HEIR: Heterogeneous Interference Recognition for Wireless Sensor Networks

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Abstract*—With the rapid development of wireless communication technology, a large number of wireless networks and devices that have different PHY and MAC layers coexist with each other. 2.4GHz Industrial, Scientific and Medical (ISM) band is becoming increasingly crowded. Wireless Sensor Networks (WSNs) which use low-power communication standard IEEE802.15.4 share the unlicensed spectrum with a plethora of other devices and technologies, such as WiFi systems underlying IEEE802.11, Bluetooth systems underlying IEEE802.15.1, and even non-communication appliance like microwave ovens. The ability to detect what radios are operating in the neighborhood is a fundamental need of WSNs, ranging from network management to network security. Since there are no explicit mechanisms to recognize such heterogeneous interference sources, WSNs often have no reasonable way to guard against them. In this paper, we describe the main working principle of heterogeneous interference sources, and present HEIR, a detector that is able to accurately identify heterogeneous interference sources. HEIR builds on the insight that there are hidden repeating patterns of signals which can be used to construct unique signatures and identify different types in most wireless protocols. The method can be implemented through signal sampling, interference estimation, feature extraction, and device classification. We show the experimental evaluation in an indoor testbed that HEIR is accurate in several different scenarios, and can live on sensor nodes' hardware. Since no any channel changes, the network topology is not interrupted, and the stable communication in real-time is ensured then.

Keywords—heterogeneous interference; identification method; sampling; estimation; feature extraction; classification

I. Introduction

Wireless sensor network (WSN) is a small, embedded, low-cost, low-power network. It will be widely deployed in the near future. It can be used in many applications, including home, office and various urban environments. IEEE 802.15.4 standard provides a simple, low-power physical (PHY) and media access control (MAC) layer protocol stack to support a data rate of 250kbps for WSNs' connection, which is wireless self-organizing and low power.

IEEE802.15.4 (2003) standard can operate in three unlicensed industrial, scientific and medical (ISM) bands and provide 27 channels: 1 at 868MHz band in Europe, 10 at 915 MHz band in North America, and 16 at 2.4 GHz band available worldwide. 2.4GHz band is the most commonly used frequency. With the growing popularity of wireless communication technology, this band is used by a lot of technologies and devices [1], including wireless local area network (WLAN) as WiFi systems underlying IEEE802.11 series standards, wireless personal area network (WPAN) as Bluetooth systems (BT) underlying IEEE802.15.1 standard and microwave oven (MWO) etc. Thus, 2.4GHz band becomes very crowded, shown in Fig. 1.

Due to the coexistence of heterogeneous wireless communication systems, collisions and congestions on shared channels will be inevitable. This will cause serious repercussions in the communication of WSNs, including retransmission increase, energy consumption, transmission latency, reception decrease and reliability reduction etc. [2]. Therefore, how to reduce the bad influence caused by heterogeneous interference and make WSNs more reliable become a hot topic nowadays.

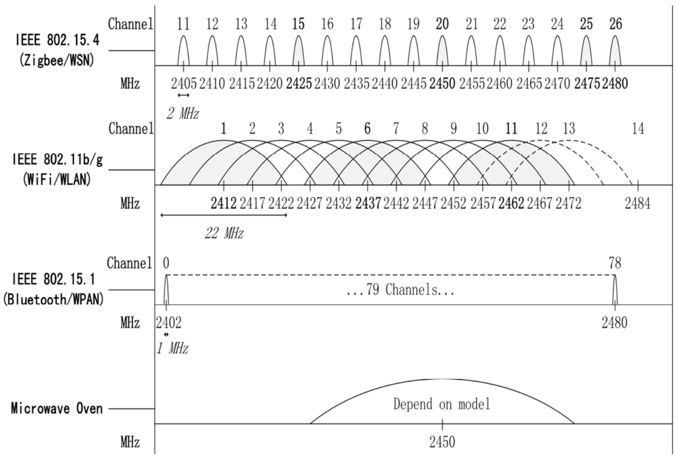

Fig. 1. Channel usage of 2.4GHz ISM band by different technologies.

Heterogeneous interference has various characteristics and properties [3]. In order to recognize them more scientifically, we must judge the existence of them first, and then classify them accurately [4]. For example, MWOs occupy multi-channels intensively, but they often work no more than half an hour. So, it is feasible to temporarily stay in a completely congested channel when MWOs' interference exists. On the other hand, WiFi with no data traffic generates little interference, but it will continue to occupy its own channel, and increase data traffic depending on usage situation of the network. Accordingly, channel switch is more effective to avoid heterogeneous interference when WiFi coexist. Moreover, if BT is detected as heterogeneous interference source, then almost all the channels will be affected for its frequency hopping mechanism. But fortunately, the duration on each channel is limited.

This paper analyzes the characteristics of common heterogeneous interference signals and makes a division, including WiFi, BT and MWO. On this basis, a smart detector HEIR is proposed, which can accurately detect existed heterogeneous interference sources in the neighborhood. HEIR is robust and works accurately even in the presence of multi-overlap signals. HEIR is online running and passive measurement with little overhead. Finally, HEIR could be implemented efficiently, because it uses time series analysis in binary and requires only modest extra.

The key insight behind HEIR is the unique hidden repeating patterns of most wireless signals, which are necessary for their operation. For example, WiFi uses a repeating cyclic prefix to avoid inter-symbol interference between consecutive OFDM symbols. BT modulates data bits using FSK on a Gaussian pulse, which repeats with a different frequency and so on. HEIR exploits the existence of these patterns to create unique signatures for each signal type.

