HMM-driven Smart White Space-aware Frame Control Protocol for Coexistence of ZigBee and WiFi

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***Abstract*—ZigBee has been adopted more and more extensively in various applications such as wireless patient monitoring in hospitals, herds monitoring in pastures, smart control in home networking and game remote controllers. Most of these applications are performance-sensitive so the throughput and packet delivery ratio should be guaranteed for ZigBee system to work properly. However, since both WiFi and ZigBee are operated in unlicensed ISM spectrum, the interferences from WiFi hotspots make the coexistence of ZigBee and WiFi a big challenge. WiFi traffic contains quite a lot of white spaces between frame clusters in time domain which could be taken advantage of to improve the performance of the system with coexistence of ZigBee and WiFi. The existing mechanisms dealing with the coexistence of heterogeneous wireless systems such as CSMA neglected this important fact. In this paper, we propose a novel approach that ensures high performance of ZigBee in spite of the presence of strong interference from WiFi, and at the same time keep the WiFi performance almost unaffected. First we learn an HMM (Hidden Markov Model) based on the data traces of the current network. With such an HMM model we can accurately characterize the dynamic distribution of the durations of white spaces in different times. Second, we estimate the theoretical performance of a ZigBee link with the presence of interference from WiFi. Third, based on the HMM model of the white space and the performance estimation we develop a novel ZigBee frame control protocol called HMM-driven Smart White Space-aware Frame Control Protocol which can obtain the optimal trade-offs between link throughput and packet delivery ratio.**

***Keywords* —ZigBee; WiFi; Frame Clusters; White Space; HMM ; Frame Control Protocol**

I. Introduction

The ISM spectrum is becoming more and more popular in wireless networks such as ZigBee and WiFi. However, the coexistence of such heterogeneous wireless systems is still an open challenge. As the number of WiFi hotspots and devices increases all the time, ZigBee and WiFi devices are increasingly located in the same environment which makes the coexistence problem more and more challenging and critical. The traditional and most popular approach is to assign orthogonal channels to ZigBee and WiFi devices. However, as the number of WiFi devices increases dramatically nowadays, the existing 802.11 b/g/n access points heavily occupy three orthogonal channels in the 2.4 GHz band, which overlap with 12 out of the total 16 channels defined in 802.15.4 - the PHY/MAC specification of ZigBee.

In fact, the channel utilization ratio in a 802.11-based network is often quite low. As shown in Fig.1, the network traffic is highly bursty with considerable amount of white spaces between frame clusters.

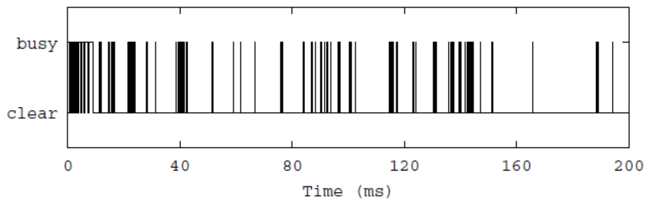


Fig. 1 WiFi channel state trace(white spaces between frame clusters)

The existing CSMA approach just neglects the prominent channel white space and thus is not satisfying. CSMA allows a WiFi device conduct the clear channel assessment by carrier sensing 802.11-modulated signals. So ZigBee signals are invisible to WiFi transmitters and the WiFi transmitters will not defer their transmissions even in presence of ongoing ZigBee transmissions. Even if this issue can be solved by adopting energy-based CCA, there may be other problems like low power of ZigBee devices. ZigBee devices have a power that is typically 20dB lower than that of WiFi devices. So the ZigBee signals can barely be sensed by WiFi devices while WiFi signals can easily be sensed by ZigBee devices. Even the in-air ZigBee packets can be sensed by WiFi devices, a ZigBee transceiver has a 16 times longer response time and is thus often preempted by WiFi when it switches from sensing to transmission, or from transmission to reception mode.

In this paper, we propose a novel approach that takes advantage of the channel white space and thus could reduce the effects of the interferences between WiFi and ZigBee devices.

