Channel Quality Correlation based Channel Probing in Multiple Channels

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***Abstract*—Many wireless networks provide a large number of available channels for data transmissions. Due to the multi-path environment, channels have different channel qualities. Therefore, selecting a good channel from the multiple channels can improve the communication effectiveness. The Packet Reception Rate (PRR) has been utilized to represent the channel quality. In order to know which channel has good quality, communication systems probe each channel and measure PRR. However, probing is time and energy consuming. In this paper, we propose a wireless channel probing approach, optimal channel probing (OCP), to efficiently select high-quality wireless channels. The OCP method utilizes a MAX-separation method to reduce the number of probing channels. In an evaluation using simulations and usrp2 real devices, we found that OCP is both effective and efficient at selecting high-quality channels and more efficient than existing channel probing methods.**

I. Introduction

Wireless networks are becoming increasingly complex today and can assign large number of available channels to the network nodes. Several existing wireless technologies (e.g., IEEE 802.11a [6], IEEE802.11b [1], IEEE802.11h [2], 802.15.3 Zigbee [3]) with multi-channels provide multiple frequencies for users. For example, IEEE 802.11a protocol has 12 channels in the 5GHz band, the IEEE 802.11b protocol has 3 channels in the 2.4GHz band, the 802.15.3 protocol has 15 channels and the cognitive radio systems [13] have a large number of channels that allow users to tune the frequency bands.

Channels can have different levels of quality, and a user tends to select a high-quality channel to transmit data from sender to receiver. However, this can be challenging because the user may not even know which channel is better than the others. A channel quality probing method could help to select a high-quality channel from multiple channels. To do this, the receiver exhaustively estimates the quality on every channel based on the measured SNR and determines whether a probed channel is good for being used or not.

However, probing is inefficient because it costs system resources such as time and energy. The probing cost can increase as the number of channels grows because all channels have to be inspected in order to select the one that has the best quality. However, the high-quality and the low-cost usually cannot be achieved at the same time and thus there involves a tradeoff between them. The solution to the tradeoff problem can be defined as maximizing a quality reward: $\texttt{reward} = \texttt{quality} - \texttt{probing number}*c$, where c is the probing cost provided by the systems based on its tolerance ability on the time and energy cost.

In this paper, we propose an optimal channel probing (OCP) algorithm to compute channels that are probed to maximize the quality reward function based on the system's requirements. To achieve this goal, the OCP algorithm consists of two major parts. The first part identifies which channels should be probed. We have observed that channels are correlated with each other in terms of their quality values in a real environment. In fact, we can measure the quality of one channel and predict the quality values of the correlated channels. As such, probing all channels are not necessary. We employ the MAX-separation method to iteratively select channels that are far from each other for being probed. The second part determines when to stop probing as the channel quality reaches the best quality reward value. It can predict the quality reward values of the channels that have not been probed. Fig. 1 shows the overview of the OCP. The OCP decides which channel should be probed. After the chosen channel's quality is measured, the OCP uses a judgment as "stop at where" to decide whether to stop at here or continue to choose the next channel.

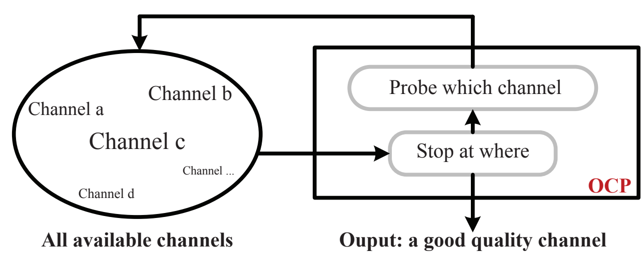

Fig. 1. Overview of the OCP

While there has been research on selecting high-quality wireless channels [4] [7] [8] [16] [10], it has focused on how to choose a good channel in terms of the channel capacity and SNR. However, in practical, the computed channel capacity can never be reached and the SNR can not be used to represent the connectivity directly. The discussion can be found in the motivation section and analyzed by Fig. 2. In this paper, we focus on the practical PRR metric. Moreover, existing work does not consider using the correlation between nearby channels to improve the probing efficiency.

In summary, this paper contributes the following:

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- We have proposed an OCP algorithm that considers the trade-off between the quality and cost in channel probing.
- The OCP approach employs PRR, a more practical channel quality metric. It also finds the channel correlation and designs a Max-separation method to deal with this correlation, which can greatly improve the efficiency of channel probing. To the best of our knowledge, this is the first work that uses the PRR metric and considers the channel correlation in wireless channel selection.
- We have evaluated OCP in real environments. The SNR traces are collected from different real environments by usrp2 [11]. We have proven the theory of the correlation between channels using these traces. The experimental results showed that the OCP method can substantially improve the efficiency of channel probing.

The remainder of this paper is organized as follows. First, some related works will be discussed in Section 2. In Section 3, we will describe the channel correlation and the suitable measurement times as the motivation. In Section 4, two methods as MAX-separation and optimal probing number have been designed. Section 5 provides some Matlab simulations and real experiments to show the OCP performs well with some different factors' impacts. Section 7 concludes the paper.

II. Related Work

There has been a great deal of research on improving channel quality in wireless communication, such as enhancing the transmission power [17], good modulation method [18], and channel probing [4]. The power enhancing method improves the transmission quality by increasing the sending power level. However, this method is expensive as it consumes much energy. The good modulation method may change a wireless communication generation to a new one such as the GSM of 2G to CDMA of 3G, but can result in expensive hardware.

A number of existing methods can allocate channels to the senders and receivers of the wireless network. For example, the ULN [20] allocates channels to different nodes in the cellular network. The DSRC [9] allocates channels to the dynamic users in the cognitive network. However, they all assume that the quality levels of the channels are the same. The CAP method [21] assigns the good quality channels to the suitable senders and receivers to improve the network's connectivity. However, this method needs to probe all available channels. The ASDCS [19] allocates a random channel to the sender and receiver. Then communication quality between the sender and receiver will be monitored. If a conflicted hidden node has been detected, the ASDCS will allocate a new channel to the sender and receiver.

