CoHop: Quantitative Correlation based Channel Hopping for Low-power Wireless Networks

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***Abstract*—Cross-Technology Interference (CTI) badly harms the transmission reliability for low-power networks such as ZigBee at 2.4GHz band. Though promising, channel hopping still faces challenges because the increasingly dense deployment of CTI leaves very few available channels. Selecting a good channel with the least overhead is crucial but challenging. Most of the existing works are heuristic methods that choose a channel far from the current one to avoid adjacent channels that may be correlatively interfered by CTI with a wider bandwidth such as WiFi. However, we observe that the correlated channels influenced by the same CTI source do not necessarily have the same channel qualities and even the opposite state, due to the uneven spectrum power density of CTI. Such channel opportunities are unexplored and wasted. In this paper, we propose CoHop, a quantitative correlation based channel hopping method for low-power wireless networks. We establish a quantitative model that describes the correlation of channel qualities to capture channel opportunities and calculate channel quality without probing, to reduce probing overhead. We implement CoHop on TinyOS and evaluate its performance in various environments. The experimental results show that CoHop can increase the Packet Reception Ratio (PRR) by 80%, compared with existing methods.**

***Index Terms*—Cross-technology interference, channel hopping, correlation, low-power, wireless networks.**

I. Introduction

The unlicensed 2.4GHz ISM band embraces various wireless technologies, such as WiFi, ZigBee, and Bluetooth. These wireless technologies are widely used in the emerging Internet of Things (IoT) applications such as smart homes or intelligent medical [1]–[3]. When used in the same area, the prosperous wireless technologies will compete for the shared spectrum resources, leading to serious Cross-Technology Interference (CTI). Actually, CTI has become a major factor affecting communication reliability, especially for low-power networks. Previous measurement studies [4]–[7] have revealed that ZigBee transmissions are seriously corrupted by the coexisting high-power WiFi, resulting in decreased communication reliability. Consequently, WiFi interference has become the major bottleneck to the performance of ZigBee networks.

Channel hopping is a promising way to increase the robustness against interference. However, widely deployed WiFi networks make it hard for ZigBee to select an interference-free channel from 16 ZigBee channels. In case of wrong selection, a channel must be selected again, which not only makes the transmission opportunities of available channels lost but also wastes energy. Existing hopping methods usually select channels by random, polling probing [8], blacklist technique [9], [10], far-channel priority [11]. Muzi [8] chooses an available channel by polling all, which leads to high overhead and delay. The blacklist technique [9], [10] skips the detection of low-quality channels to reduce overhead. However, due to the dynamics, the channels that temporarily experience poor quality are likely to be blacklisted, making it difficult to fully capture the channel opportunities. ARCH [11] considers that performance is correlated across neighboring channels and therefore selects the spectrally distant channels.

Most of the existing methods ignore the availability of adjacent channels and just regard all the adjacent channels experiencing the same CTI that have the same channel state (busy or idle). However, based on the preliminary study in Section II, we find that due to the non-uniform spectrum power density of CTI, correlated channels affected by the same CTI source do not necessarily have the same channel quality and may even have the opposite channel state. Such an observation inspires us to utilize the channel opportunities ignored before in channel selection to further enhance communication reliability.

However, exploring such channel opportunities is challenging. First, there is no existing channel correlation model which quantitatively considers the channel opportunities caused by the non-uniform spectrum power density. Due to the asymmetry of channel bandwidths between WiFi and ZigBee, without such a quantitative model, it is difficult to capture these channel opportunities because ZigBee devices can only detect one channel at a time without knowing the quality of other channels. Second, how to choose a new channel with satisfying quality is non-trivial even if we have the quantitative channel correlation model. Since a WiFi channel (20MHz) is overlapped a lot with the adjacent and is wider than a ZigBee channel (5MHz), probing one ZigBee channel usually cannot accurately recognize the correlation and capture the available channel opportunities. During the next probing, due to the bursty and fast WiFi traffic, the interference can be from other WiFi devices operating on another overlapped WiFi channel, causing failures of correlation probing and channel selection. The channel probing sequence thus should

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be elaborately designed to take full advantage of the channel correlation. Third, channel correlation is dynamic because the coexisting interference is time-varying. How to detect the changes of channel correlation and adaptively update the correlation model should be intelligently designed.

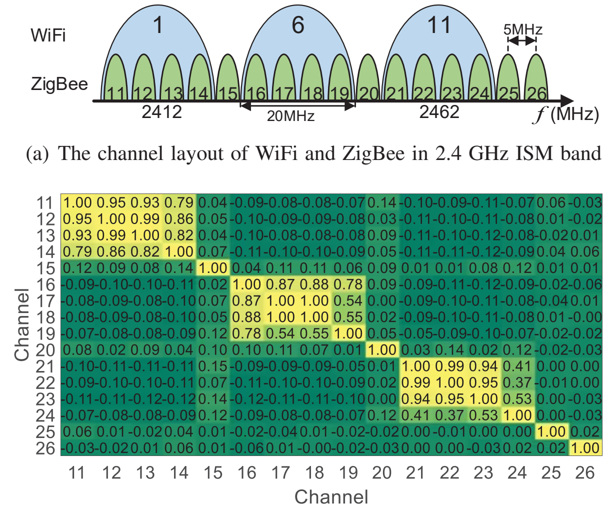
In this paper, focusing on the above three challenges, we propose CoHop, a novel channel hopping method for low-power wireless networks that discovers and utilizes the unexplored channel opportunities on adjacent channels in CTI environments. The key insight of CoHop is the adjacent channels of a busy ZigBee channel can have different quality and even opposite channel state due to the non-uniform spectrum power density of coexisting WiFi interference. The technical highlight of CoHop is to select an available channel with limited probing overhead based on the quantitative correlation. First, we find the non-uniform power spectrum density of WiFi interference results in the poor quality of ZigBee channels near WiFi central frequency but possibly good quality for ZigBee channels far from the WiFi central frequency. Hence, we establish a channel correlation model that quantitatively describes the correlation of qualities among adjacent channels. Second, a channel selection algorithm is carefully designed to minimize probing overhead and maximize hopping precision. To avoid inaccurate probing caused by bursty WiFi traffic, we design a prediction-based probing method to optimize the probing sequence. Third, to cope with the channel dynamics, we design an online updating mechanism for the correlation model based on the channel probing results obtained during the channel selection process. The contributions of this work are summarized as follows.

