A Prediction Algorithm for Coexistence Problem in Multiple WBANs Environment

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ABSTRACT

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 detection 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 detection with various packet transmit rates of sender node and speeds of 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.

Categories and Subject Descriptors

C.2.3[COMPUTER-COMMUNICATION NETWORKS]: Network Operations - *Network monitoring*

General Terms

Experimentation

Keywords

WBAN, Coexistence problem, Naive Bayesian classifier, *PRR*, *SINR*

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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 detection with various packets transmit rates of sender node and speeds of 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.

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 predicting 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.

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 [9,10].

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:

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

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.

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

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 [11]. 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.

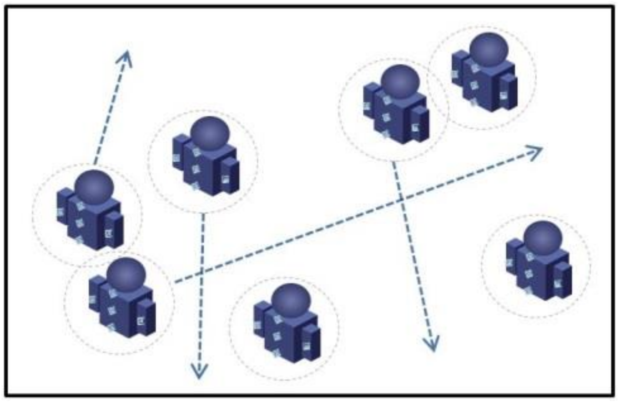


Figure. 1. Multiple WBANs environment

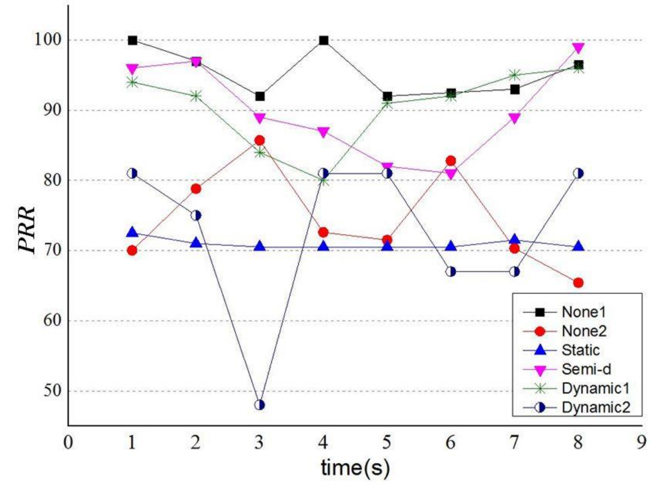
In this paper, we propose a prediction algorithm for coexistence problem in multiple WBANs environment. In addition, we classify the coexistence condition into four states, such as *static*, *semi-dynamic*, *dynamic* and *none*, according to the holding time of interference. *Static* indicates that WBAN 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.

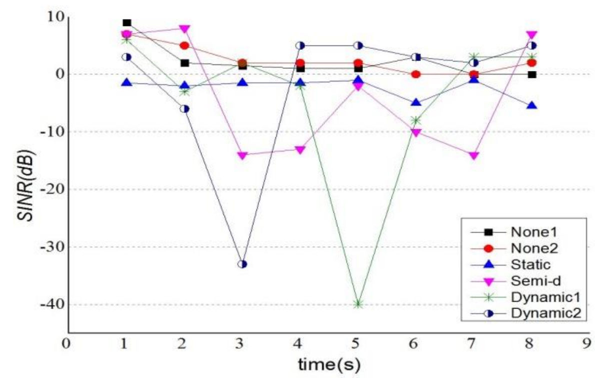
3.2 Training Data and Prior Probability

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 1.

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 [12]. 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.



(a) *PRR*



(b) *SINR*

Figure. 2. *PRR* and *SINR* value according to the coexistence condition

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 Interfere nce Strength) are for concurrent transmission and *N* is noise level measured at the coordinator node. In detail, *RSS* is average receive d signal strength from four sensor nodes and *RIS* is received inte rference signal strength from other WBAN. We obtain $SINR_{holding-time}$ using calculated *SINR* value.

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.

Table 1. 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	

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. 2. 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 $\alpha \leq SINR_{holding-time} < \beta$ and it is hard to obtain by intuitive knowledge only. Consequently, we gained the training data Table 1 by analyzing *PRR* and *SINR* values on the Fig. 2.

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*.

Table 2. Prior probability

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

The prior probability can be derived from the training data in Table 1, and the results are shown in Table 2. We predict 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:

- $P(s)\,P(PRR \geq PRR_{threshold}|s)P(0 < SINR_{holding-time} < \alpha|s)P(n|s) = 0$
- $P(s-d)P(PRR \geq PRR_{threshold}|s-d)P(0 < SINR_{holding-time} < \alpha|s-d)P(n|s-d) = 0$
- $P(d)\,P(PRR \geq PRR_{threshold}|d)\,P(0 < SINR_{holding-time} < \alpha|d)\,P(n|d) = \frac{1}{72}$
- $P(n)\,P(PRR \geq PRR_{threshold}|n)P(0 < SINR_{holding-time} < \alpha|n)\,P(n|n) = 0$

4. PERFORMANCE EVALUATION

4.1 Simulation Mode

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. 3.