II. Related Work

The coexistence of heterogeneous wireless systems in unlicensed ISM bands is a hot topic. In [1], Adaptive Frequency Hopping (AFH) is proposed for Bluetooth and WiFi coexistence. AFH is further improved in [2] by sensing and predicting the WiFi behavior using the model proposed in [3]. oPPtX protocol was proposed by Srinivasan et al.[4] to improve the performance of bursty 802.15.4 links. OppTx take advantage of the correlations in packet delivery and loss to set transmission backoff delay. Xinyu Zhang, etc [5] proposed the Cooperative Busy Tone mechanism which designates a separate node (either a ZigBee client closer to the WiFi transmitter, or a dedicated high-power ZigBee transceiver) as a signaler that emits the busy tone to prevent WiFi preemption. However, all these approaches neglected the probabilistic feature of channel white space. The WISE frame control protocol proposed in [6] exploited the channel white space between frame clusters, but they imposed a relatively simple probabilistic distribution-Pareto distribution of the inter-arrival time of frame clusters over each time windows. They used sliding window scheme, so a Pareto model is fit to the current window. However they assumed that the white spaces within a sliding window follows i.i.d Pareto distribution, which is often not the case. By observing Fig.1 we can see that there are strong correlations between the neighboring white spaces. The inter-arrival times of WiFi frame clusters within a sliding window are not independent of each other.

III. HMM MODELING OF WIFI WHITE SPACE

In this section we'll first introduce the Pareto Model of WiFi white space proposed in [6], and then we'll discuss the limitations of this method and then propose our advanced HMM model of WiFi white space.

Jun Huang, etc [6] proposed the Pareto Model of WiFi white space based on the fact that the arrival process of WiFi frame clusters has the feature of self-similarity and according to [6], the self-similarity is a feature of arrival process with heavy-tailed or power law distributed inter-arrival time. Pareto process is a widely used power law distribution so they adopted Pareto to fit the distribution of the inter-arrival times. In this model, they assumed that all the white spaces within a sliding window follows i.i.d Pareto distribution, which satisfies

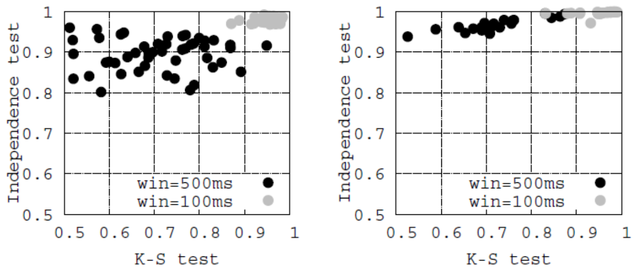
$$\Pr(x>t)=\begin{cases}(\frac{\alpha}{t})^{\beta}, & t>\alpha \\ 1, & otherwise\end{cases} \quad (1)$$

where α and β are the scale and shape of Pareto model respectively and x is the duration of the white space. They set α to 1 millisecond. In other words, their model only accounts for the inter-cluster space that is longer than 1 ms, because shorter white spaces cannot be used by ZigBee links. In Pareto model, β is given by λ/(λ-α), where λ is the average inter-arrival time of frame clusters.

Then they did the Kolmogorov-Smirnov Test (K-S Test) to test whether the white spaces within the sliding windows follow the Pareto distribution, and did the independence test to test whether the white spaces within each sliding window are independent to each other.

Fig. 2 shows the test result. When the window size is relatively small(100ms), it seems that the adapted probabilistic model fits the test data trace very well. However, the independence test is just an rough estimation of the independence, it's not an accurate measure of independence. When the sliding window size increases, the independence test result will reduce dramatically. In fact, by observing Fig. 1, we can see that at the time steps say t_i where the white space duration is short, usually there are a bunch of white spaces close to t_i with short durations. This regularity of the durations of the white spaces conflicts with the independence assumption.

We argue that the durations of the white spaces (Δt_1, Δt_2, Δt_3,..., Δt_N , i.e. the inter-arrival times of WiFi frame clusters) follow a Hidden Markov process, that's to say the current inter-arrival time is determined by previous k inter-arrival times in the case of k-order Markov process. In this paper we use 1-st order Hidden Markov Model, i.e. k=1. Thus we get rid of the invalid assumption and the limitations brought in by this assumption, thus further improve the ZigBee performance.



(a) OSDI trace. (b) SigCOMM trace.

Fig.2 Goodness-of-fit tests of Pareto model for real-life WiFi traces

Fig. 3 shows an example of HMM. In an HMM, there are a set of states say $\{S_1,S_2,S_3,...,S_T\}$, each state has an initial state probability$\{P_{01},P_{02},P_{03},...,P_{0T}\}$ that determines which state would be more likely to be the first state. And each state has a probabilistic distribution of its observation vectors. We use $\{\Theta_1,\Theta_2,\Theta_3,...,\Theta_T\}$ to describe the parameters of the states' distributions. The transition probability matrix M where M_{ij} = $\Pr(S(t+1)=S_j \mid S(t)=S_i)$ determines how a state could transit to another state.