- We propose CoHop, a new quantitative correlation-based channel hopping method that accurately captures the unexplored channel opportunities on adjacent channels of a busy channel in CTI environments.
- CoHop adaptively selects an available channel based on quantitative correlation with low overhead and high precision. The probing sequence is optimized based on the Pearson Correlation Coefficient and the prediction-based probing algorithm.
- We implement a prototype of CoHop and evaluate its performance in controlled environments and real-world scenarios. The evaluation results show that CoHop can increase PRR by 80%, compared with existing methods.

The rest of the paper is organized as follows. In Section II, we propose the quantitative correlation model based on our observation to motivate this work. We present the design of CoHop in Section III and the evaluation results in Section IV. The related works are discussed in Section V. Finally, we conclude this paper in Section VI.

II. Preliminary Study

In this section, we first investigate whether the adjacent channels of a poor channel have channel opportunities to transmit reliably. We find that when experiencing the same WiFi interference, even though the adjacent channels of a poor channel are noisy, these channels may have opportunities to be reliable for ZigBee transmissions. To capture these channel opportunities unexplored before, a new quantitative model is then proposed.



(a) The channel layout of WiFi and ZigBee in 2.4 GHz ISM band

(b) Pearson correlation coefficient among 16 ZigBee channels

Fig. 1. The correlation among 16 channels under controlled WiFi interference.

A. Underutilized Noisy Channel

When CTI collides with the ZigBee transmissions, the strength of interference and noise significantly increases, leading to a low Signal to Interference plus Noise Ratio (SINR). Hence, SINR is usually used as an indicator of channel quality.

To investigate whether there exist channel opportunities on adjacent channels of a busy channel or not, we explore the relationship between channels. ZigBee channels overlap with WiFi channels in the 2.4GHz ISM band, as shown in Fig. 1(a). We deployed three WiFi routers simultaneously transmitting in WiFi channels 1, 6, and 11 to create CTI and use 16 TelosB nodes respectively operating on 16 ZigBee channels to collect Receive Signal Strength (RSS) samples outdoors without any other interference. And then we calculate the SINR according to the RSS samples.

To study the relationship among adjacent channels, we adopt the Pearson Correlation Coefficient (PCC) [12] to measure the correlation of channel qualities. The PCC between ZigBee channel i and j is

$$C_{i,j} = \frac{\sum_{k=1}^{n} S_i^k S_i^k - n\overline{S_i}\,\overline{S_j}}{\sqrt{\left(\sum_{k=1}^{n}\left(S_i^k\right)^2 - n\left(\overline{S_j}\right)^2\right)\left(\sum_{k=1}^{n}\left(S_j^k\right)^2 - n\left(\overline{S_j}\right)^2\right)}} \quad (1)$$

where S_i and S_j are SINR sequences calculated by the RSS samples in ZigBee channel i and j, and n is the length of S_i and S_j, which is set to 3 in our experiment. The mean of S_i and S_j are respectively denoted as $\overline{S_i}$ and $\overline{S_j}$. For simplicity, in this paper, we use notation "Ch. i" to represent "ZigBee channel i" in short.

The experiment runs for half an hour and the experimental results are shown in Fig. 1(b). From the results, we can find that ZigBee channels overlapped with the same WiFi channel

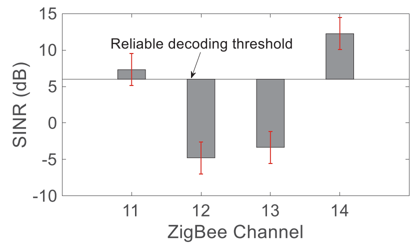


Fig. 2. SINR of ZigBee in Ch. 11-14 under the interference of WiFi channel 1.

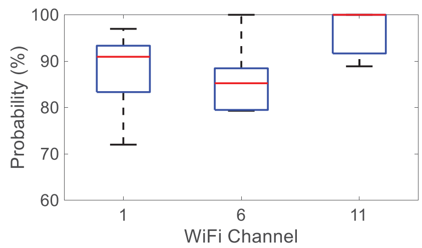


Fig. 3. The probability of available boundary-channel under WiFi channel 1, 6 and 11.

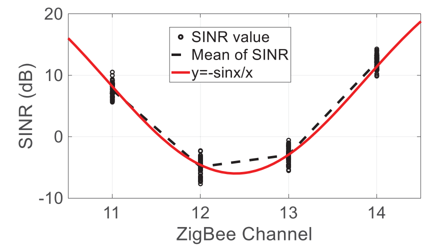


Fig. 4. The correlation of the SINR and the WiFi power spectrum.

have a strong correlation. For instance, the PCC between Ch. 11 and Ch. 12-14 are 0.95, 0.93, 0.79, respectively. But the PCC between Ch. 11 and other channels are usually in ± 0.1. The results are consistent with the existing studies [11], [13] on the correlation of channel reliability (PRR<90%). However, existing methods regard the channel availability on adjacent channels as equivalent and only capture the long-term statistical correlation.