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

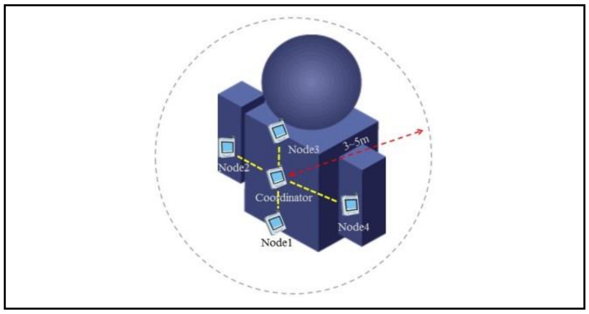


Figure. 3. A single WBAN

value to 0.9 and 0dB for *PRR* and *SINR* respectively to guarantee superior quality of communication. And we designate α=3 and β=19 of the Table 1 and Table 2 taking the speed of mobile WBAN into account.

The simulation of this paper is conducted on a field 24m×16m. Then, we set 12 WBANs, one as the mobile WBAN and 5 as fixed interferential WBANs, at the field to make a multiple WBANs environment. 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. 4, the 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.

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

In this paper, we demonstrate reliability and accuracy of the proposed algorithm by comparing the predicted result of coexistence state about speed of the mobile WBAN with the result of naive Bayesian classifier applied *PRR*, $SINR_{holding-time}$ and *previous state* gained from simulation progress. We set two simulation cases depending on changes of speed of the mobile WBAN. As shown in Table 3, coexistence condition is predictable to *static*, *semi-dynamic*, *dynamic* or *none* according to the speed of mobile WBAN for each interval.

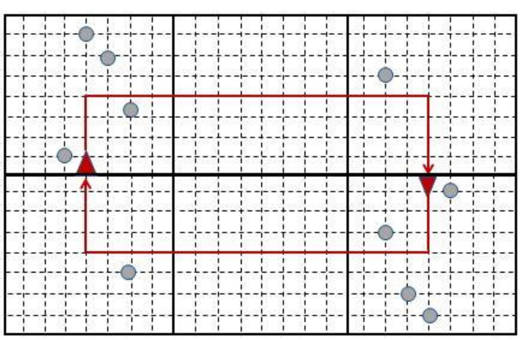


Figure. 4. Simulation field

Table 3. Predicted coexistence state per speed

	Case 1		Case 2	
	Speed (m/s)	Coexistence-state	Speed (m/s)	Coexistence-state
section 1	0.2	*Semi-dynamic*	0.4	*Dynamic*
				Dynamic
section 2	0.2	*Semi-dynamic*	0.2	*None*
section 3	0	*Static*	0.4	*None*
				Dynamic
section 4	0.4	*None*	0.2	*None*
section 5	0.4	*Dynamic*	-	-
		None		

Zhou *et al.*, set the jammer node to introduce interference to the communication between receiver and sender node [13]. 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 [14, 15]. 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 [16], 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 [17].

Table 4. *PRR* and $SINR_{holding-time}$

	Case 1			Case 2		
	PRR **(pts/s)**		$SINR_{holding-time}$ **(s)**	***PRR*** **(pts/s)**		$SINR_{holding-time}$ **(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			

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 4 shows measured average *PRR* and $SINR_{holding-time}$ for each interval in simulation Case1 and Case2. Contrary to *PRR*, the $SINR_{holding-time}$ 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 *section2* and *section3*'s *PRR* values that are below threshold in Case1. But, *PRR* values of *section1* and *section5* in Case1 are relatively high even though there is interference existed. It is the same in Case2 and we got to know that *PRR* value is measured relatively high when mobile WBAN passes interferential WBAN fast through Case2. 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 mobile WBAN have an substantial influence on the *PRR* value by analyzing results of simulation.

In Case1, 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 *section2* of Case2.

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 prior respected result. Consequently, Fig. 5 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.