Several channel probing methods have been proposed to balance the channel quality and probing cost [4] [7] [8] [16] [10], but they do not consider the channel correlation, which is an important performance factor when probing channels. Moreover, none of the existing research performs experiments in the real environment, some of which even does not involve an evaluation because their algorithms do not have analytic solutions. In addition, none of these methods utilize touchable metrics such as PRR for optimizing probing. It is because using PRR to design a solution is more difficult, although PRR can represent the channel quality more directly than SNR and channel capacity.

Other important recent works [15] [14] combine current and past channel quality assessments at the receiver to predict the channel quality. Especially, the NEWMAC [15] utilizes a machine learning method to train the past channel quality assessment. But, in our OCP, we do not use the information collected in long period, because we can not compute out how much changing of environment will make all past information useless. Our OCP measures the current channels' qualities and selects a good channel and do transmission on it.

III. Motivation

Several parameters can be used to represent the channel quality, including the channel capacity, PRR and SNR. Since these parameters are not the same, to maximize the quality rewards, the probing times are different. As shown in Fig. 2, to maximize the SNR reward, the probing needs to stop at the 41-st channel. However, to maximize the PRR reward, 10 channel probing can give a maximum PRR of 1. As such, in order to ensure successful data transmission, only 10 channel probing is enough as opposed to the 41 channel probing.

The works [16] [10] propose the channel capacity to represent the channel quality based on the Shanon equation. However, the channel capacity is difficult to measure and the channel capacity of the Shanon equation is an unreachable upper limitation rate. Considering the data coding and modulation, the real maximum transmission rate will be lower than the channel capacity.

In this paper, we suggest using PRR to represent the quality and propose several designs to maximize the PRR reward. The PRR can be measured by counting the number of the received packets. A simple method is used to estimate the PRR by SNR based on a widely known Eq. (1) [22].

$$prr = (1 - \frac{1}{2} e^{-\frac{snr}{2}\frac{1}{0.64}})^{8*f} \tag{1}$$

Counting the number of packets which are used by PRR probing costs more time and energy than the SNR probing. Therefore, we measure only the SNR of channels and estimate the PRR (packet received rate) by Eq. (1). In this equation, the f is the length of the packet. By default, we set f to 5 Bytes.

A. Channel Correlation

The correlation character refers to any statistical relationship between two random variables and it is represented by the correlation coefficients ρ_{xy} as Eq. (2).

$$\rho_{xy} = \frac{E(x,y) - E(x) \cdot E(y)}{\sqrt{D(x) \cdot D(y)}} \tag{2}$$

The E(x) and D(x) mean the mathematical expectation and variance of the random variable x. If $\rho_{xy} > 0$, the x and y have a positive correlation. On the contrary, if $\rho_{xy} < 0$, x and

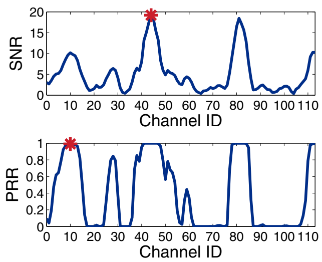

Fig. 2. Different probing times of SNR and PRR

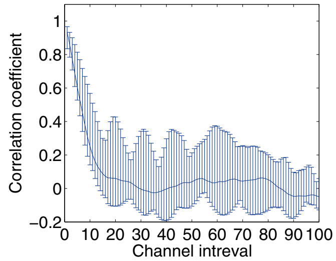

Fig. 3. Errorbar of the correlation coefficient with the PRR trace

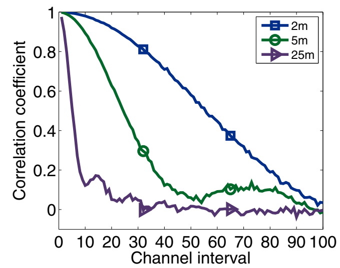

Fig. 4. Correlation coefficient

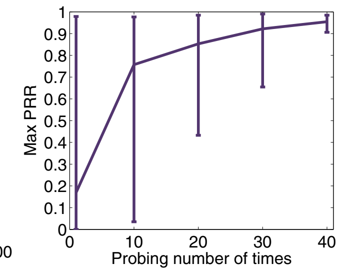

Fig. 5. MAX PRR and Measurement Times

y have a negative correlation. When $\rho_{xy} = 0$, it means there is no correlation between x and y.

The correlation coefficients are computed based on the PRR of different channels. We collect the SNR on 500 different channels by using usrp2 hardware in 6 different environments and transform them into PRR by Eq. (1). The channel region of the trace is 5.0∼5.5G and the frequency of the channel interval is 1M. Thus, the PRR of the 500 channels (i.e., [s(1) s(2),...s(500)]) will be substituted by the Eq. (2) to compute the correlation coefficient $\rho_{s(w),s(w+\tau)}$ with the interval τ of different channels. For example, $\rho_{s(w),s(w+1)}$ is the correlation coefficient between the neighboring channels.

In Fig. 3, we utilize an errorbar to describe the correlation coefficients' regularity at each τ with the PRR of the 6 environment. In this figure, the x-axes represents the channels' interval τ, which begins from 1 and ends with 100. The y-axis represents the correlation coefficients. We can see the largest correlation coefficient is 0.98 and lowest one is 0.82 at $\tau = 1$. Thus, the neighboring channels have strong positive correlations which are stable in different environments. As the frequency interval increases, the positive correlations are weaker and more related to 6 different environments than a sole large value. The correlation coefficients are 0.17 ∼0.7 at $\tau = 10$. As the frequency interval continues increasing, there is no certain positive correlation at all. The correlation coefficients are $-0.1 \sim 0.4$ at $\tau = 20$.

The experiment results show that the closed channels lead to strong positive correlations no matter in what environment. As the interval of the channels becomes larger, the correlation becomes weak and eventually disappear.