Algorithmically, HEIR samples signals through single channel scanning and detects heterogeneous interference sources through interference estimation model. It extracts feature vectors using the following core idea: if a signal has hidden repeating pattern, then a delayed version of the signal correlated with the original one will show peaks at specific delay intervals. These intervals form a signature for each signal and can be used to extract feature vectors. We build on prior work in cyclostationary signal analysis to design an efficient feature extraction technique based on time series analysis in binary and develop a novel decision tree to classify component signal types.

We evaluate HEIR using testbed experiments in an indoor office environment. Experimental results show that it is accurate in several different scenarios, and can live on the sensor nodes hardware. The sensor nodes can always connect to the network without changing current channel, so that the network topology maintains stable. The device classification of heterogeneous interference sources facilitates WSNs' centralized decision making and channel management. HEIR provides a scientific basis for the further design of heterogeneous interference avoidance strategies on the upper layers, such as routing algorithm.

II. BACKGROUND AND MOTIVATION

IEEE802.15.4 standard partly considers the coexistence problem with other standards. To avoid packet loss caused by heterogeneous interference, IEEE802.15.4 standard utilized energy detection based on spectrum scanning as network's channel management approach [5]. The scheme needs to scan channel energy of all nodes, evaluate usage situation of all channels, and then switch to less occupied channel for communication. However, this could make nodes temporarily detach the network in energy detection, which is not conducive to network topology. In addition, the mechanism can not identify heterogeneous interference on the channel directly. Furthermore, channel energy detection is not accurate enough for heterogeneous interference, because it can either indicate background noise or signal strength of a receiving packet. In actual wireless communication, heterogeneous interference will increase channel energy, but it is not the only criminal.

Many researchers evaluate heterogeneous interference through link quality estimation. Baccour etc. studied the coexistence problem about WSN and other wireless systems through link quality estimator [6]. The conclusion they made meets our actual experience. If there are some overlapped signals, WSN will be interfered by WiFi and BT seriously, but vice versa is little. In addition to empirical research, they also provided a number of complex analytical models. S. U. Yoon etc. researched channel hopping through optimization and weighting of link quality [7]. Link quality estimation periodically sends control packets to evaluate whether the heterogeneous interference exists, but it can not make any classification of device types. On the other hand, the method is not accurate enough all the time and always brings a lot of overhead on real performance.

Cognitive radio is another important method. This method analyzes electromagnetic spectrum, and scans channel energy. Patro etc. used existed WiFi interface card to measure spectrum and identify device in the 2.4 GHz band [8]. Since IEEE802.15.4 chip is different from IEEE 802.11 interface card in technical characteristics, it can not be suitable for WSN. In addition, this method needs full spectrum scanning and machine learning for device classification, the technical complexity is high indeed. Chowdhury etc. proposed spectrum sense based on sensor nodes and offline classification of heterogeneous interference sources [9]. This method matches observed spectral characteristics and stored reference waveform through full spectrum scanning. On this basis, it successfully analyzes WiFi and MWO. After that, it is recommended for heterogeneous interference avoidance strategy like channel selection, packet scheduling and sleep-wake cycle. This method doesn't operate scanning and receiving at the same time, which results topology interruption. On the other hand, offline classification algorithm is not suitable for applications in real-time. Cognitive radio can accurately discern any different kinds of radios and represents the direction of future research, but its implementation is too complex, technical cost is relatively high, and some major mechanism is not suitable for embedded sensor networks in real-time nowadays.

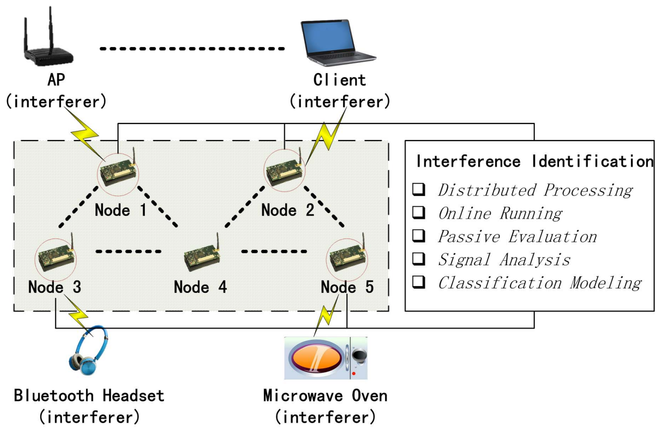

Fig. 2. Overview of HEIR's function.

Cyclostationary signal analysis has been used widely in a variety of applications, which was pioneered in the early 90's through the work of Gardner [10]. DOF builds on these prior work has designed the feature extraction technique based on FFT and classification technique based on hierarchical SVMs [11]. Although the technique is robust to the presence of multiple interfering signals and can reuse the same SVM decision tree for classifying all component signal types, its computational complexity is not suitable for running live on sensor nodes hardware.

Boano etc. used RSSI readings to improve channel simulation model and analyze different heterogeneous interference sources (such as WiFi, BT, and MWO), but they didn't make any device classification [12]. This interference identification mechanism uses signal analysis and classification modeling, considers the balance of accuracy and complexity. Furthermore, it gives us a lot of inspiration.

This article bases on these efforts above, analyzes detail signal characteristics of common heterogeneous interference sources, makes device classification, and proposes a heterogeneous interference detector HEIR, which is able to accurately identify signal types through signal sampling, interference estimation, feature extraction, and device classification (see Fig. 2). The real experiment on indoor office testbed shows its robustness and accuracy in different experimental scenarios.