During our experiments, we find that the adjacent channels of a busy channel do not necessarily have equivalent channel quality and may even have reliable channel opportunities. According to the PRR-SINR model [14], a 6dB SINR is good enough to reliably decode the ZigBee packets. Hence, we use 6dB as the threshold, S_{th}, to judge the channel state as busy or idle. We plot the SINR of Ch. 11-14 in Fig. 2. From the figure, we find even though Ch. 11-14 suffer the same WiFi interference, they experience quite different channel qualities and have even opposite channel states. Even though the average SINR of Ch. 12 and 13 are -4dB and -3dB which is too low to transmit, the average SINR of Ch. 11 and 14 are higher than 6dB, leading to the opposite channel states. The results reveal that the adjacent channels (Ch. 11/14) of a busy channel (Ch. 12/13) can have transmission opportunities that are ignored and unexplored by previous methods.

We further measure how often the channel opportunities exist in the busy channels during our experiment. We calculate the percentages of the occurrence mentioned above where at least one adjacent channel of a busy channel influenced by the same WiFi interference is available, when WiFi operates in channel 1/6/11. The results are shown in Fig. 3. The mean percentages in WiFi channels 1, 6, and 11 are 87%, 86%, and 96%, respectively. The results show that adjacent noisy channels are underutilized and there are many channel opportunities for reliable transmissions.

B. Quantitative Correlation

The above results motivate us to explore those opportunities on adjacent channels of a busy channel to improve the transmission reliability and spectrum efficiency.

During our experiments, we find that reliable transmission opportunities always exist in the boundary channels that are far from the central frequency of a WiFi channel, when four ZigBee channels experience the same WiFi interference. For example, in Fig. 2, when WiFi operates in WiFi channel 1, the middle channels (Ch. 12 and 13) have poor qualities but the boundary channels (Ch. 11 and 14) can still provide reliable transmissions.

The above observation inspires us that such a phenomenon may be caused by the non-uniform power spectrum of WiFi. The power spectrum of WiFi signal [15] is not uniformly distributed on the whole 20MHz, but follows the function, $y = \sin(x)/x$. Since the channel bandwidth of ZigBee is only 2MHz, four ZigBee channels will suffer different interference strengths even under the same WiFi interference. Hence, the lower interference strength in the boundary channels can have better SINR to provide reliable transmission opportunities. To validate our hypothesis, we collect SINR of Ch. 11-14 under interference in WiFi channel 1 for half an hour and plot the results in Fig. 4. We find the mean SINR of four channels perfectly fits the function, $y = -\sin(x)/x$, which is the negative of the power spectrum distribution function.

By comparing the fitted function and the WiFi power spectrum standard, we find that their zero points are at $\pm\pi$ and ± 11. Moreover, the offset frequency of four ZigBee channels to the center of overlapped WiFi channel, denoted as Δf, are $3+5(i-3)$ MHz, $i \in \{1,2,3,4\}$, where i is the left to the right number of four channels overlapped with WiFi. The SINR correlation among four channels satisfies the following formula:

$$S_j = a_{ij} S_i + (a_{ij} - 1)b, \tag{2}$$

where S_i and S_j represent the mean quality in Ch. i and j, and b is the interfering parameter, determined by interference devices and transceiver distance, and a_{ij} is the ratio of Ch. j to Ch. i calculated by the standard power spectrum function, which is expressed as

$$a_{ij} = \frac{-\sin(\pi \Delta f_j/11)/(\pi \Delta f_j/11)}{-\sin(\pi \Delta f_i/11)/(\pi \Delta f_i/11)}. \tag{3}$$

Then iteratively calculating correlations of all the 16 ZigBee channels, we can obtain a proportional relationship between all channels, denoted as $\mathbf{A}$. Hence we can directly calculate the SINR of an unprobed channel based on the model by the SINR of two probed channels.

However, obtaining the correlation model in practice is challenging. ZigBee nodes can only probe one channel at once. Without simultaneously probed SINR results in multiple channels, it is non-trivial to obtain the accurate quantitative channel model. Different probing sequences can lead to totally different and even contradictory results. Applying the model in practice and utilizing those unexplored channel opportunities still need to be elaborately designed.

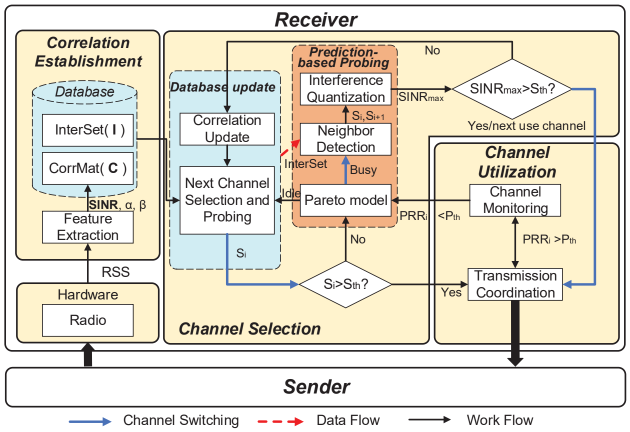


Fig. 5. The overview of CoHop.

III. Design

In this section, we present the design of CoHop that leverages the quantitative model to reactively hop to an available channel with minimum probing overhead when the current channel becomes poor. We first present an overview of CoHop and then introduce major components in detail.

A. Overview

CoHop is a receiver-oriented method like ARCH [11]. Namely, the communication channel is decided by a receiver, and the sender transmits data accordingly. Initially, all the nodes use the same common channel such as Ch. 26. To avoid too much channel contention on the common channel, when transmitting bursty data, the transceivers will hop channels on demand, and return to the common channel after transmissions to wait for the following transmissions for other links. Hence, the major designs are on the CoHop receiver.