Fig. 4 shows that there is no "security" interval τ. As such, the correlation is related to the environment. In this figure, the 2m, 5m and 25m are reflection distances in different environments. By some derivations, we proved that if the $\tau \rightarrow 0$, the correlation coefficient $\rho(w, w+\tau) = 1$. If the $\tau >> 0$, the correlation coefficient will relate to many environment factors as LOS path distance, NLOS path distance and so on. The complex but reasonable mathematical derivation process is in appendix 4. The final result of the mathematical derivation matches our observation in real environment experiment. Fig. (4) is built by 3000 Monte Carlo Simulations based the Eq. (14) which is in appendix 4. We test the correlation coefficient with different τ in three different environments which have the longest distances as 2m, 5m, 25m. The frequency interval of channel is 1M. In the figure, we see the 2m, 5m, 25m environments have different "security" intervals as 90, 40, 10.

As noted in Section I, we can avoid probing the correlated channels to reduce the unnecessary cost. We propose a method that probes only uncorrelated channels.

B. Number of Probing Times

In this section, the tradeoff problem between the quality and number of probing times will be analyzed.

Fig.5 is used to describe the relationship between quality and probing times. All of the data in the figure are collected in real environment. In this figure, the mean of MAX PRR is increasing as the number of the channel probing times becomes larger. Our OCP method should give a good answer on when the probing should stop in terms of quality of the PRR.

As in the figure, the only 1 channel's probing may probe a large PRR as 0.98 a good quality. Then the OCP method should stop at the good quality channel. The only 1 channel's probing may also probe a low PRR as 0 a bad quality. At this time, the OCP method should continue to probe next channel until obtain a good channel. But, more probes will bring more cost. The OCP method should stop at a good quality channel as least probe as possible.

IV. Optimal Channel Probing Design

In this section, we describe the OCP method in details. We first design a MAX-separation method that iteratively determines which channel should be probed at the next stage. We then propose an optimal probing stopping method that estimates the quality reward of the next channel and decides whether it should stop at the current stage or not. Fig.6 provides an overview of the OCP method.

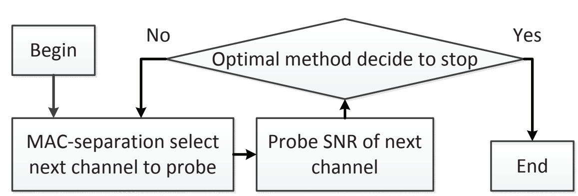

Fig. 6. OCP algorithm flow chart

A. Selecting Probing Channels

As noted in Section III, two channels that are close to each other often have a positive correlation, whereas those far away from each other are not correlated. Since probing the correlated channels can induce unnecessary cost, we propose a MAX-separation method that probes only the uncorrelated channels.

The MAX-separation makes use of two sets of channels, the probed set and the candidate set, which are disjoint. The probed set is the set of distinct channels that have been probed so far, and the candidate set consists of channels for being selected in the next iteration. We first sort the channels in terms of their frequencies in an ascending order, denoted by a list l. The probed set is initially empty and the first element of l is selected by the first channel for being probed. The probed set is then incrementally updated with the probed channel from the candidate set until a stopping criterion is met. From the candidate set, a channel that is farthest away from all probed channels is selected as the next probing channel.

Specifically, let $P = \{p_1, p_2, \ldots, p_n\}$ be the probed set and $C = \{c_1, c_2, \ldots, c_k\}$ be the candidate set such that $P \cap C = \phi$. The idea of the MAX-separation is to choose the channel c_h such that for all $j \in \{1, 2, \ldots, k\}$:

$$\min_{i=1}^{n} dist(c_h, p_i) \geq \min_{i=1}^{n} dist(c_j, p_i)$$

Here, $dist$ is defined as the Euclidean distance. The rationale of this idea is to probe unrelated channels through maximizing the minimum distance between the next channel and the already probed channels.

Fig. 7 shows an example of using the MAX-separation method. The channels are sorted into a list $l = \{c_1, c_2, \ldots, c_n\}$. The first channel l_1 is selected from the first position of l. The second channel l_2 is from the last position of l because it is the farthest away from the first channel. The third channel l_3 is located in the middle of l because the minimum distance between l_1 and l_3, and between l_2 and l_3 is maximized. The fourth channel is picked from the middle of the largest internal of the c_1 and c_n. The MAX-separation method is optimal when we only consider the optimal location of the next channel in the candidate set. The proof is in appendix 5.

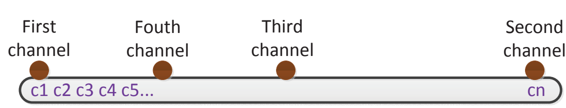

Fig. 7. Middle Division Method

As the algorithm 1, the MAX-separation can make sure the shortest division of the next channel probing to be longest. Then we can avoid the certain positive channel qualities' correlation as possible as we can.

B. Probing Stopping Criterion

The optimal stopping method [5] can stop the optimization process when a best reward is obtained. This method was used to predict the rewards in future and choose the optimal time to take action. For example, a woman wants to sell her house. An agency offers a new price for her house every day, but she needs to pay a fixed agency fee to the agency every day until she decides to sell her house. The woman does not know the next day's offer but she can use past offered price to make a deal. The optimal stopping method will tell woman when to stop to get the biggest reward.

Algorithm 1 MAX-separation

Input: The measured channels' ID as C=[c_1...,c_i,c_j].

Output: An unmeasured channels' ID l_{next}.

1: Sort the C in ascending ID.
2: Compute the ID difference on every c_m and c_{m+1} as $p_m = c_{m+1} - c_m$.
3: Find out the maximal value of the ID differences and record the ID as $k = \{k|p_k = MAX([p_1, p_2, p_3...])\}$.
4: $l_{next} = c_k + \frac{\lfloor c_{k+1} - c_k \rfloor}{2}$.

The main theory is that if the predicted rewards are smaller than the current reward, the optimization process stops and takes the current reward.

The optimal Eq. (3) describes the optimal stopping. In this equation, $V_j(x_1, ..., x_j)$ is the maximum reward starting from stage j with probed value as $x_1...x_j$ and $y_j(x_1, ..., x_j)$ is the reward at j stage. It is optimal to stop at j if $V_j(x_1, ..., x_j) = y_j(x_1, ..., x_j)$, or to continue otherwise.

$$\begin{aligned} V_j(x_1, ..., x_j) = \max\{&y_j(x_i, ..., x_j), \\ &E(V_{j+1}(x_1, ..., x_j, X_{j+1})|X_1 = x_1, ..., X_j = x_j)\} \end{aligned} \quad (3)$$

When applying the optimal stopping method to the problem of channel probing, the cost of probing at each iteration is considered. At n^{th} probing iteration, the quality reward is $Max(X_1, X_2...X_{n-1}, X_n) - n \cdot c$, where X_n indicates the probed quality of the n^{th} channel.