III. HETEROGENEOUS INTERFERENCE SOURCES

A. *WiFi/WLAN*

Wireless LAN (WLAN or WiFi) is based on the IEEE 802.11 standard and its revised version of different technologies. IEEE 802.11b, g and n are in the 2.4 GHz band. According to the restrictions, there are up to 14 channels that can be chosen from: 13 in Europe, 11 in North America. Channel 14 is allowed for Japan and IEEE 802.11b only. The channel width of IEEE802.11b and g is 22 MHz. The difference between two neighbor channels' center frequencies is only 5 MHz. So, two adjacent channels will certainly overlap. Channel 14 is an exception, which is 12 MHz away from its former channel (see Fig. 1). IEEE 802.11n is also working on the channel above, but it supports 40 MHz wide channel bonding and multi-antenna-based multi-input multi-output (MIMO) technology. In this paper, IEEE 802.11n will be set to the single channel mode like IEEE802.11b or g. Typically, in order to achieve maximum throughput, non-overlapped channels are used, such as channel 1, 6 and 11 (bold channel in Fig. 1). An IEEE802.11 channel overwrites 4 IEEE 802.15.4 channels. When WiFi's transmission is active, RSSI readings of MICAZ sensor nodes can show a clear peak of signals, and detect the transmission time and duration roughly. According to various standard versions, different modulation and data rate may be used: IEEE 802.11b is up to 11 Mb/s, IEEE802.11g is up to 54 Mb/s, IEEE 802.11n is up to 72 Mb/s in a single flow channel. Although there are different data rates, but beacons sent by access point (AP) are different from normal data stream. IEEE 802.11b uses direct sequence spread spectrum modulation (DSSS), but revision g and n use orthogonal frequency division multiplexing (OFDM).

Each AP periodically sends a beacon frame, notices and remains connection with all clients in the network. In order to maintain compatibility with all interface cards that connected to the network, beacons use the lowest data rate (1 or 2 Mbit/s) for transmission. Minimum theoretical beacon length is about 30 bytes, including a 28-byte management frame and 2-byte beacon interval field, but most beacons exceed 100 bytes. Therefore, it can be detected by RSSI sampling at 8,192 Hz. IEEE802.11 sends 10 beacons per second in default, so beacon frequency is 10Hz (exact value is 9.766Hz). The default beacon cycle is 100 time units (about 102.4 milliseconds). When WiFi transmits on the channel, beacons are very good indicators, and can be distinguished from RSSI readings. However, when the channel is heavily used, beacons become difficult to identify because IEEE802.11 standard does not provide the retention slot for beacons. This means that, APs access communications medium using CSMA / CA mechanism as all other competitors, which results in a possible beacon delay. If APs are away from measuring sensor nodes, a growing number of beacons will be lost in the data traffic. Other WiFi's traffic can transmit at a higher speed, which is very difficult to identify. Some short data frames can not be measured even by 11 kHz RSSI sampling, because the transmission speed is too fast. These flows do not have typical characteristics, due to various upper layer protocols and applications. Figure 3 illustrates WiFi's transmissions on a busy network channel.

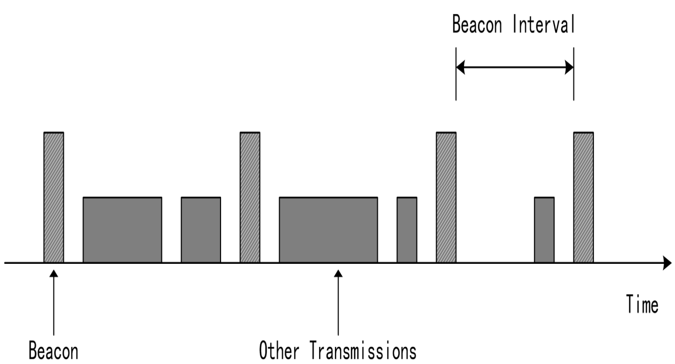

Fig. 3. WiFi's transmissions on a busy network.

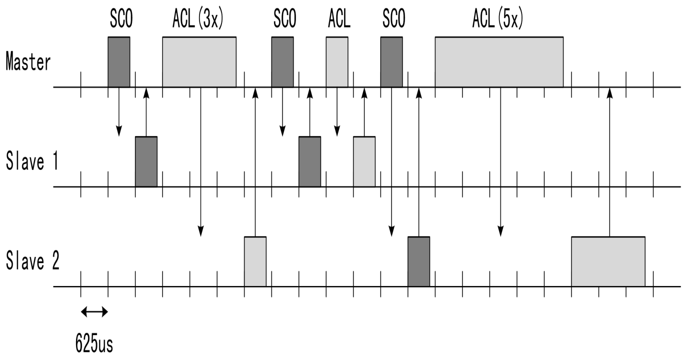

Fig. 4. Bluetooth's transmissions on SCO and ACL.

B. Bluetooth/WPAN

Bluetooth is a low-cost, medium-power, short-distance, and robust wireless personal area network (WPAN) underlying IEEE802.15.1 standard. It also operates on the 2.4GHz band, and uses 79 different channels with 1 MHz wide (see Fig. 1). It supports adaptive power control and different data rates to adapt wireless environment. Currently, BT has different available versions. The transmit power may be 2.5 and 100 mW. Version 2.0 + Enhanced Data Rate (EDR) is up to 3 Mbit/s. It uses adaptive frequency hopping (AFH), which changes 1600 times per second and makes itself less interfered by other wireless technologies. The time interval between two hopping frequency is 625 microseconds, which is called a time slot and could be detected by 11 kHz sampling rate. BT uses time division multiple access / time division duplex (TDMA / TDD) mechanism to access transmission channel. BT supports two physical link types: Synchronous Connection Oriented (SCO) link and Asynchronous Connectionless (ACL) link. SCO link is typically used for voice transmission, and strictly based on single-slot packet. Its transmission time is no more than one time slot (625us) on a channel. ACL link is packet-based, and able to use 1, 3 or 5 time slots (see Fig. 4) without any channel change. Therefore, the traffic load and channel occupancy depend on applications' features and wireless environments in a large part. The flow changes from low (normal flow of wireless input device) to high (File Transfer (FTP) burst traffic or spread spectrum transmission of wireless audio headset).