Fig. 5 shows an overview of CoHop that consists of three major components: correlation establishment, channel selection, and channel utilization. Initially, each receiver establishes a correlation model based on the measured channel qualities in terms of SINR and the collected interference information (Section III-B). Based on the obtained correlation model, the receiver will select an available channel to communicate with the sender when the current channel becomes poor. The receiver continuously monitors the current channel quality and switches channel when the quality is lower than a predefined threshold. Once deciding to switch channel, the CoHop receiver will select a new good channel based on our channel selection algorithm (Section III-C). To reduce the probing overhead, we optimize the probing sequence by designing a prediction-based probing method based on the quantitative channel correlation model and the Pareto-based WiFi traffic model. After finding a good channel, the receiver coordinates with the sender for transmission consistency (Section III-D) to continue transmission.

B. Correlation Establishment

To use the quantitative channel correlation model in practice, we should design a practical method to measure channel qualities on different channels and obtain the model on ZigBee devices with limited resources. Note that the off-the-shelf hardware of ZigBee such as CC2420 can collect the strength of noise and interference by probing the channel when there is no ZigBee transmission and get ZigBee signal strength by decoding ZigBee packets. We use a $4ms$ window to extract the strength of WiFi interference from the RSS sequence. Compared with the noise, the effective signal has a bursty larger amplitude. Hence, we isolate each busy period by changing the point detection algorithm [16] that locates the abrupt changes in data. The RSS collected during the busy period is our interested strength of noise and interference which is used to calculate SINR. To distinguish the noise and the busy period, we empirically set a threshold, r_{th}, as $-85dBm$. Therefore, the RSS sequence of Ch. i can be segmented as

$$R_i = \{r_1,\cdots,\underbrace{r_p,r_{p+1},\cdots,r_{p+q}}_{>r_{th}},\cdots,r_n\}. \tag{4}$$

The mean RSS of a busy segment is denoted as $I_i = \overline{r}$. Then the SINR of Ch. i can be obtained after getting the ZigBee signal strength P_i, i.e. $S_i = P_i/I_i$.

Then we iteratively measure the SINR on 16 channels, to construct the correlation matrix, denoted as $\mathbf{C}$, forming as follows:

$$\mathbf{C}=\begin{bmatrix} 1 & C_{11,12} & C_{11,13} & \cdots & C_{11,26} \\ C_{12,11} & 1 & C_{12,13} & \cdots & C_{12,26} \\ C_{13,11} & C_{13,12} & 1 & \cdots & C_{13,26} \\ \vdots & \vdots & \vdots & 1 & \vdots \\ C_{26,11} & C_{26,12} & C_{26,13} & \cdots & 1 \end{bmatrix} \tag{5}$$

where $C_{i,j}$ is the correlation coefficient between Ch. i and Ch. j; "1" and "-1" indicate perfectly positive and negative correlation, respectively. Obviously, this is a symmetric matrix, i.e. $C_{i,j} = C_{j,i}$. Through the correlation establishment component, each node can establish a correlation model and obtain a set of detected interference, I, on the basis of this for future channel selection.

C. Channel Selection

Due to the dynamic interference, a good strategy is important for selecting an available channel when the current channel quality degenerates to unusable, with the minimum probing overhead.

1) Probing Sequence Optimization: To measure the channel qualities influenced by the same WiFi interference, the probing sequence must be elaborately designed. To obtain the channel correlation or recognize the current WiFi influencing, CoHop should get the information of multiple channels simultaneously. However, due to the channel asymmetry, a ZigBee node can only detect one ZigBee channel at once. Hence, if sequentially probing all the channels, we may gather wrong information because of the time difference of probing between channels. For example, when probing one channel during the WiFi transmission and switching to an adjacent channel for next probing, the probing may happen just in the gap of two

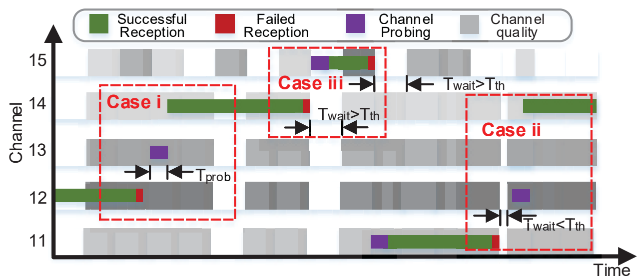


Fig. 6. Illustration of prediction-based channel probing method. WiFi operates on WiFi channel 1. The deeper gray a time slot is, the lower SINR is. T_{wait} and T_{prob} represent the waiting and probing time, respectively.

WiFi transmissions, leading to the wrong judgment that these two channels are not influenced by the same WiFi.

The misleading probing result happens when the probing that intends to detect the same WiFi interference fails because the WiFi transmissions are fast and dynamic. Hence, we propose a prediction-based probing sequence optimizing method that predicts the WiFi traffic and detects the adjacent channel when the next WiFi traffic is likely to transmit. In this way, CoHop eliminates the impacts of probing time differences with a high probability.