We let V^* be the maximum reward of the channels in the candidate set. If the $X_1 \geq V^*$, the probing should be stopped. Otherwise, the probing process continues. The V^* can be computed as Eq. (4).

$$\begin{aligned} V^* &= E\max\{x - c, V^* - c\} \\ &= E\max\{x, V^*\} - c \\ &= \int_{-\infty}^{V^*} f(x) \cdot V^* dx + \int_{V^*}^{\infty} f(x) \cdot x dx - c \\ &if \quad X_n > V^* \quad stop \\ &if \quad X_n < V^* \quad continue \end{aligned} \quad (4)$$

Since the optimization objective is the PRR, which can be predicted according to the SNR in Eq. (1), the probability density f(x) of PRR can be transformed by the probability density f(k) of SNR. In a frequency selective fading environment, the SNR obeys the exponential distribution as shown in Eq. (5) [18]. After the transformation, the final f(x) is shown in Eq. (6). In this equation, b represents the mean SNR.

$$f(s) = \frac{1}{b} e^{-\frac{s}{b}} \tag{5}$$

$$f(x) = -0.16 \frac{x^{\frac{1}{40}-1}(2-2\sqrt[40]{x})^{\frac{1.28}{b}}}{b \cdot f \cdot (\sqrt[40]{x}-2)} \tag{6}$$

We substitute f(x) into the Eq. (4) to compute a V^*. The Eq. (4) can determine a channel at which the optimization stops. One challenge is that the Eq. (4) cannot be solved due to the integral calculus. To address this, we transform Eq. (4) into a set of formulae f_s.

Theorem 1: Eq. (4) is equivalent to Eq. (7). The evidence is in appendix 1.

$$\begin{aligned} X_n &> E\max\{X, X_n\} - c \quad stop \\ X_n &< E\max\{X, X_n\} - c \quad continue \end{aligned} \tag{7}$$

The PRR region is divided into N equal intervals as the Fig. 8. Each interval is related to an SNR value, so there are N+1 SNR values $k_0, k_1, k_2...k_N$. With a larger N, the result of f_s is closer to that of Eq. (4). In this paper, we set the interval number as N=50. Note that the minimum PRR value prr=0 can cause an abnormal SNR value, so we set the minimum PRR value as prr=0.001.

The probability of the quality in every interval is $q_j = \int_{k_i}^{k_{i+1}} f(k)dk$. Since the distribution of SNR values is exponential, the probability is transformed into $q_j = \frac{1}{e^{\frac{k_i}{b}}} - \frac{1}{e^{\frac{k_{i+1}}{b}}}$.

When an SNR value of a channel is measured, the closest k_m is selected to represent it. When we split Eq. (4) into the 50 smaller regions, the new optimal probing equation is shown as Eq. (8).

$$\begin{aligned} &X_n \geq E\max\{X, X_n\} - c \quad stop \\ &X_n \leq E\max\{X, X_n\} - c \quad continue \\ &E\max\{X, X_n\} = \sum_{1}^{m} q_i \cdot X_n + \sum_{i=m}^{N} q_i \cdot \frac{i}{N} \\ &where: m = \arg_m(\min(\left|X_n - \frac{m}{N}\right|)) \\ &where: q_j = \frac{1}{e^{\frac{k_i}{b}}} - \frac{1}{e^{\frac{k_j}{b}}} \\ &where: k_m = -1.28\log(2 - 2\sqrt[40]{\frac{m}{N}}) \end{aligned} \tag{8}$$

To solve Eq. (4), we need to estimate the mean SNR (i.e., b in the Eq. (8)) and analyze whether different channels have the same parameters b.

Theorem 2: the parameters b have no relationship with the frequency of channels. The evidence is in appendix 2.

Theorem 3: Utilizing the average of the first n samples as $\bar{S}$ to estimate the b, the estimation error is $\frac{\bar{S}}{\sqrt{n+1}}$. The evidence is in appendix 3.

Regarding Theorem 2, because the mean SNR has no relationship with the frequency, different channels are exponentially distributed. The parameter b is one value in an environment no matter what the channel is. Martinsek et al. [12] estimate the unknown parameters b in the optimal stopping method when samples are exponentially distributed. Their technique suggests to utilize the average of the first n samples to estimate the b and provides a sketchy "n" value as $n = o(c^{-1})$.

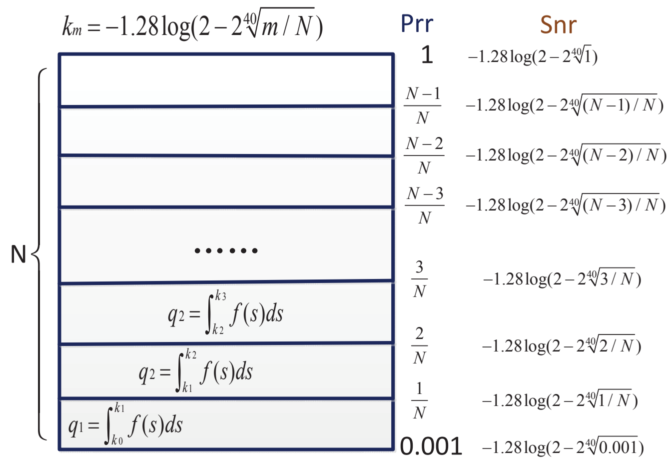

Fig. 8. N equal intervals of the PRR region

Regarding Theorem 3, the estimation error is big when the number of samples is small. However, to reduce the number of probing times, there are often not enough channels for increasing the sample number. To address this problem, we set b_p to the prior estimation of b. To compute the weight of the error and real value based on the Theorem 3, we design the Eq. (9) to estimate b.

$$\hat{b} = \frac{\sqrt{n+1}}{1+\sqrt{n+1}}\bar{S} + \frac{1}{1+\sqrt{n+1}} b_p \tag{9}$$

$$b_p = -1.28\log(2 - 2\sqrt[40]{0.5}) \tag{10}$$

Here, the optimal probing stopping method has finished. Considering the estimation mistake of b at the early probing stages, we design a recall mechanism. In the Eq. (8), we change the X_n to the maximum quality of the probed channels. Then the optimal probing stopping algorithm is shown in the algorithm 2.