It should be noted that there are some new patented technologies, such as "Logitech Advanced 2.4 GHz wireless technology," whose signal characteristic is very similar to BT. This technique can be used for wireless input devices as same as BT, but it uses frequency-agile hopping instead. That is to say, channels changes only when interference occurs. If there is no additional spectrum knowledge, this technology is likely to be mistaken for BT. Otherwise, discovery and initial connection phase are not researched in this work, and the new Bluetooth 4.0 version is not considered.

C. Microwave Oven/MWO

Microwave ovens are widely used appliances to heat food through high power, which operates in the 2.4 GHz band. Common MWOs' center frequency is about 2.45 GHz, spreading at least 5 MHz width. The average output power of MWOs is 800 watts or so (a specific type of precise technical specifications can be typically found on a label behind). Most output energy is limited in the cooking position by shielding, but some microwave will leak into the environment. If the working channel of WSN is close to the center frequency of microwave, the interference level will be high. When WSNs work on the channel away from microwave oven's center frequency, the interference level will be reduced.

MWOs have a separate magnetron that transmits high frequency wave. Since the magnetron must work at full power, different power levels can only be set by users through turning on and off. Therefore, heating will work between two off-times (see Fig. 5). Microwave emission cycle is usually based on the frequency of power supply (50Hz in Europe, or 60Hz in North America). Electromagnetic waves are emitted only half a cycle. Unlike digital signals of wireless communication, periodic channel obstruction can be easily identified. In addition, the microwave signal should be measured in the heating time, because there is no microwave radiation on the off-time.

IV. KEY INSIGHT

According to the above heterogeneous interference sources analysis, we get a key insight that almost every wireless protocol for communication has a hidden repeat mode. For example, the OFDM technology used in wireless network physical layer has a cyclic prefix (CP) at the end of each OFDM symbol block, which is repeated from the beginning. It helps to avoid inter-symbol interference, and keep the orthogonality of OFDM sub-carriers. Therefore, CP is an important property of physical layer and requirement of correct operation for OFDM technology. Similarly, each other protocol operating in the ISM band has a unique repeating pattern, which is necessary for its correct operation.

These types are fundamental and important properties of the corresponding physical layer, and included in each packet (whether a data packet, ACK, or each bit stream). It should be noted that these types are not a certain specific hardware implementation with some personality or parameter settings of physical layer (for example, different channel transmission time of a 1500B WiFi's packet is according to what kind of bitstream it used). Therefore, these types can potentially form a robust signature mechanism that is constant to different hardware or physical layer's parameters.

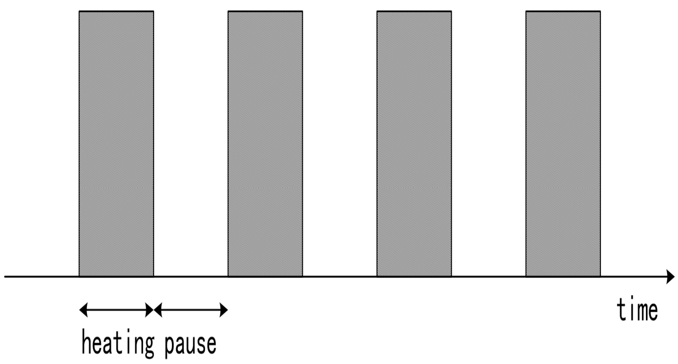

Fig. 5. Working procedure of MWO.

Then, how can we use the characteristics of these hidden patterns to detect the signal type? We can use the following method from cyclostationary signal analysis: if a signal has a repeating pattern, then if we correlate the received signal against itself delayed by a fixed amount, the correlation will peak when the delay is equal to the period at which the pattern repeats. Specifically, the receiving signal samples can be denoted by $x[n]$. Consider the following function, which is known as Cyclic Autocorrelation Function (CAF):

$$R_x^{\alpha}(\tau)=\sum_{n=-\infty}^{\infty}x[n]x^*[n-\tau]\exp(-j2\pi\alpha n) \qquad (1)$$

Since the random patterns in $x[n]$ will be aligned, the above value will be maximized for an appropriate value of τ corresponding to the time period between repeating patterns. Further, these peak values occur only at periodic intervals in n. Hence, the second exponential term $\exp(-j2\pi\alpha n)$ is in effect computing the frequency α at which this hidden pattern repeats. Such frequency can be defined as pattern frequency, and CAF is at the particular pattern frequency α and delay τ. CAF will show a high value only for delays and pattern frequencies that correspond to repeating patterns.

HEIR uses these pattern frequencies as signatures for different signal types. In the following sections we expand on this insight and explain the design of the identification and classification algorithms, which are main contributions of this article. However, to make these algorithms practical on WSN nodes' hardware, we need to efficiently improve the Cyclic Autocorrelation Function.

V. Design of Identification Algorithm

A. Overview

HEIR operates on RSSI samples from CC2420 RF chip, which do not undergo any demodulation, decoding or synchronization. These samples are processed to estimate interference intensity, extract signal feature, and then detect device types. HEIR's design can be divided into four steps: (1) signal sampling (2) interference estimation (3) feature extraction (4) device classification. Finally, HEIR output the result. An overview of the architecture is shown in Fig. 6.

