Subcarrier Sensing for Distributed OFDMA in Powerline Communication

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Abstract—Powerline communication (PLC) is a preferred choice for smart home network. In this paper, a new system structure is proposed for PLC, which is based on distributed orthogonal frequency division multiple access (DOFMDA). Subcarrier sensing, i.e., sensing every OFDM subcarrier to see if it is occupied or not, is proposed to replace the conventional carrier sensing multiple access (CSMA) for multi-user contention of a channel. This structure, borrowed from cognitive radio, allows multiple users to opportunistically share the same channel on different subcarriers and therefore increases the channel capacity. Two subcarrier sensing methods are proposed: one is based on information theory and the other is based on successive energy comparison. Simulations are provided to verify the methods.

I. INTRODUCTION

In future smart home, it is conjectured that most of the home appliances are connected through either a wired or wireless network. Powerline communication (PLC) is a preferred choice for the network due to the following reasons: firstly, no RF conversion hardware is required in PLC, which allows lower cost and does not produce RF radiation compared to wireless solutions; secondly and most importantly, power outlets are almost everywhere in a smart home and no additional lining is required.

Nevertheless, PLC has a few challenges to be solved before it can be widely adopted in a smart home. Apart from regulatory constraints, PLC systems also need to cater for electromagnetic noise of current radio systems as well as noise generated from electrical appliances such as switching power supplies, brush motors and halogen lamps. While HomePlug standard [1] is trying to overcome these issues by designing PLC systems to adapt to these unwanted interferers, we believe cognitive radio technologies can be extended to PLC to further enhance the performance. Cognitive radio is widely expected as the next Big Bang in wireless communications. There have been tremendous academic researches as well as application initiatives in this area, such as the IEEE 802.22 standard on wireless regional area networks (WRAN) and the Wireless Innovation Alliance including Google and Microsoft as members. The basic idea of a cognitive radio is spectral reusing/sharing, which allows secondary networks/users to use the spectrum allocated/licensed to primary users when they are not active. To do so, secondary users are required to frequently perform spectrum sensing, i.e., detecting the presence of the primary users. While most of the investigations (and even motivations) for cognitive radio are focusing on wireless applications, we believe that cognitive radio concept can be extended to PLC systems, although no “radio” is involved in the latter, to overcome the harsh channel environment.

In this paper, a new system structure is proposed for PLC. The structure is based on distributed orthogonal frequency division multiple access (DOFMDA). In a non-centralized network, users are not aware which subcarriers have been occupied by other users in the network. Therefore, before using the shared channel, each user must sense the channel to see which subcarriers are occupied. This is called subcarrier sensing. Subcarrier sensing is different from the conventional channel sensing, which senses the availability of the whole channel. In conventional carrier sensing multiple access (CSMA), a user senses the whole channel and uses the whole channel if it is not occupied by others. Subcarrier sensing allows multiple users to share the same channel on different subcarriers and therefore increases the channel capacity by allowing opportunistic usage. The structure is similar to the OFDM based spectrum pooling [2], a type of cognitive radio system. In the following two subcarrier sensing methods are proposed. Simulations are provided to verify the methods.

II. SYSTEM STRUCTURE

In current PLC standards HomePlug 1.0 and HomePlug AV [1], CSMA or time division multiple access (TDMA) is used for multiple access. In CSMA, each user senses the whole channel and use the channel only if the whole channel is unoccupied. Even if only a few subcarriers are used or have strong interferences, the whole channel cannot be utilized. To cater for different quality of service (QoS) requirements, OFDMA is a good choice, where users can be allocated with suitable subcarriers based on their QoS requirement and channel conditions. In a non-centralized network, users are not aware which subcarriers have been occupied by other users in the network. Therefore, before using the shared channel, each user must sense the channel to see which subcarriers are occupied. Our proposed system structure is the subcarrier sensing based OFDMA, which is shown Figure 1. The structure can also be used for other applications.

