	20	0.96	0.982	4.5
				0.976	0.972	1.5
section 3	0.982	0.96	4.5	0.941	0.935	6
	1	1	1.5			
section 4	0.976	0.972	1.5	0.976	0.972	1.5
	1	0.982	2			
section 5	1	1	0	1	.0982	2
				1	1	0

predictable coexistence states are *none* and *semi-dynamic* respectively but Fig. 5 shows that actual state is *dynamic* and result of proposed algorithm is same with actual state too.

From the simulation, we can observe that it cannot recognize coexistence condition accurately by just using a single *PRR* value or a single *SINR* value. However, the result of naive Bayesian classifier, the proposed algorithm which jointly considers *PRR* value, $SINR_{holding-time}$ and *previous state*, is equal to actual state. Consequently, Table 6 shows that the proposed algorithm is more reliable and accurate in the performance than considering *PRR* or *SINR* value by itself to detect coexistence condition in multiple WBANs environment.

[Table 6.] Performance result

	Actual state	***PRR* (rate5)**	***PRR* (rate10)**	***SINR***	**Proposed algorithm**
section 1	*Semi-dynamic*	*None*	*None*	*Semi-dynamic*	*Semi-dynamic*
section 2	*Semi-dynamic*	*None*	*Dynamic*	*Semi-dynamic*	*Semi-dynamic*
section 3	*Static*	*None*	*Dynamic*	*Static*	*Static*
section 4	*None*	*None*	*None*	*None*	*None*
	None	*None*	*None*	*None*	*None*
section 5	*Dynamic*	*None*	*None*	*Dynamic*	*Dynamic*
	None	*None*	*None*	*None*	*None*

(a) Case 1

	Actual state	***PRR* (rate5)**	***PRR* (rate10)**	***SINR***	**Proposed algorithm**
section 1	*Dynamic*	*None*	*None*	*Dynamic*	*Dynamic*
	Dynamic	*None*	*None*	*Semi-dynamic*	*Dynamic*
section 2	*None*	*None*	*None*	*None*	*None*
section 3	*None*	*None*	*None*	*None*	*None*
	Dynamic	*None*	*None*	*Dynamic*	*Dynamic*
section 4	*None*	*None*	*None*	*None*	*None*

(b) Case 2

	Actual state	***PRR* (rate5)**	***PRR* (rate10)**	***SINR***	**Proposed algorithm**
section 1	*Semi-dynamic*	*Dynamic*	*Dynamic*	*Semi-dynamic*	*Semi-dynamic*
section 2	*Static*	*Dynamic*	*Dynamic*	*Static*	*Static*
section 3	*Dynamic*	*None*	*None*	*Semi-dynamic*	*Dynamic*
	Dynamic	*None*	*None*	*Dynamic*	*Dynamic*
section 4	*Dynamic*	*None*	*None*	*Dynamic*	*Dynamic*
	Dynamic	*None*	*None*	*Dynamic*	*Dynamic*
section 5	*None*	*None*	*None*	*None*	*None*

(c) Case 3

	Actual state	***PRR* (rate5)**	***PRR* (rate10)**	***SINR***	**Proposed algorithm**
section 1	*Semi-dynamic*	*Dynamic*	*Dynamic*	*Semi-dynamic*	*Semi-dynamic*
section 2	*Dynamic*	*None*	*None*	*Semi-dynamic*	*Dynamic*
	Dynamic	*None*	*None*	*Dynamic*	*Dynamic*
section 3	*Dynamic*	*None*	*None*	*Semi-dynamic*	*Dynamic*
section 4	*Dynamic*	*None*	*None*	*Semi-dynamic*	*Dynamic*
section 5	*Dynamic*	*None*	*None*	*Dynamic*	*Dynamic*
	None	*None*	*None*	*None*	*None*

(d) Case 4

Chapter 5

Conclusion

In this paper, we propose a prediction algorithm for coexistence problem by applying *PRR*, $SINR_{holding-time}$ difference values and *previous state* to naive Bayesian classifier to get an advanced reliable and accurate performance in multiple WBANs environment. Consequently, the algorithm proposed in this paper provides fairly higher reliability to detect coexistence comparing to existing studies considering a *PRR* or *SINR* value itself. Furthermore, this study plays a major role for the first attempt to classify coexistence condition into several states more than detection. And we leave the suitable handling mechanism of each coexistence states and evaluation in more general network topologies for future work.

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