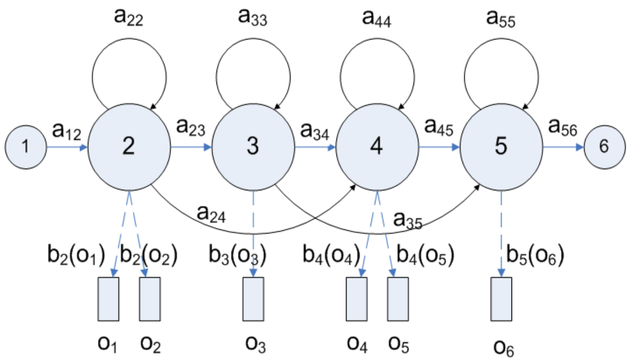


Fig. 3 An example of HMM

In our application, the states are hidden, we don't know them directly (but we can infer them from the observations by HMM inference algorithm). We can just obtain the observations, i.e. the durations of the white spaces. So the white spaces (Δt_1, Δt_2, Δt_3,..., Δt_N) serves as the observation sequence $(O_1,O_2,O_3,...,O_N)$. We use the Pareto distribution or Mixture of Paretos or optionally GMM (Gaussian Mixture Model) as the observation distribution for each state. With preobtained data traces of the traffic in the current network, we can learn all the parameters of this HMM model.

In practice, we can associate each white space with a hidden state, or optionally we can associate a group of (say 10 consecutive white spaces) white spaces with a hidden state. The former strategy should get better result but will result in heavier computation load. Because with the latter strategy we are actually doing some kind of averaging over the 10 consecutive white spaces so we'll lose some detailed information of the Markov process.

Assume at time step t_i , i.e. the *i*th white space has just passed. We want to know the duration of the (i+1)th white space. The durations of all the previous white spaces (i.e. all the observations up to i) $(O_1,O_2,O_3,...,O_i) = (\Delta t_1, \Delta t_2, \Delta t_3,..., \Delta t_i)$ is already known, we can infer from the trained HMM model the current state and the probability distribution of the next state based on the maximum likelihood estimation. Let $P_{i+1}(m)$ be the estimated probability that the next state is S_m ($1 \le m \le T$), i.e. $P_{i+1}(m) = P(S(i+1) = S_m)$, then

$$\Pr'(x > t) = \sum_{m=1}^{T}[P_{i+1}(m) \cdot \Pr(x > t \,|\, S(i+1) = S_m)] \qquad (2)$$

is the probability distribution of the duration of the next white space. Note we use the subscripts to denote the distinct states from the finite states set $\{S_1,S_2,S_3,...,S_T\}$, and use the indices in the parenthesis to denote the states at a particular time step. $\Pr(x > t \,|\, S(i+1) = S_m)$ is equivalent to $\Pr(x > t \,|\, S_m)$ which is the conditional probability of $x > t$ given that the hidden state is S_m. Since the HMM is already trained, the observation distribution within each state including S_m is known thus $\Pr(x > t \,|\, S_m)$ can be easily calculated.

IV. Smart White Space-aware Frame Control Protocol

To avoid the collision with WiFi signals, the simplest strategy is to decrease the packet size of ZigBee. However, this will greatly reduce the system throughput. So we need to get an optimal tradeoff between the overall throughput and the packet delivery ratio. Our guideline for this optimal tradeoff is trying to finish the ZigBee transmission within the current white space before the arrival of the next WiFi frame cluster. Since the average lifetime of a white space is limited, we need to divide a ZigBee frame into sub-frames and give an ID for each frame session. The following contents in this sections show how to optimize this sub-frame size τ .

Based on the Pareto White Space model, we can get the following conditional collision probability for a given frame size τ

$$C(\tau,\rho) = \Pr(t < \rho + \frac{\tau}{D} \,|\, \rho) = 1 - \left(\frac{\alpha}{\frac{\tau}{D} + \rho}\right)^{\beta} \qquad (3)$$

where D is the channel rate of ZigBee, ρ is the white space age when a frame is ready for transmission, α and β are the scale and shape of the Pareto model of white space.