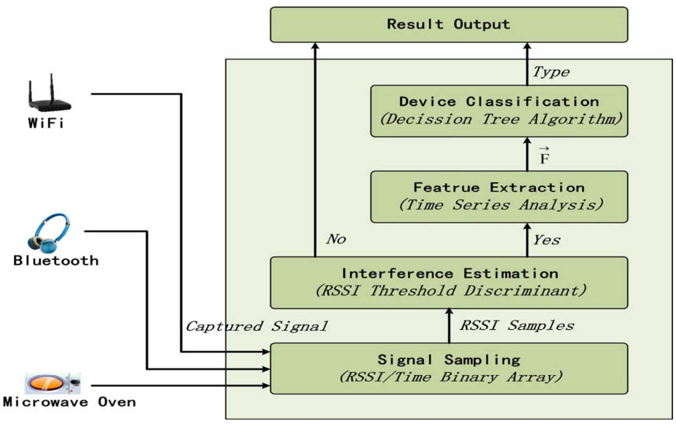

Fig. 6. Overall architecture and every stack of HEIR.

B. Signal sampling

Many WSN applications and protocols use RSSI values to detect channel's traffic and interference, or estimate transmission distance. Thus, RSSI is an extremely useful metric that can be used for channel management, positioning and so on. RSSI is an indicator of receiving signal power on wireless channel, which can be obtained from CC2420 RF chip of MICAZ node. All measurement and analysis software can be developed on TinyOS 2.x platform. According to product's data sheet, the measurement range is from -100 to 0 dBm, accuracy is ± 6 dB, linear dynamic range is ± 3 dB, average time of sampling is 8 symbol periods (128 microseconds). RSSI value can be converted to dBm through RSSI_OFFSET, which is about -45 dB. But when measuring the strong narrowband interference, there may be some errors (value is out of range) in RSSI readings. In this paper, the problem is corrected by properly activating CC2420 chip's peak detector between rising edges. Threshold values and interference characteristics are measured and analyzed in a single test environment. Sampling cycle is 1 second. Sampling frequency is 11321Hz. RSSI readings are coded and stored in binary.

C. Interference Estimation

First, we define variables as follows:

- T_s is the sampling interval.
- V_{rssi} is a vector of a set of RSSI instantaneous value collected in T_s.
- $|V_{rssi}|$ is the number of RSSI instantaneous value collected in T_s.
- $\overline{V}_{rssi}$ is the average value of RSSI in T_s.

$$\overline{V}_{rssi}=\sum_{i=1}^{|V_{rssi}|}\frac{V_{rssi}(i)}{|V_{rssi}|} \qquad (2)$$

- $HI_{threshold}$ is the heterogeneous interference threshold, its default value is -85dBm, which is under default idle channel assessment (CCA) threshold (-77 dBm) in chips, but higher than noise in urban background.
- V_{active} is 0/1 vector. If $V_{rssi} > HI_{threshold}$, $V_{active}(i)=1$; else, $V_{active}(i)=0$.
- $|V_{active}|$ is the number of V_{active} vector.

Then, we define HI Estimation Model as follows:

Definition 1. HI Value (P)

$$\begin{cases}\overline{V}_{rssi}\ge HI_{threshold}, P=\overline{V}_{rssi}-HI_{threshold}\\ \overline{V}_{rssi}< HI_{threshold}, P=0\end{cases} \qquad (3)$$

Definition 2. Active Ratio (A)

$$A=\sum_{i=1}^{|V_{active}|}\frac{V_{active}(i)}{|V_{active}|} \qquad (4)$$

Definition 3. HI Intensity (I)

$$I=P\cdot A \qquad (5)$$

HI Estimation Model judges whether the interference exists and calculates the intensity with the average value of RSSI obtained by monitoring window.

D. Featrue Extraction

As described in the former, feature extraction step is supposed to find the prominent pattern frequencies which represent the frequencies at which repeating patterns manifest in the different PHYs. Therefore, we can borrow the ideas from cyclostationary signal analysis to design the feature extraction algorithm. However, instead of using the complicated CAF, an equivalent representation called Spectral Correlation Function (SCF) can be used, which is equal to the frequency transform of the CAF.

$$S_x^{\alpha}(f) = \sum_{\tau=-\infty}^{\infty} R_x^{\alpha}(\tau)\exp(-j2\pi\tau) \tag{6}$$

Since frequency transforms are unitary, it should be noted that both representations are equivalent. If the CAF peaked for a certain value of τ, then the SCF will peak for a particular value of f that is inversely proportional to τ. Intuitively, the reason for this is that if a hidden pattern repeats at a lag of τ, then by definition it repeats for every integer multiple of τ. Then, the SCF can be computed efficiently for discrete time windows as follows

$$S_x^{\alpha}(f) = \frac{1}{M}\sum_{k=0}^{M-1} X_{kN}(f)X_{kN}^{*}(f-\alpha) \tag{7}$$

$X_{kN}(f)$ is the FFT of the received signal for the k'th time window of length N samples, * is the complex conjugate, and the summation is over M consecutive time windows of the received signal. The key significance is that the SCF can be expressed as a product of the FFT of the received signal. Hence to compute the SCF at any pattern frequency α, one just has to take the product of the received signal's FFT with itself albeit shifted in the frequency domain by α. Although FFT is efficient to implement, its computational overhead of online passive extraction of signal feature is still huge for existing WSN nodes' hardware.

Considering the limited memory of sensor nodes, we have chosen a further simple looking approach for binary signal frequency components instead of SCF. The spatial and temporal characteristics is calculated and analyzed from the binary array of signal. As we all known, the computation of channel occupancy and idle is very cumbersome, so this method process the sampled signal based on correlation.

$$X_s = X_B(t) \cap X_B(T), t \in [T, n] \tag{8}$$

$$t_s \equiv T \pmod{t} \tag{9}$$

From $t = T$ to n, the binary value of signal at t and T is logically conjunct, where T is the signal cycles, n is the number of elements in the array. X_s is the computed signal value, which is added to the position of co-sequence at time t_s. The frequency components of signal arise at the maximum value of time series, which can reach a maximum value of $n/T\text{-}1$. The algorithm has lower complexity compared to FFT, and no floating point arithmetic compared to Goertzel.