V. Evaluation

The evaluation of our OCP method consists of three parts. The first two parts are based on MATLAB simulation. The third part is an SNR trace driven experiment. By simulation, we can use a large number of Monte Carlo with Matlab to test the robustness of the OCP performance. The trace driven experiments tests whether the OCP is effective or not in a real environment.

The OCP is designed to maximize the quality reward function. In the first part of the evaluation, we manually vary the cost of the quality reward function and examine the result of the OCP. In the second part and third part, we test the

Algorithm 2 Optimal stopping

Input: Channel l_{next} to probe at next stage by the MAX-separation. The cost c happens at every channel probing.
Output: The final channel l_f to do transmission.

```
X_max = 0 , i = 0.
for i < the available channel number do
    i = i + +.
    Ask the MAX-separation for a next stage channel l_next.
    Measuring the SNR of the l_next as X_n.
    if X_max > X_n then
        X_max = X_n
        l_f = l_next
    end if
    Computing the E max{X, X_max} by equ(8).
    if X_max > E max{X, X_max} − c then
        break
    end if.
end for
Output the l_f
```

efficiency of OCP in terms of the packets transmission rate for a given time.

A. Varying Costs in Simulation

Systems can have different tolerant levels on the time and energy cost. As such, every probing cost c can be different on these systems. We vary the value of c to examine the behavior of the quality reward function "PRR − n∗c" under different cost values.

The experiment is built by a multi-path environment model. The 20 paths with random reflection distances and random reflection coefficients are combined at the receiver. We measure the 5.0-5.5Ghz channels' RSSI with the channel interval of 0.001G and assume the noise power is same. The mean SNR is set to 6.93∼20.79 db random values and every result comes from 3000 Monte Carlo.

In addition to OCP, we consider two other baseline methods, including 1) the regular probing stopping method, which does not consider the channel correlations (i.e., the MAX-separation method), and 2) N method, which stops channel probing at the N^{th} channel probing iteration.

Fig. 9 and Fig. 10 show the selected PRR and the number of probing times with different costs in the quality reward function, respectively. In Fig. 9 , we observe that at a small cost level, c=0.001, the OCP tends to reach the largest PRR channel. In this case, the selected channel is equal to that of all 500 channels being probed. To find such a channel, the OCP probes only 47 channels rather than all 500 channels. At a large cost system, c=0.25, the OCP is the same as when only one channel is probed.

Fig. 9 and Fig. 10 indicate that, across all cost values, OCP can select a channel with higher quality than the regular probing stopping method in less time. These results indicate that the use of the MAX-separation method does improve the efficiency of channel probing.

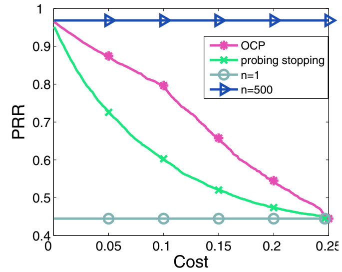

Fig. 9. The selected PRR with different cost.

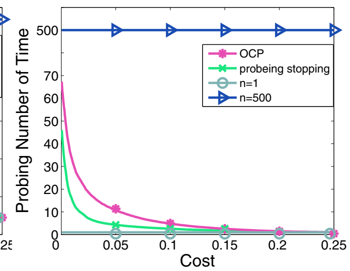

Fig. 10. The probing number of times with different cost.

B. Measuring Packets Transmission using Simulation

In the second part of the evaluation, we design an application to test the OCP performance (i.e. efficiency) in terms of the number of packets transmitted under certain time limits. We evaluate whether the OCP method can transmit more packets within a limited time T than the baseline methods. Here, T can be divided into 2 parts: 1) the time spent on channel probing to find a high-quality channel and 2) the time used to transmit packets. Obviously, more probing time occupies more portion of T, then it has less time to transmit packets, resulting in less number of packets being transmitted. In the reward function, the cost c is $\frac{t_c}{T-n \cdot t_c} \cdot E\max(X_n, X)$ in this system, where $E\max(X_n, X)$ can be obtained by the Eq. (8) and t_c means the time spent on each probing.

In addition to the probing stopping and N methods, we consider two other baseline methods: 1) the threshold method, which stops channel probing when $prr > threshold$, and 2) the upper limitation method, which *theoretically* calculates the maximum number of packets that a method can reach regardless the channel correlations.

Fig. 11 illustrates the OCP and other methods that transmit packets in 16 different mean SNR environments, ranging from 6.93db to 20.79db. The total time is set to T=500s and the transmission speed is set to 1 packet/s. The channel probing cost t_c = 1s. We build the same multi-path model as described in Section V-A in this simulation. All simulation results are from the mean of 1000 Monte Carlo. As Fig. 11 shows, the OCP can transmit more packets than all other baseline methods.

In Fig. 12, we test the performance of the OCP under different time periods T=300, 400, ..., 900. The mean SNR is set to a random value ranging from 6.93db to 20.79 db and the simulation setting is the same as the one in Fig. 11. We can see that the OCP outperforms all other methods across all timing points.

In Fig. 13, the number of available channels is varied from 20 to 440. We examine whether OCP can transmit more packets than the other methods when using different numbers of available channels. Again, the OCP performs the best among all methods.