To predict the transmission timing of the next WiFi traffic, we adopt the Pareto model, a widely used model to predict WiFi traffic [17]. Thus, the length of a busy period can be inferred by the node. The probability that the length of the next busy period is greater than t, $P(x>t)$, can be modeled as:

$$P(x>t)=\begin{cases} (\frac{\alpha}{t})^{\beta}, & t>\alpha \\ 1, & others \end{cases} \tag{6}$$

where α and β are the model scale and shape respectively. Specifically, α is the minimum busy period, and β is given by $\frac{\lambda}{\lambda-\alpha}$, where λ is the average length of busy periods. We focus on the period that $t>T_{prob}$, where T_{prob} is the period required for channel switching and probing. The channel switching time is only hundreds of microseconds, which is almost negligible. T_{prob} is set to $4ms$ in our current implementation to reliably collect multiple SINR samples. As shown in Fig. 6, there are three cases for the probing prediction:

i) The current channel will be busy during the following T_{prob} period. The receiver then is going to probe an adjacent channel with the same interference to get the latest SINR. For example, in Fig. 6, when Ch. 12 becomes poor, Ch. 13 will be probed because the predicted busy period is longer than T_{prob}.

ii) The current channel will be idle for a short time T_{wait}, which is less than a threshold T_{th} but will become busy again for more than T_{prob}. The CoHop receiver will wait for T_{wait} and then probe a channel suspected to be influenced by the same WiFi. In our current implementation, T_{th} is set to $1ms$. For example, in case ii of Fig. 6, Ch. 14 is used after Ch. 11 because Ch. 12 suspected to be influenced by the same WiFi, has been probed.

iii) The current channel will be idle for a long time, longer than threshold T_{th}. Then the CoHop receiver will probe the channel that is likely to have no correlation with the current

Algorithm 1: Interference Quantification

Input: S_i, S_{i+1}, S_{th}, D_{th}, f_i, f_{i+1} and matrix $\mathbf{A}$
Output: f_c and S

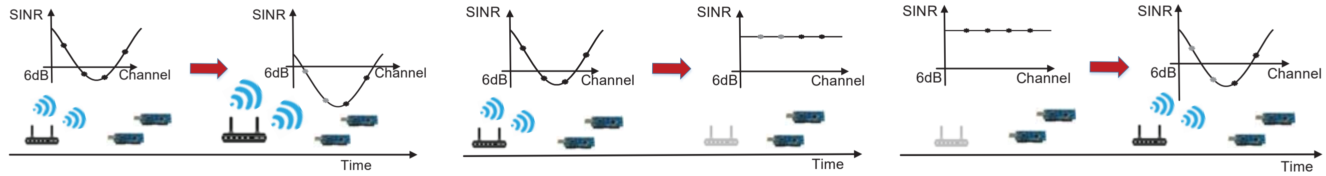
$b=\frac{S_i-a_{i,i+1}S_{i+1}}{a_{i,i+1}-1}$]
if $S_i>S_{i+1}$ *and* $|S_i-S_{i+1}|>D_{th}$ **then**
  f_c=f_i+$7MHz$;
  $S_{i+2}=a_{i,i+2}S_i+(a_{i,i+2}-1)b$;
  $S_{i+3}=a_{i,i+3}S_i+(a_{i,i+3}-1)b$;
  return
  $\mathbf{S}$=$\{S_i,S_{i+1},S_{i+2},S_{i+3}\}$ and f_c
else
  if $S_i<S_{i+1}$ *and* $|S_i-S_{i+1}|>D_{th}$ **then**
    f_c=f_i−$3MHz$;
    $S_{i-1}=a_{i,i-1}S_i+(a_{i,i-1}-1)b$;
    $S_{i-2}=a_{i,i-2}S_i+(a_{i,i-2}-1)b$;
    return
    $\mathbf{S}$=$\{S_{i-2},S_{i-1},S_i,S_{i+1}\}$ and f_c
  else
    f_c=f_i+$2MHz$;
    $S_{i-1}=a_{i,i-1}S_i+(a_{i,i-1}-1)b$;
    $S_{i+2}=a_{i,i+2}S_i+(a_{i,i+2}-1)b$;
    return
    $\mathbf{S}$=$\{S_{i-1},S_i,S_{i+1},S_{i+2}\}$ and f_c
  end
end

channel based on the history interference set, I, because probing the correlated channels will only detect noise without interference. As the Case iii shown in Fig. 6, $T_{wait}>T_{th}$, then CoHop decides to probe Ch. 15.

2) Interference Quantification: After detecting an adjacent channel for the probing prediction, the qualities of other two channels under the same interference can be calculated, based on the known channel qualities and the central frequency of current WiFi interference, f_c, according to Eq. (2). However, in practice, f_c is unknown. Hence, to reduce the probing overhead and find an available channel quickly, the key is to identify the WiFi interference channel and then calculate unknown channel quality from the known under the same interference.

Note that the power spectrum of WiFi is known as prior. Hence, if the qualities of two adjacent channels S_i and S_{i+1} are measured, then f_c and $\mathbf{S}$, can be obtained. The detailed procedure is shown in Algorithm 1, where D_{th} is the SINR difference between two adjacent channels and $\mathbf{S}$ is a vector included the qualities of four channel interfered by the same WiFi interference source. Then whether there is an available channel can be determined by $\mathbf{S}$. If not, a channel with the minimum correlation to the current channel is selected for probing by the correlation matrix, $\mathbf{C}$. The reason for not choosing a negative correlation channel is that the busy periods of channels may cross, and once negative correlation channels are selected, they are likely to be busy again at the next period. If there is an available channel, the sender and receiver will coordinate the transmitted channel for the following transmissions.

3) Correlation Update: Under dynamic interference, the correlation will be time-varying. For example, in Fig. 7(a), SINR may vary with the Tx power changes of the same WiFi



(a) Increase (b) Leave (c) Join

Fig. 7. The three cases of interference variation. (a) WiFi Tx power is increased, (b) WiFi interference device leaves, (c) WiFi interference device joins. The black dots represent measured values, while the gray dots denote estimated values.