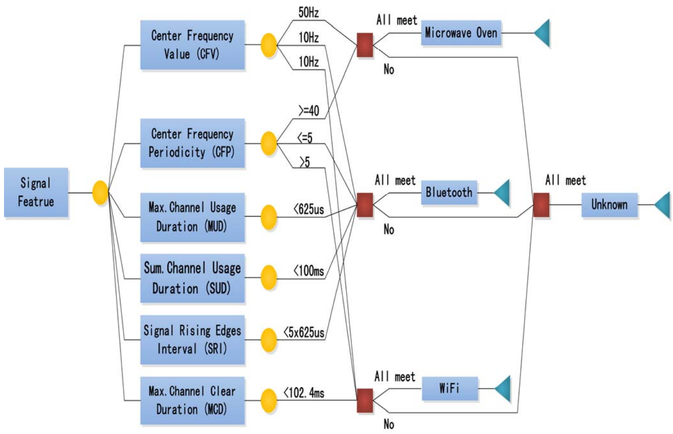

Fig. 7. Decision tree for classification.

Finally, we summarize HEIR's feature vector. We first determine the union of the unique sets of time series contained in each signal type's signature. Let this union consist of following elements at different consecutive time windows, V_{cf} (center frequency value), P_{cf} (center frequency periodicity), UD_{max} (maximum channel usage duration), UD_{sum} (summation channel usage duration), I_{sre} (signal rising edges interval), CD_{max} (maximum channel clear duration), then the feature vector $\vec{F}$ is defined as:

$$F(i) = (V_{cf}, P_{cf}, UD_{\max}, UD_{sum}, I_{sre}, CD_{\max})_i, \forall i = 1, \ldots, M \tag{10}$$

E. Device Classification

HEIR builds a novel decision tree based on the signal feature vector to efficiently identify heterogeneous interference signals. The classifier takes feature vector $\vec{F}$ as input, and predicts signal types as WiFi, MWO, BT or unknown devices. The work is carried out in accordance with step sequence. If the classification matches the result, the algorithm terminates. Figure 7 shows the decision tree algorithm for classification. Hereinafter, a brief description of the algorithm presents the determination conditions used for different heterogeneous interference sources.

1) MWO: If a signal is microwave oven's interference, then the number of cycles with a frequency of 50 Hz should be greater than or equal to 40 (according to the European average frequency). This condition is very simple and works well. But it will cause problems at the beginning or end of the heating phase, because the number of valid signals is not sufficient.

2) BT: The number of rising edges is an important recognition feature which matches the timing of BT slots. So, the time between two rising edges matches the slot time. The transmission always starts at the beginning of a time slot, but not fully used it. The maximum continuous time of channel occupancy is [0 ... 5] × 625 microseconds. In addition, the probability that two single channels are used at the same time is very little as frequency hopping. Hence, the total occupancy of all channels should be less than tenths of a second even in the worst case of communication overload. Furthermore, the number of 10 Hz cycles should be less than 6. The conditions set forth above run effectively, and have passed the test on the headset audio streaming, mobile phones File Transfer Protocol (FTP) traffic and wireless Bluetooth mouse.

3) WiFi: WiFi is the last classification decision after other excluded options in the algorithm. WiFi signals are mainly determined by beacon frames of APs since time features of data traffic are very different in IEEE802.11 except beacons. Beacons arise every 102.4ms. If the maximum channel idle duration is 102.4ms, and the number of 10 Hz cycles is greater than 5, the signal is considered as WiFi.

4) Unknown: If the category is not matched, the signal is considered to be unknown, which may be unknown sources or harmonics interference of known sources. For example, if WiFi uses channel 1 and 6, then the channel 15 of WSN may be disturbed by WiFi's harmonics.

5) Overlap: When several heterogeneous interference sources are working on a single channel, the algorithm returns only major source. The determination is in accordance with the following priority:

- MWO do not monitor traffic on the channel, but it will cover WiFi or BT, and occupy the channel extensively. Thus, when the three coexist, MWO is the dominant signal. However, the interference range of a MWO is quite limited. While signals become weak rapidly far away, other signals will be dominant again.
- WiFi has a pre-set and constant usage of the channel. However, if the channel is occupied, it will retreat. When WiFi and BT coexist, broader distributed spectrum of WiFi is able to endure narrowband interference of BT. Thus, WiFi is the dominant interference source compared to BT, since it causes more packet loss.
- BT device uses the technology of Adaptive Frequency Hopping (AFH), Adaptive Power Control (APC) and Channel Quality Driven Data Rate (CQDDR). These technologies make BT initiative to avoid channel occupation. Therefore, BT is a weak heterogeneous interference source.

VI. Implementation

A. Evaluation Metrics

1) Outage Probability: It is defined as

$$Pout = \frac{Number\ of\ correct\ identification\ results}{Number\ of\ \ total\ identification\ results}$$

Outage Probability is the appropriate metric that reflects the interference identification accuracy of algorithm, which is in the range [0…1]. It indicates the overall effectiveness of identification algorithm.

2) Error Distribution: It is defined as

$$F(error) = P(X \le error)$$

The CDF of error is used to show the overall error in algorithm's estimate in the presence of interferers. It reflects the ability to estimate an interferer correctly.

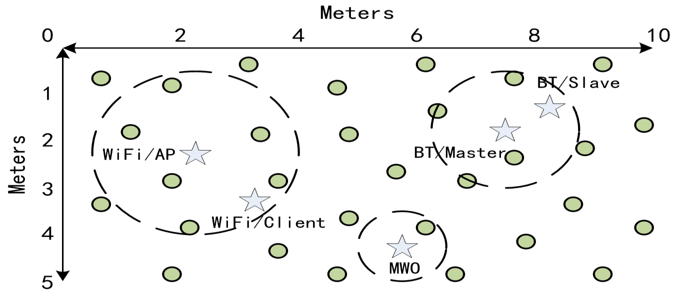

Fig. 8. Experiment scenarios.