It is assumed that in the network, every user knows the OFDM structure, that is, the cyclic prefix (CP) length and the FFT size. When a new user tries to join the network, it senses the channel to identify which subcarriers are vacant based on subcarrier sensing. It first does the following on the received signal: discards the part corresponding to the CP and then implements a FFT. There are two hypotheses on each subcarrier: \( H_0 \), signal/interference absent on the subcarrier;
Interference and avoid using the subcarriers with strong interference. Subcarrier sensing can detect power supplies, brush motors and halogen lamps is a major interference. In powerline communications, narrowband interference generated from electrical appliances such as switching power supplies, brush motors and halogen lamps is a major factor affecting the performance. In order to avoid using the subcarrier with strong interference. Subcarrier sensing can detect the interference and avoid using the subcarriers with strong interference.

Since narrowband interference is treated as signal, the remaining noise is normally white, that is, \( \eta_i(n) \) are independent and identically distributed (iid). It is assumed that no information on the transmitted source signals by other users is available at the receiver. Therefore, \( s_i(n) \) is modeled as a random variable with unknown distribution. It is also assumed that signal and noise are independent.

There are some challenges for subcarrier sensing. First, since the number of subcarriers is usually large, sensing each subcarrier separately has very high complexity. Secondly, the propagation channels of source signals are unknown and therefore some classic methods, such as the likelihood ratio test (LRT) [3] and matched filtering (MF)-based methods [3], [4], cannot be used. Thirdly, received signal at a subcarrier could have no special statistical properties, which turns some popular signal processing methods, such as cyclostationary detection (CSD) [5], eigenvalue based sensing [6], [7] and covariance based sensing [8], unusable. Facing these challenges, we propose two methods which first finds the number of occupied subcarriers and then determines the indices of the occupied subcarriers.

III. SUBCARRIER SENSING BASED ON INFORMATION THEORY

Let us stack the received signals at all subcarriers into vectors as

\[
\mathbf{x}_i = \begin{bmatrix} x_i(0) & \cdots & x_i(N-1) \end{bmatrix}^T, \tag{3}
\]

\[
\mathbf{s}_i = \begin{bmatrix} s_i(0) & \cdots & s_i(N-1) \end{bmatrix}^T, \tag{4}
\]

\[
\boldsymbol{\eta}_i = \begin{bmatrix} \eta_i(0) & \cdots & \eta_i(N-1) \end{bmatrix}^T. \tag{5}
\]

Let the number of occupied subcarriers be \( q \). Then vector \( s_i \) only has \( q \) nonzero entries. Define the statistical covariance matrix of the received signal as

\[
\mathbf{R}_x = \mathbf{E}[\mathbf{x}_i\mathbf{x}_i^H]. \tag{6}
\]

We can verify that

\[
\mathbf{R}_x = \mathbf{R}_s + \sigma_n^2 \mathbf{I}_N, \tag{7}
\]

where \( \mathbf{R}_s \) is the statistical covariance matrix of the source signal and \( \sigma_n^2 \) is the noise power. Obviously the rank of the matrix \( \mathbf{R}_s \) equals to the number of occupied subcarriers \( q \). If we have found the rank \( q \), it is natural to choose the \( q \) subcarriers with highest power as occupied subcarriers.

The rank detection problem has been studied in signal processing for years. If \( \mathbf{R}_x \) is precisely known, it is easy to find the rank based on the eigenvalue decomposition of \( \mathbf{R}_x \). In fact, \( \mathbf{R}_x \) should have exactly \( N-q \) eigenvalues equaling to \( \sigma_n^2 \), while other eigenvalues are larger than this. Checking the minimum eigenvalues, we can easily find \( q \). The problem is that we have only limited number of samples, and therefore we can only estimate \( \mathbf{R}_x \) to a certain precision. It is known that when \( \mathbf{R}_x \) is estimated from limited samples, the eigenvalues of it will be all different with probability one [9]. Thus it is difficult to detect the rank merely by checking the minimum eigenvalues.

We assume that \( M \) OFDM symbols are used for sensing. The maximum likelihood (ML) estimation for \( \mathbf{R}_x \) is the sample covariance matrix defined as

\[
\hat{\mathbf{R}}_x(M) = \frac{1}{M} \sum_{i=0}^{M-1} \mathbf{x}_i\mathbf{x}_i^H. \tag{8}
\]