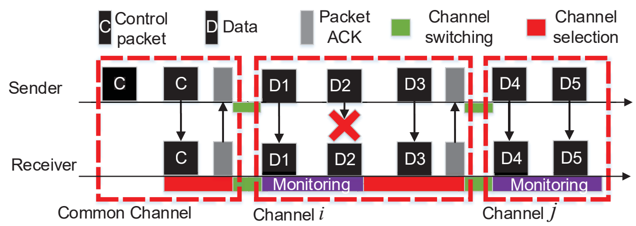


Fig. 8. Coordination between the sender and receiver.

interference, incurring the changes of parameters in the model. The correlation among multiple channels can also disappear or occur when the WiFi devices leave or join the environment, as Fig. 7(b) and Fig. 7(c) shown. Hence, CoHop integrates a correlation update module to keep the correlation up-to-date.

In CoHop, we adopt a moving average method to deal with the model parameter changes of cases in Fig. 7(a). Denote the latest measured SINR of Ch. i as S_i^{prob}. The channel quality of Ch. i, S_i, will be updated to $\hat{S}_i$, by $\hat{S}_i = \rho S_i + (1-\rho)S_i^{prob}$, where ρ is a weighting parameter which is set as 0.4 in our implementation to maximize the use of newly detected information. For the leaving case, CoHop directly records the new measure SINR in each channel independently. For the join case, CoHop measures the SINR in each channel and fits the model parameters to update the correlation matrix $\mathbf{C}$. Besides, the receiver will also determine the WiFi channel of the joined interference and update the interference set I.

In some extreme cases, the interference set may vary significantly. And the variation can lead to the correlation invalid, resulting in an inaccuracy of channel selection and packet loss. To avoid frequent and worthless channel hopping in these cases, CoHop re-polls all channels after a series of selection errors to establish the correlation again. We explore the appropriate reestablishment opportunities in Section III-D.

D. Channel Utilization

After selecting the used channel, channel coordination between the sender and receiver will be carried out. And the receiver will continuously monitor the channel to trigger next channel hopping or correlation reestablishment.

1) Coordination: CoHop uses Ch. 26 as the common channel because it is less overlapped with commonly used WiFi channels. Once the receiver decides channel hopping, it will add the next used channel information in the ACK message for the data packet. Then the sender will learn the channel used in the next slot. The sender and the receiver will hop to the selected channel in the next transmission slot to continue the transmissions. Fig. 8 shows a simple example of channel coordination. The red rectangular boxes represent the channel used during transmission. When the current channel i becomes poor after losing packet D2, the receiver will select the next channel, i.e. Ch. j, and then send this information to the sender in the ACK of next packet, D3. In this way, the sender and receiver keep consistent on the used channel.

2) Monitoring: During transmission, the receiver continuously monitors the transmission reliability in terms of PRR. Here we use PRR as an indicator to trigger channel hopping. When PRR is lower than 90%, we regard the current channel becomes poor. CoHop also monitors the continuous usage of poor channels. If the poor channels with PRR less than 90% are continuously selected four times, CoHop will re-establish the correlation model.

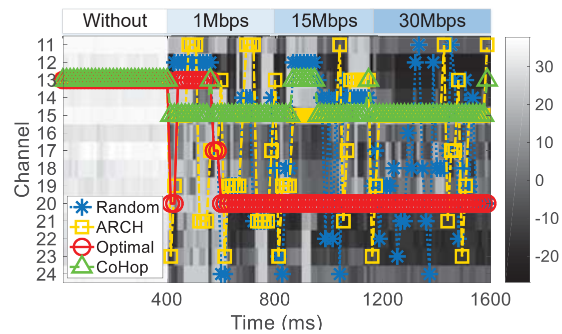


Fig. 9. Channel hopping behaviors under varying interference intensity.

IV. Evaluation

We implement a prototype of CoHop on TelosB motes with TinyOS 2.1.2 and evaluate its performance from various aspects.

A. Experiment Setup

We first evaluate the effectiveness of CoHop's components. To get the ground-truth of the channel quality to validate our correlation establishment and channel selection algorithms, we use 16 TelosB motes working on the 16 ZigBee channels to simultaneously collect the RSS samples for half an hour in a conference room. A Tx deployed sends packets in Ch. 26 to multiple receivers for making them work simultaneously. The receivers receiving control packets hop to the corresponding channel to collect data immediately. Then we use the collected RSS traces to fairly evaluate different methods. Without losing generality, we set the Tx power to -10dBm to match the actual work environment. The distance between the sender and the

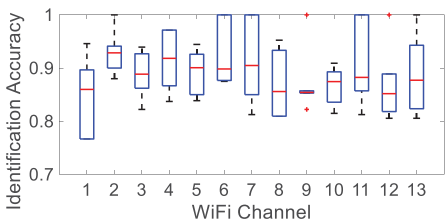


Fig. 10. The interference identification accuracy for the WiFi channel.

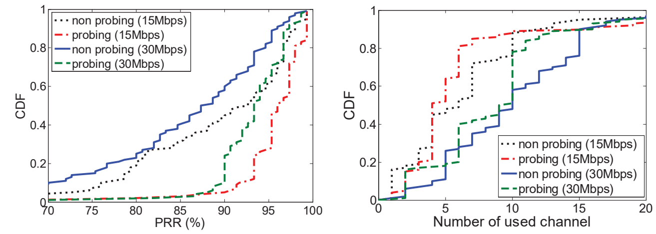
receivers is $3m$. The RSS sampling rate on receivers is 15KHz. To obtain different patterns of WiFi interference, three pairs of laptops in WiFi channels 1, 6 and 11 are used to generate a stream of UDP segments using the iperf tool [18] with the transmission rate of 1Mbps, 15Mbps, and 30Mbps. We then evaluate CoHop through online experiments in real-world environments and conduct experiments in controlled and real situations. The interference generation is using the iperf tool in controlled experiments. For real experiments, we directly observe the reliability of multiple methods in real-world environments, including office, classroom, and dormitory. Then we study the overhead of CoHop in terms of energy efficiency in controlled environments. For comparison, we also implement the random method and ARCH [11].