B. Experiments Setup

HEIR is implemented in nesC on TinyOS 2.0 and running on MICAZ sensor nodes. The testbed for the experimental results consists of an indoor office environment. The measurements were taken when the office was empty. A randomly deployed multi-hop network including 30 nodes spreads over a 10m×5m square (see Fig. 8). The radio wave range is 1m. The source node sends 32 bytes packet per one second. HEIR operates on the digital RSSI samples collected and recorded by CC2420 chips. The average sampling rate is 11321Hz. We evaluated the accuracy of HEIR and estimated how different factors impact its performance such as device type, parameters setting, interferers number, and mobility. Our current implementation is geared towards 3 common signal types in the ISM band – WiFi, Bluetooth, and microwave. We chose interference sources including TP-LINK TL-WR740N 150M wireless broadband router as WiFi AP, HP Compaq nx6330 laptop as WiFi Client, SAMSUNG GT-B9062 smart phone as Bluetooth Master, Sony Ericsson Xperia Neo MT15i smart phone as Bluetooth Slave, and Midea AG720FA5-NS Microwave oven.

C. Parameters Setting

The detailed experiment configuration is summarized in Table I. The specific algorithm parameters are set in Table II.

TABLE I. Configuration Parameters

Settings	Parameters			
	WSN	***WiFi***	***BT***	***MWO***
Default Channel	20	10	-	-
Center Frequency	2450MHz	2455MHz	-	2450MHz
Modulation	O-QPSK	DSSS/OFDM	GFSK	-
Transmission Power	-20dbm	low power	1/2.5/100 mW	0-700W
Dot Pitch	1m	1m	1m	-
Interference Range	-	0~2m	0~1m	0~1m
Packet Size	32Bytes	300/600/900/1200Bytes	-	-
Data Transmission Rate	200Kbps	6/12/24/36/48/54Mbps	1Mbps	-
File Transmission Rate	-	200Kbps	100Kbps	-

TABLE II. ALGORITHM PARAMETERS

Settings	Parameters
Sending Interval	1s
Sampling Frequency	11321 Hz
Interference Threshold	-85dbm
Process Window Time	1s

D. Performance Analysis

1) Single interferer impact: We actived each interferer device group in turn, measure in 10 minutes and compute the Pout and CDF of error. Figure 9 (left) shows that the algorithm correctly estimates a heterogeneous device's impact. Across all device types, algorithm's estimation lies above 70% in outage probability. Figure 9 (right) shows that the overall error of algorithm's estimation is within 0.25 for more than 95% of the cases for all 3 devices.

2) Multiple interferer impact: We repeated the experiment for different overlapped combinations of interferer device group respectively, including WiFi/BT, WiFi/MWO, BT/MWO, WiFi/BT/MWO. In each run, we measured in 10 minutes and computed the Pout and CDF of error. Figure 10 (left) shows 4 different overlapped combinations of different interferer. We found that the algorithm is able to correctly estimate multi-overlapped heterogeneous devices' impact and accurately identify the major interferer. The algorithm indicates the exact impact of different strong and weak interferer combination, because different combination affects different clarity of dominant signal. Thus, the outage probability lies above 90% in BT/MWO group and falls down to more than 70% in WiFi/BT/MWO group. Figure 10 (right) shows the CDF of error in interference estimation for different combination devices. The clarity of dominant signal affects the result. The best situation is BT/MWO combination within 0.1 for more than 95% of the cases. The overall error slightly increases with the number of devices increases. The error is within 0.3 for more than 95% of the cases when operating 3 devices. The slight increase in error is due to the increased overlap in transmissions from multiple devices.

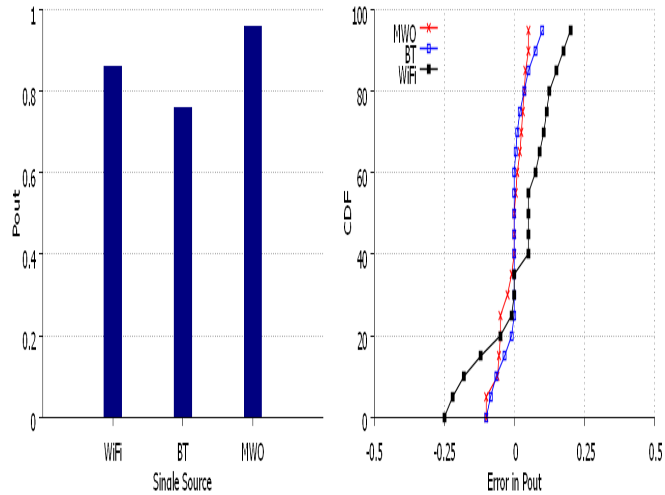

Fig. 9. Accurately identifying impact of each single interferer.