Theses figures illustrate that the OCP transmit more packets than the upper limitation in theory, which indicates that the MAX-separation method can improve the performance when

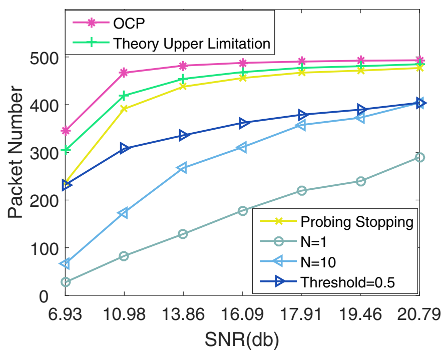

Fig. 11. Successful packet transmission number with different SNR

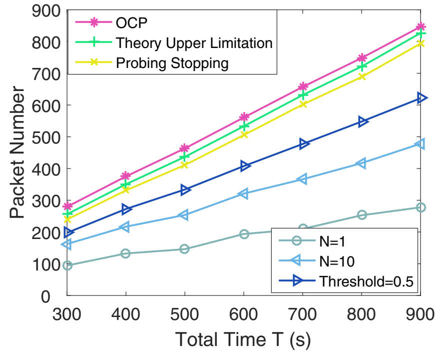

Fig. 12. Successful packet transmission number with different Total time T

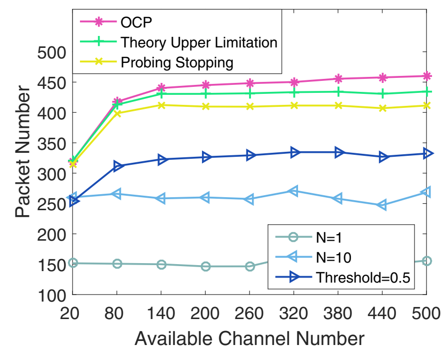

Fig. 13. Successful packet transmission number with different available channel number

maximizing the quality reward function.

C. Evaluation in a Real Environment

In the last part, we utilize the usrp2[11] hardware to collect the SNR on 5.0∼5.5Ghz 500 channels under 54 different environments and perform trace driven experiments. Besides SNR, we utilize the same experiment settings as the first two parts.

Fig. 14 indicates the number of packets transmitted using the OCP method within a total time T=300∼900. We can see that the OCP can transmit more packets than the upper limitation and the optimal probing stopping methods. The optimal probing stopping method is close to the upper limitation and better than the N methods. Fig.15 shows the efficiency of the six methods when using different available channel numbers. The results are similar to the simulation results in the second part. In summary, the OCP method is more efficient than the existing methods.

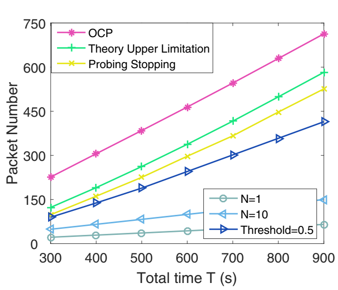

Fig. 14. Successful packet transmission number with different total times in a trace driven experiment

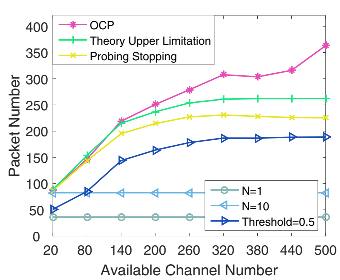

Fig. 15. Successful packet transmission number with different available channel number in a trace driven experiment

VI. Conclusion

In this paper, we have analyzed the problem on how to select high-quality channels with less probing time. We have studied the correlation between channels and proposed an OCP algorithm that accounts for the channel correlation. We have proposed a MAX-separation method to determine which channel to probe and an optimal probing stopping method to determine how many channels to probe. Our evaluation shows that the OCP is efficient under different system settings and more efficient than existing methods. Future work will include building a route among different nodes using the OCP method to improve the channel quality and avoid data collisions.

VII. Acknowledgements

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References

[1] I. 802.11a Working Group et al. Wireless lan medium access control(mac) and physical layer(phy) specifications-amendment 1:high speed physical layer in the 5ghz band. 1999.

[2] I. 802.11h Working Group et al. Wireless lan medium access control(mac) and physical layer(phy) specifications-amendment 5:spectrum and transmit power management extensions in the 5ghz band in europe. 2003.

[3] E. Callaway, P. Gorday, L. Hester, J. A. Gutierrez, M. Naeve, B. Heile, and V. Bahl. Home networking with ieee 802.15. 4: a developing standard for low-rate wireless personal area networks. *Communications Magazine, IEEE*, 40(8):70–77, 2002.

[4] N. B. Chang and M. Liu. Optimal channel probing and transmission scheduling for opportunistic spectrum access. *Networking, IEEE/ACM Transactions on*, 17(6):1805–1818, 2009.

[5] T. S. Ferguson. http://www.math.ucla.edu/ tom/stopping/. University of California at Los Angeles.

[6] I. . W. Group et al. Wireless lan medium access control (mac) and physical layer (phy) specifications. 1997.

[7] S. Guha, K. Munagala, and S. Sarkar. Jointly optimal transmission and probing strategies for multichannel wireless systems. In *Information Sciences and Systems, 2006 40th Annual Conference on*, pages 955–960. IEEE, 2006.

[8] S. Guha, K. Munagala, and S. Sarkar. Optimizing transmission rate in wireless channels using adaptive probes. In *ACM SIGMETRICS Performance Evaluation Review*, volume 34, pages 381–382. ACM, 2006.

[9] Y. Han, E. Ekici, H. Kremo, and O. Altintas. Throughput-efficient channel allocation in multi-channel cognitive vehicular networks. In *IEEE INFOCOM 2014-IEEE Conference on Computer Communications*, pages 2724–2732. IEEE, 2014.

[10] Z. Ji, Y. Yang, J. Zhou, M. Takai, and R. Bagrodia. Exploiting medium access diversity in rate adaptive wireless lans. In *Proceedings of the 10th annual international conference on Mobile computing and networking*, pages 345–359. ACM, 2004.

[11] E. R. LLC. Universal soft radio peripheral. 2006.

[12] A. T. Martinsek. Approximations to optimal stopping rules for exponential random variables. *The Annals of Probability*, pages 876–881, 1984.