B. Benchmarks

We start with four benchmark experiments to validate the effectiveness of CoHop's major components.

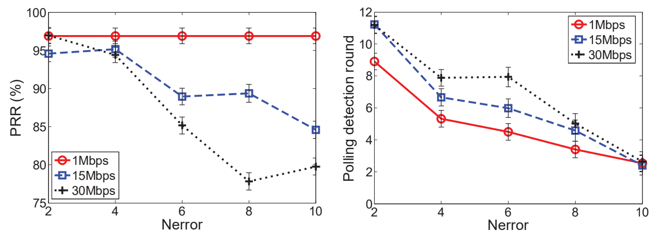
1) Channel Selection Accuracy: We evaluate the selection accuracy of CoHop by observing the channel hopping behaviors. The top display of Fig. 9 shows the varying WiFi interference rates, and the following shows a comparison between the corresponding channel hopping behaviors of various algorithms. It is noteworthy that we don't care about Ch. 25 and 26 which have less overlap with commonly used WiFi channels. As a baseline for comparison, we also compare the optimal algorithm which always chooses the maximum SINR channel. The optimal algorithm is to process data cyclically to select the optimal channel. Essentially, the optimal algorithm is the upper limit of performance and cannot be implemented online, while in fact, as long as SINR is more than 6dB, it is considered that the channel is equal optimal.

As shown in Fig. 9, we set the initial channel to 13, and under the interference-free environment (period 1-400ms), all methods continue to use Ch. 13 for data transmission. When the WiFi interference rate is turned to 1Mbps, the quality of Ch. 13 decreases sharply. CoHop can quickly adapt to this change by switching to Ch. 15 which exhibits higher SINR. However, ARCH algorithm first hops to Ch. 23 whose quality is poor, according to the principle of far channel priority. This causes the channel hopping to be performed again. The similar behaviors are observed when the WiFi interference rates are 15Mbps and 30Mbps. In addition, CoHop's performance is better than the random algorithm. Especially at 30Mbps, the random selection algorithm does channel hopping frequently. Obviously, the channel hopping frequency of CoHop is far less than other methods. The reason behind this result is that



(a) CDF of PRR (b) CDF of number of used channels

Fig. 11. Impact of the prediction-based probing method.



(a) Performance of PRR (b) Round of polling probing

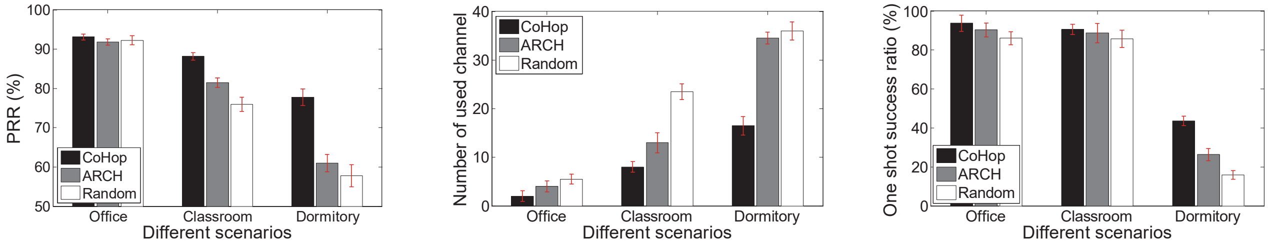
Fig. 12. Impact of the correlation update frequency.

CoHop makes a selection based on the quantitative correlation, while ARCH algorithm relies on binary correlation and the random scheme does not consider any correlation among channels.

2) Interference Identification Accuracy: In CoHop, the premise of interference quantization is to correctly identify the interference channel. Fig. 10 shows the effectiveness of interference identification for the WiFi channel. CoHop achieves a max identification accuracy of 100% for most WiFi channel and average interference identification accuracies of 89.1%. The above results show that the interference identification method can distinguish different WiFi channels with high accuracy.

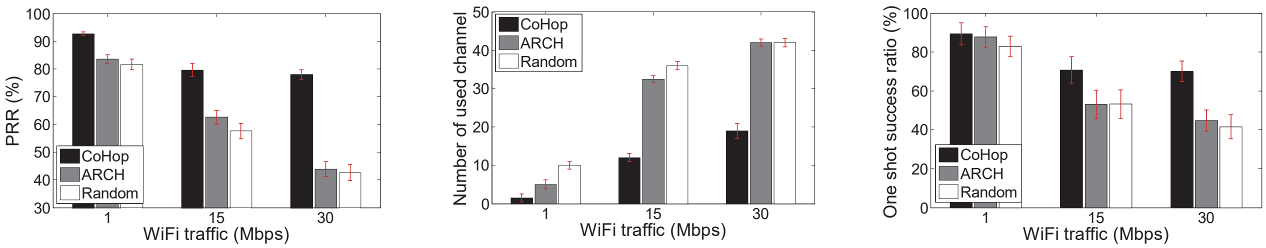
3) Prediction-based Probing Effectiveness: We further explore the effectiveness of the prediction-based probing method under different interference rates. Fig. 11 (a) depicts PRR with and without the prediction-based probing method. The method with probing achieves high reliability with an average value of 93%, while it drops to 85% without probing at 30Mbps. The significant enhancement is also clearly shown in Fig. 11 (b). For any interference intensity, the number of used channels is significantly reduced after using the prediction-based probing method.