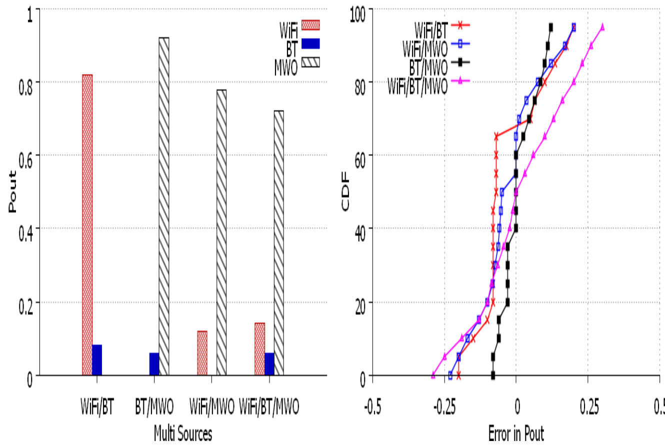

Fig. 10. Identification in the presence of multi-overlapped interferer

3) Different interference settings: We evaluated the algorithm's ability to adapt to different parameter settings in data rate, packet size, link type, and transmit power respectively. Every time we only adjust one parameter, and the other parameters are set to default values. We measured in 10 minutes for each setting and compute the Pout. Figure 11 (a) shows that algorithm's estimation derived from WiFi's rate adaptation closely match the truth. Since higher rates bring higher complexity in signal sampling, feature extraction, and device classification through time series analysis, interference increases as the rate increases. Figure 11 (b) shows that the algorithm is able to correctly track the slight increase of interference at larger packet size of WiFi. Figure 11 (c) shows that the algorithm's accuracy is affected by the link type of BT. ACL have a lower outage probability due to the changeable feature on traffic load and channel occupancy. Figure 11 (d) shows that the outage probability is not affected by the change of MWO's power. Because the power level is only set by turning on and off, the feature of signal cycle is still clear enough to be identified.

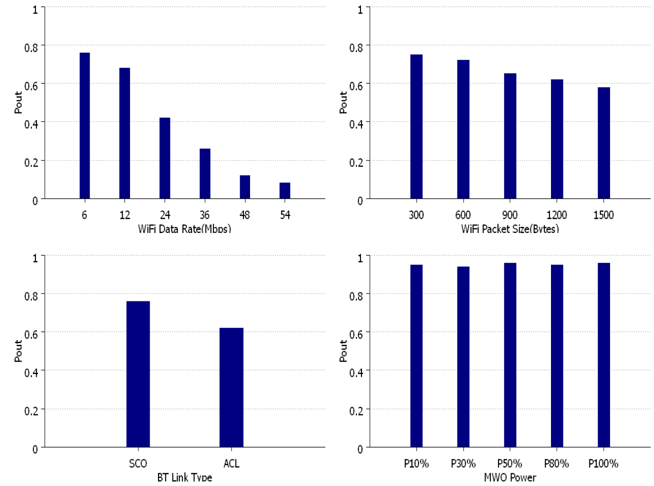

Fig. 11. Impact of different parameters in single interferer.

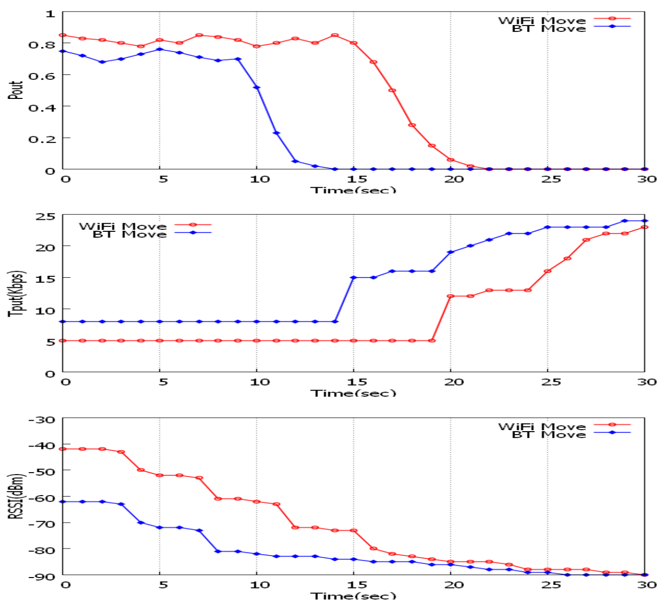

Fig. 12. Ability to track the moving interferer.

4) Mobility and distance: Any practical interference estimation mechanism must be able to handle client mobility, i.e. it should be able to update the conflict situation in real-time to reflect the change of interference patterns that arise due to the movement. In order to evaluate the algorithm's ability to handle mobile clients, we performed the experiment under WiFi and BT interferer respectively. In each run, the moving speed is 0.2m/s, and the moving distance is 6m. We measured in 30 seconds each time and computed the Pout and throughput. Figure 12 (bottom) shows the signal strength at the test sensor node, while the middle and top plots shows the throughput and outage probability of the algorithm at each instant in the experiment. As shown in the figure, Pout decreases as the interferer moves. Furthermore, it closely matches the trend that is shown by instantaneous throughput during the experiment. Experimental results confirm the algorithm's accuracy in dynamic wireless environment.

VII. Conclusion and Outlook

As we all known, there is almost no co-existence problems in the unlicensed band before, since different protocols could use non-overlapped bands. Given the low density of radios in the neighborhood, it is almost impossible that radios step on each other's toes. However, with the increase of protocols that operate in the ISM band and the increasing density of radios around us, wireless networks and devices in the ISM band will need to operate and co-exist in this crowded space in the future. This paper presents an overview of common heterogeneous interference sources and time characteristics of different signals in the ISM 2.4 GHz band through online passive monitoring on a 2MHz wide channel. The signal characteristics obtained from analysis can help to improve interference estimation, feature extraction and device classification. On this basis, a heterogeneous interference identification algorithm HEIR is designed and implemented on MICAZ node in the indoor office environment.

HEIR opens up a number of avenues for future work, like designing a smart heterogeneous interference avoidance policy. We also plan to apply HEIR to other applications in channel management, adaptive MAC protocol, cognitive WSN design or deployment debug. There are some new categories of devices can be added in the future, such as wireless DECT (digital enhanced cordless phones) or wireless video camera working on the unlicensed bands.

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