[13] J. Mitola III and G. Q. Maguire Jr. Cognitive radio: making software radios more personal. *Personal Communications, IEEE*, 6(4):13–18, 1999.
[14] P. J. Pietraski. Method for channel quality prediction for wireless communication systems, Mar. 22 2011. US Patent 7,912,490.
[15] W. Rehan, S. Fischer, and M. Rehan. Machine-learning based channel quality and stability estimation for stream-based multichannel wireless sensor networks. *Sensors*, 16(9):1476, 2016.
[16] A. Sabharwal, A. Khoshnevis, and E. Knightly. Opportunistic spectral usage: Bounds and a multi-band csma/ca protocol. *Networking, IEEE/ACM Transactions on*, 15(3):533–545, 2007.
[17] E. Shpak et al. Enhancing wireless lan capacity using transmission power control, June 14 2005. US Patent 6,907,229.
[18] B. Sklar. *Digital communications*, volume 2. Prentice Hall NJ, 2001.
[19] E. Sullivan, T. Johnson, and B. Lee. Dynamic channel switching for high-definition peer-to-peer 802.11-based video streaming. In *2016 13th IEEE Annual Consumer Communications & Networking Conference (CCNC)*, pages 699–704. IEEE, 2016.
[20] R. Wang, C. Zhou, A. Mazumder, A. Das, H. Kierstead, and A. Sen. Upper and lower bounds of choice number for successful channel assignment in cellular networks. In *2015 IEEE International Conference on Communications (ICC)*, pages 3370–3375. IEEE, 2015.
[21] Y. Wu, Y. Zhao, and Y. Liu. Channel adjustment for performance enhancement in wireless networks. In *Cyber-Enabled Distributed Computing and Knowledge Discovery (CyberC), 2015 International Conference on*, pages 463–472. IEEE, 2015.
[22] M. Zuniga and B. Krishnamachari. Analyzing the transitional region in low power wireless links. In *Sensor and Ad Hoc Communications and Networks, 2004. IEEE SECON 2004. 2004 First Annual IEEE Communications Society Conference on*, pages 517–526. IEEE, 2004.

VIII. Appendix

A. appendix 1

Theorem 1 Eq.(4) is identical related to the Eq.(8).

$$\begin{aligned}
&y_n = (E\max\{X, X_n\} - c) - X_n \\
&= (\int_{-\infty}^{X_n} X_n dF(x) + \int_{X_n}^{+\infty} x dF(x) - c) - X_n \\
&if \quad X_{n+1} > X_n \\
&y_{n+1} - y_n \\
&= \int_{X_n+1}^{+\infty} x dF(x) - \int_{X_n}^{+\infty} x dF(x) - \\
&\quad (\int_{X_n+1}^{+\infty} X_{n+1} dF(x) - \int_{X_n}^{+\infty} X_n dF(x)) \\
&= -\int_{X_n}^{X_{n+1}} x dF(x) - (\int_{X_{n+1}}^{+\infty} X_{n+1} - X_n dF(x) \\
&\quad - \int_{X_n}^{X_{n+1}} X_n dF(x)) \\
&= -\int_{X_n}^{X_{n+1}} x - X_n dF(x) - \int_{X_{n+1}}^{+\infty} X_{n+1} - X_n dF(x) \\
&< 0
\end{aligned} \tag{11}$$

So, y_n is negative monotonic with the X_n.

$$\begin{aligned}
&\mathrm{V}^* - E\max\{X, V^*\} - c = 0 \\
&if \;\; X_n \geq E\max\{X, X_n\} - c \\
&X_n \geq V^* \qquad stop \\
&if \; X_n \leq E\max\{X, X_n\} - c \\
&X_n \leq V^* \qquad continue
\end{aligned}$$

B. appendix 2

Theorem 2:the parameters b have no relationship with the frequency f. The signal model is:

$$s(t) = \sum_{i=1}^{n} \frac{1}{di} \Gamma i \cdot \cos(w_i t + \theta i)$$

Do a transformation

$$\begin{aligned}
&s(t) = E_0 \sum_{i=1}^{n} C_i \cos(w_i t + \theta i) \\
&where \\
&E_0 = \sum_{i=1}^{n} \frac{1}{d_i} \Gamma_i \\
&\sum_{i=1}^{n} C_i = 1
\end{aligned}$$

Do the orthogonal decomposition to the equation.

$$\begin{aligned}
&s(t) = T_c(t)\cos(w_c t) - T_s(t)\sin(w_c t) \\
&where: \\
&T_c(t) = E_0 \sum_{i=1}^{n} C_i \cos(\theta) \\
&T_s(t) = E_0 \sum_{i=1}^{n} C_i sin(\theta)
\end{aligned}$$

According to the central-limit theorem, $T_c(t)$ and $T_s(t)$ obeys the normal distribution $N(0, \frac{E0}{2})$.

$$\begin{aligned}
&s(t) = \sqrt{T_c(t) + T_s(t)} \\
&f(s) = \frac{s}{(\frac{Eo}{2})^2} e^{-\frac{s^2}{2(\frac{Eo}{2})^2}}
\end{aligned}$$

It is the rayleigh distribution. Define the n as the noise power. The snr means $r = \frac{s^2}{n}$.

$$f(r) = \frac{1}{\frac{1}{n}(\frac{Eo}{2})^2} e^{-\frac{r}{\frac{1}{n}(\frac{Eo}{2})^2}}$$

So the $b = \frac{1}{n}(\frac{Eo}{2})^2$ has no relationship with the frequency w.

C. appendix 3

Theorem 3:Utilizing the $\bar{X}$ to estimate the b by n samples, the estimation error's math expectation is $\frac{\bar{X}}{\sqrt{n+1}}$. The problem will be defined as $E((b - \bar{X})^2 - \alpha \cdot \bar{X}^2) = 0$, $E(\sqrt{\alpha}\bar{X}) = E(\left|b - \hat{b}\right|)$. Because the SNR obeys the exponent distribution, $\frac{2n\bar{X}}{b} \sim \chi^2(n)$. $\chi^2()$means the chi square distribution.

$$\begin{aligned}
&\frac{2n\overline{X}}{b} \sim \chi^2(n) \\
&\mathrm{var}(\frac{2n\overline{X}}{b}) = 4n \\
&E(\frac{2n\overline{X}}{b}) = 2n
\end{aligned}$$

The b is the math expectation of $\hat{X}$, it is because the $\hat{X}$ only comes limited number of samples.

$$
\begin{aligned}
&E((b-\bar{X})^2-\alpha\cdot\bar{X}^2)=0\\
&E((b-\bar{X})^2)=\alpha E(\bar{X}^2)\\
&E((b-\bar{X})^2)=\mathrm{var}(\bar{X})=\frac{b^2}{n}\\
&E(\bar{X}^2)=\mathrm{var}(\bar{X})+E(\bar{X})^2\\
&E(\bar{X}^2)=\frac{b^2}{n}+b^2=\frac{n+1}{n}b^2\\
&\alpha\frac{n+1}{n}b^2=\frac{b^2}{n}\\
&\alpha=\frac{1}{n+1}\\
&\sqrt{a}=\sqrt{\frac{1}{n+1}}
\end{aligned}
$$

So the estimation error is $\frac{\bar{X}}{\sqrt{n+1}}$.