Similarly, we can get the conditional collision probability for a given frame temporal size τ based on our proposed HMM White Space model:

$$C'(\tau,\rho) = 1 - \sum_{m=1}^{T}[P_{i+1}(m) \cdot \Pr(x > \rho + \frac{\tau}{D} \,|\, S(i+1) = S_{m,\rho})] \qquad (4)$$

Our goal of frame adaptation is to maximize the transmission efficiency while limit the collision probability. Protocol header has a fixed size, the transmission efficiency is a monotonic increasing function of the sub-frame size τ . Given a collision probability threshold T, our optimization problem can be formulated as follows:

$$\textit{Maximize} \quad \tau \qquad (5)$$

$$\textit{Subject to} \quad : C(\tau,\rho) < T \qquad (6)$$

$$\tau \le M \qquad (7)$$

where M is the maximum allowed frame size of ZigBee. Solving this optimization problem, we get the optimal sub-frame size:

$$\tau = \min(\rho \times \gamma, M) \qquad (8)$$

where

$$\gamma = D \times ((1-T)^{\frac{\alpha-\lambda}{\lambda}} - 1) \qquad (9)$$

where λ is the average inter-arrival time of frame clusters in the Pareto model.

Similarly, in our proposed HMM White Space model, we can also solve this optimization problem and get the optimal sub-frame size τ with the estimated distribution of the duration of the upcoming white space based on previous white spaces. The problem can be formulated as the following optimization problem:

$$\textit{Maximize} \quad \tau \qquad (10)$$

$$\textit{Subject to} \quad : C'(\tau,\rho) < T \qquad (11)$$

$$\tau \le M \qquad (12)$$

V. Experiments

In this section we'll see the differences between the 2 methods in the power of predicting the upcoming white spaces.

In our experiments, we use 4 HMM hidden states and 3 Gaussian mixtures. Both the training and test data is artificially synthesized, and one of the sequences of white spaces is shown in Fig. 4.

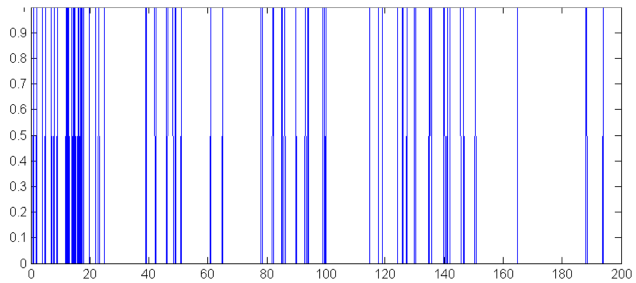


Fig. 4 Inter-frame-cluster white spaces in our simulation

For both Pareto and HMM, we first use the training data to train the model parameters. And then use the models to predict the duration of the upcoming white spaces. For any test white space sequence (Δt_1, Δt_2, Δt_3,..., Δt_N), we use the 2 models to predict Δt_i respectively based on the previous white spaces (Δt_1, Δt_2, Δt_3,..., Δt_{i-1}) for all i (i=1,2,...,N-1). Although we can predict the probabilistic distribution of the upcoming white space Δt_i , we'll only use the expectation value in this performance evaluation. And then calculate the average prediction error over the (N-1) predictions.

TABLE I. PREDICTION ERROR OF THE UPCOMING WHITE SPACES

Model	**Average Prediction Error**			***Average***
	Run1	***Run2***	***Run3***	
Pareto	4.3017	4.3017	4.3017	4.3017
HMM	2.4012	2.5129	2.6601	2.5247

From the table we can see that HMM is more accurate in predicting duration of the upcoming white spaces based on the previous information about the white spaces we have got. Superiority over Pareto could be observed more clearly if we build up the whole WiFi and ZigBee environment and use the real-life data in the implementation.

VI. CONCLUSION

In this paper we develop a HMM-driven Smart White Space-aware Frame Control Protocol for ZigBee that can deal with interference from WiFi. We can see that exploiting the WiFi channel white space is very useful for the coexistence of ZigBee and WiFi. The approach proposed in [6] has some invalid assumptions which affects the overall system performance. Our protocol is based on the previous work of [6] and we propose the HMM model of the channel white space that get rid of the invalid assumptions and thus further improves the performance of that obtained in [6]. Some more delicate and complex mechanisms such as the Segmental Hidden Markov Model may further improve the performance.

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