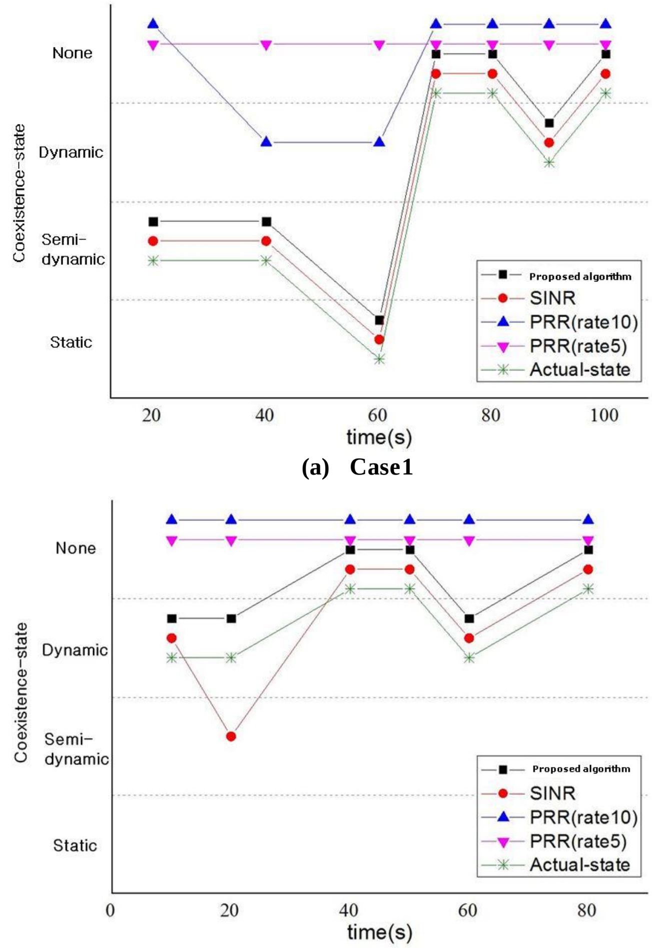


Figure. 5. Result graph

5. CONCLUSION AND FUTURE WORK

In this paper, we proposed 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.

6. ACKNOWLEDGMENTS

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7. REFERENCES

[1] IEEE 802.15.6 WPAN Task Group 6 BAN. DOI= http://www.ieee802.org/15/pub/TG6.html.

[2] Deylami, M. and Jovanov, E., 2012. Performance Analysis of Coexisting IEEE 802.15.4-based Health Monitoring WBANs. *In Proceedings of the Engineering in Medicine and Biology Society.* 2464-2467.

[3] Kazemi, R., 2011. A Novel Genetic-Fuzzy Power Controller with Feedback for Interference Mitigation in Wireless Body Area Networks. *In Proceedings of the Vehicular Technology Conference.* 1-5.

[4] Qixing Pang and Leung, V.C.M., 2007. Channel Clustering

and Probabilistic Channel Visiting Techniques for WLAN Interference Mitigation in Bluetooth Devices. *IEEE Trans. on Electromagnetic Compatibility*, 914-923.

[5] Villegas, Eduard Garcia, 2007. Effect of Adjacent-Channel Interference in IEEE 802.11 WLANs. *In Proceeding of the Cognitive Radio Oriented Wireless Networks and Communications*, 118-125.

[6] Dian Fan, Xianbin Wang, 2011. Cross-layer Interference Minimization-Oriented Channel Assignment in IEEE 802.11 WLANs. *In Proceeding of the Personal Indoor and Mobile Radio Communications*, 1083-1087.

[7] Chulho Won, 2005. Adaptive Radio Channel Allocation for Supporting Coexistence of 802.15.4 and 802.11b. In Proceeding of the Vehicular Technology Conference. 2522-2526.

[8] DaeGil Yoon, 2006. Packet Error Rate Analysis of IEEE 802.11b under IEEE 802.15.4 Interference. *In Proceeding of the Vehicular Technology Conference*. 1186-1190.

[9] Ahmed,S, 2010. A Bayesian Routing Framework for Delay Tolerant Networks. *In Proceeding of the WCNC*.

[10] Marsland,S , 2009. Machine Learning: An Algorithmic Perspective. *A Chapman & Hall*.

[11] Barakah, D.M., 2012. A Survey of Challenges and Applications of Wireless Body Area Network and Role of a Virtual Doctor Server in Existing Architecture. *In Proceeding of the Intelligent Systems, Modelling and Simulation*. 214-219.

[[12] YongGye Baek, Jinsung Cho, 2007. KHIX: A Scalable and Reconfigurable Embedded System Operating. *In Proceeding of the Korea Computer Congress*.

[13] Gang Zhou, 2005. RID : Radio interference Detection on Wireless Sensor Networks. *In Proceeding of the INFOCOM*, 891-901.

[14] Angrisani, L., 2008. Performance measurement of IEEE 802.11b-based networks affected by narrowband interference through cross-layer measurements. *IET journal*, 2(1), 82-91.

[15] Ruitao Xu, 2011. MuZi: Multi-channel ZigBee Networks for Avoiding WiFi Interference. *In Proceeding of the Cyber, Physical and Social Computing*, 323-329.

[16] Minsuk Kang, 2007. Adaptive interference-aware multi-channel clustering algorithm in a zigbee network in the presence of WLAN interference. *In Proceeding of the Wireless Pervasive Computing*.

[17] Univ. of Johns Hopkins, 2010. On the mechanisms and effects of calibration RSSI measurements for 802.15.4 radios. *In Proceeding of the European Conference on Wireless Sensor Networks*.