D. appendix 4

In order to test the universality of the observations' results. We analyze the reason of certain positive correlation in theory. Because the different channels' qualities result from the multipath effect environment, we build the receiving model in the multipath environment which has two or more paths between the sender and receiver. We put forward the signal at every paths arriving model as Eq. (12) by Friss.

$$E_i(t)=G\cdot\lambda\cdot\frac{\Gamma_i}{d_i}\sin(\frac{2\pi c}{\lambda}t+\frac{d_i-d_0}{\lambda}2\pi) \tag{12}$$

In this equation, d_0 is the LOS(line-of-sight) path distance, d_i is the i-th NLOS path distance, Γ_i is the i-th reflection coefficient, The constant G is the transmission power multiplies by receiving gain, $E_i(t)$ is the amplitude of the i-th NLOS path signal. λ is the wavelength. The NLOS paths' signals add each other at the receiver and the Received Signal Strength Indicator(RSSI) can be represented by Eq. (13), where c is the light speed and f is the frequency of the signal.

$$
\begin{aligned}
s_f&=(\sum_{m=1}^{M}E_m(t))^2 \qquad (13)\\
&=G\cdot\left(\frac{c}{f}\right)^2\cdot(\sum_{m=1}^{M}\frac{\Gamma_m}{2d_m^2}+\sum_{m\neq m'}\frac{\Gamma_m\Gamma_{m'}}{d_m d_{m'}}\cos(\frac{d_m-d_{m'}}{c}2\pi f))
\end{aligned}
$$

By using such receiving model, we can compute out the $\rho(w,w+\tau)$ as Eq. (14). To the space limit, the derivation processes will be omitted in this paper of Eq. (13) and Eq. (14). In the equation, "a " and "b" are the available channels' highest frequency and lowest frequency.

From the Eq. (14) we see if the $\tau\rightarrow 0$, the correlation coefficient $\rho(w,w+\tau)=1$. If the $\tau >> 0$, the correlation coefficient will relate to many environment factors as LOS path distance, NLOS path distance and so on.

$$
\begin{aligned}
&\rho(w,w+\tau)=\frac{A}{B}\\
&A=\sum_{m\neq m'}^{M}\{E_{m,m'}\cdot(A_1-A_2)\}\\
&B=\sqrt{\sum_{m\neq m'}^{M}\{E_{m,m'}\cdot(B_1)\}\cdot\sum_{m\neq m'}^{M}\{E_{m,m'}\cdot(B_2)\}}\\
&A_1=\frac{\cos(S\tau)}{2}+\frac{\sin(2Sb+S\tau)-\sin(2Sa+S\tau)}{4S(b-a)}\\
&A_2=\frac{(\sin(Sb)-\sin(Sa))\cdot(\sin(Sb+S\tau)-\sin(Sa+S\tau))}{S^2(b-a)^2}\\
&B_1=\frac{1}{2}+\frac{\sin(2Sb)-\sin(2Sa)}{4S\cdot(b-a)}-\frac{(\sin(Sa)-\sin(Sb))^2}{S^2(b-a)^2}\\
&B_2=\frac{1}{2}+\frac{\sin(2Sb+2S\tau)-\sin(2Sa+2S\tau)}{4S\cdot(b-a)}\\
&\qquad-\frac{(\sin(Sa+S\tau)-\sin(Sb+S\tau))^2}{S^2(b-a)^2}\\
&S=\frac{dm-dm'}{c}2\pi \qquad E_{m,m'}=(\frac{\Gamma_m\Gamma_{m'}}{d_m d_{m'}})^2\\
&if \qquad \tau\rightarrow 0\\
&\lim_{\tau\rightarrow 0}\rho(w,w+\tau)=\frac{\frac{1}{2}+\frac{\sin(2Sb)-\sin(2Sa)}{4S\cdot(b-a)}-\frac{(\sin(Sa)-\sin(Sb))^2}{S^2(b-a)^2}}{\frac{1}{2}+\frac{\sin(2Sb)-\sin(2Sa)}{4S\cdot(b-a)}-\frac{(\sin(Sa)-\sin(Sb))^2}{S^2(b-a)^2}}\\
&\qquad=1
\end{aligned} \tag{14}
$$

E. appendix 5

It is no doubt that the first spot and the second spot should be at the beginning of the line and end of line as in Fig(7). We will begin to analyze where to locate the third spot then to the the M-th spot.

Theorem 4: a+b=1,to maximize the smallest value of a and b. a=b=0.5

prove: we assume $a\leq b$. And we maximize the a, the upper bound of a is b. So the solution is a=b=0.5.

Theorem 5: In order to maximize the shortest interval after the division, the optimal spot location is the middle of the longest interval q.

Prove: As the theorem 4, the middle of the q will divide the q into the longest smaller interval which is equal to q/2. If we divide another interval w, it will result to a longest smaller interval w/2. Because the $w/2<q/2$, so the optimal spot location is the middle of the q.

Then we will locate the third spot at the middle of the line. And every later spot will locate at the middle of the longest division. It means we probe the third channel in the middle of c_1 and c_n. We probe the later channel in the middle of the biggest interval of the c_1 and c_n as the fourth channel in the Fig(7). Such method is an optimal method when we only consider the optimal location of the next channel or a greedy method in other words.