4) Impact of Correlation Update Frequency: Due to WiFi interference is time-varying, the correlation model may be invalid over time, resulting in repeated channel hopping. To avoid frequent and worthless channel hopping, CoHop re-probes all channels after a series of error hops. To find the appropriate re-establishment opportunities, we further explore the impacts of the number of consecutive errors, N_{error}, before update correlation by polling. As shown in Fig. 12 (a), when N_{error} is 4, PRR of three cases is 97%, 94%, and 92% respectively at 1Mbps. Nevertheless, PRR drops down to 80% when re-probing is used after 10 errors at 30Mbps. This means that frequent probing can improve reliability. For balancing



(a) PRR (b) Number of used channels (c) One shot success ratio

Fig. 13. The online performance in real scenarios.



(a) PRR (b) Number of used channels (c) One shot success ratio

Fig. 14. The online performance under controlled environments.

overhead and reliability, we plot the polling probing round required for three cases in Fig. 12 (b). By comparing the two figures, we find that it is reasonable to set N_{error} to 4, which can provide high reliability and less polling times.

C. Online Performance

We present the overall online performance of CoHop in real-world experiments, in terms of PRR, the number of used channels, and the one-shot success ratio. One-shot success ratio indicates that the available channel can be selected by one channel hopping. The experiment results are shown in Fig. 13. CoHop keeps high reliability in three real-world scenarios. Even in the high interference dormitory, PRR of CoHop can reach 77%. The number of used channels of CoHop is 16.5, while the other two methods exceed 35. Similarly, CoHop also achieves a higher one-shot success ratio in three scenarios compared with the other two methods. This is because CoHop leverages the quantitative correlation to select the next channel.

Moreover, we explore the influence of interference intensity in real-world environments. The results are shown in Fig. 14. While PRR of three methods have small differences at 1 Mbps, CoHop's PRR keeps 78% at 30Mbps, which increases by 80% compared with the others. The number of used channels of CoHop is 19 at 30Mbps, but the others are higher than 40. For the one-shot success ratio, CoHop is also superior to others. The results above suggest CoHop can still provide high network reliability in real-world experiments.

D. Energy Efficiency

We measure the energy efficiency of CoHop directly to demonstrate power consumption. Energy efficiency refers to the total number of delivered data per energy consumption unit. According to the datasheet of CC2420 [19], the current consumption of receive and transmit mode of telosb are 18.8mA and 11mA respectively. As shown in Fig. 15, the energy efficiency decreases with increasing WiFi traffic, and CoHop's performance is twice as efficient as the others at 30Mbps. This is because the increasing poor channel selection probability results in low reception ratio and low energy efficiency at strong interference, while for CoHop, the energy efficiency keeps high even.

V. Related Work

We review related works that enhance communication reliability for low-power networks in three categories: passive avoidance, interference awareness, and positive collaboration.

The normal mechanisms of passive avoidance are fully exploring predictable transmission gaps in time [17], [20] or frequency [8]–[11]. WISE [17] resists CTI by probing WiFi white space to resize the data frame for ZigBee. TIIM [20] characterizes the CTI pattern by adopting machine learning techniques. The above methods are to avoid CTI in time, while our main concern is spectrum isolation by hopping to interference-free channels. Muzi [8] chooses an available channel by polling all. The blacklist technology used in [9], [10] avoids hopping to interfered channels by blacklisting bad channels. ARCH [11] holds on that the channel with a large distance away from the currently-used channel should be selected. While the methods above are shown to be highly effective, channel correlation is evaluated in binary instead of quantification, which do not make full use of boundary-channels. In this paper, we propose a channel hopping method based on quantitative correlation to uniquely investigate the available opportunities of boundary-channels to combat CTI.

Different from passive avoidance, the interference tolerance methods aim at resisting the presence of interference by improving system robustness [21]–[23]. For instance, ZiSense [21] leverages interference feature extraction to avoid unnecessary wake-ups. Smoggy-Link [22] maintains a model to obtain fine-grained spatiotemporal link information for adaptive link selection. This research direction is orthogonal to channel

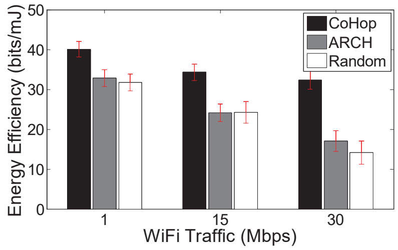


Fig. 15. The energy efficiency in controlled environments.

hoping we're focusing on because the signal processing can be integrated into CoHop to improve system robustness.

There are also plenty of positive coordination approaches that fight against interference by cooperating with WiFi through auxiliary mechanism [24]–[26], rather than simply promoting themselves [27], [28]. For example, Weeble [24] solves the coexistence problem by adaptive preamble support. G-Bee [25] safeguards the packets from WiFi interference by placing the ZigBee packets on the guard band of ongoing WiFi traffic. ECC [26] uses WiFi CTS to generate the white space and explicitly notify ZigBee via CTC to use it immediately. However, the above methods bring about a lot of overhead than CoHop, due to the coordination of heterogeneous devices.

VI. Conclusion

This paper presents a careful analysis of channel interference characteristic of ZigBee by the WiFi network at 2.4 GHz ISM band. Based on the observation that correlated channels affected by the same CTI source do not necessarily have the same channel quality and may even have the opposite channel state, we propose CoHop, a novel method of channel hopping based on quantitative correlation. CoHop adaptively selects an available channel based on quantitative correlation with low overhead and high precision and the channel selection module is based on PCC and prediction-based probing algorithm which can optimize probing sequence. Moreover, our model can be implemented directly on off-the-shelf devices. Lastly, compared with existing channel selection algorithms, CoHop can increase PRR by 80%, which simultaneously enhances channel hopping precision.

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