Based on the estimated covariance matrix and information theory for model selection, some methods such as minimum description length (MDL) and Akaike information criteria (AIC) have been proposed to find the rank. Wax and Kailath [9] further extend the two methods to a general form, which yields a consistent estimate of the rank. Let \( \mu(n), n = 0, 1, \cdots, N-1 \), be the ordered (descending order) eigenvalues of \( \hat{\mathbf{R}}_x(M) \). The extended criteria is as follows. Let

\[
\phi(p) = -M \log \frac{\prod_{n=p}^{N-1} \mu(n)}{\left( \sum_{n=p}^{N-1} \mu(n)/(N-p) \right)^{N-p}} + \alpha(M)p, \tag{9}
\]

where \( \alpha(M) \) satisfies: as \( M \) approaches to infinite,

\[
\alpha(M) \rightarrow \infty, \ \alpha(M)/M \rightarrow 0. \tag{10}
\]
The rank is estimated as

\[ q = \arg \min_p \phi(p). \tag{11} \]

The major difficulty of the method is the eigenvalue decomposition if \( N \) is large. In HomePlug 1.0 standard [1], \( N = 256 \), while in HomePlug AV standard [1], \( N = 3072 \). It is prohibitive to do eigenvalue decomposition for a matrix with such large size.

It is reasonable to assume that \( s_i(n) \) are statistically independent for different subcarriers \( n \). Then it is easy to verify that

\[ \mathbf{R}_s = \text{diag}(\rho(0), \ldots, \rho(N-1)), \tag{12} \]

where

\[ \rho(n) = \mathbb{E}(|s_i(n)|^2). \tag{13} \]

Hence, the eigenvalues of \( \mathbf{R}_x \) are

\[ \rho(n) + \sigma_n^2 = \mathbb{E}(|x_i(n)|^2), \quad n = 0, 1, \ldots, N-1. \tag{14} \]

A simple estimation for the eigenvalues is therefore the average received signal power:

\[ \mathbb{E}(|x_i(n)|^2) \approx \frac{1}{M} \sum_{i=0}^{M-1} |x_i(n)|^2, \quad n = 0, 1, \ldots, N-1. \tag{15} \]

Based on this estimation and the information theory, we have the following sensing method.

**Algorithm 1:** Subcarrier sensing based on information theory (SSIT)

1. Compute the average received signal power
   \[ y(n) = \frac{1}{M} \sum_{i=0}^{M-1} |x_i(n)|^2, \tag{16} \]
   \[ n = 0, \ldots, N-1. \]

2. Reorder sequence \( y(n) \) into \( y_1(n) \) with descending order.

3. Compute
   \[ \psi(p) = -M \log \frac{\prod_{n=p}^{N-1} y_1(n)}{\left( \sum_{n=p}^{N-1} y_1(n)/(N-p) \right)^{N-p}} + \alpha(M)p, \tag{17} \]
   \[ p = 0, 1, \ldots, N-1. \]

4. Find \( q = \arg \min_p \psi(p) \), which is the estimation for the number of occupied subcarriers.

5. Find the \( q \) subcarriers with highest powers and define them as occupied subcarriers.

It is proved in [9] that any \( \alpha(M) \) satisfying (10) yields a consistent estimation when \( M \) approaches to infinite, that is, the estimated rank is the true rank if \( M \) is sufficiently large. However, in practice, we only have limited number of samples. For limited \( M \), it is not guaranteed that the estimated rank is the true rank. Based on the simulation for limited \( M \), we recommend to choose \( \alpha(M) = \lfloor \log_2(M) \rfloor - 1 \).

**IV. SUCCESSIVE MAXIMUM TO MINIMUM ENERGY COMPARISON**

Energy detection is a basic sensing method [10], [11], [12]. It can be directly used for subcarrier sensing as follows: we first set a threshold \( \gamma \) and then checks if \( y(n) > \gamma \sigma_n^2 \); if “yes”, the subcarrier \( n \) is occupied; otherwise, not occupied. To guarantee a reliable detection, the threshold must be set according to the noise power and the number of samples [11], [12]. Accurate knowledge on the noise power is then the key of the energy detection. Unfortunately, in practice, the noise uncertainty always presents. Due to the noise uncertainty [11], [12], the estimated (or assumed) noise power may be different from the actual noise power. Inaccurate estimation of the noise power leads to SNR wall and high probability of false alarm [11], [12].

To solve this problem, we can use the special properties of OFDM for real-time noise power estimation. In OFDM, usually there are a few null subcarriers used as guard band. There is no transmission on these subcarriers. So the received signal power on such a subcarrier should approach to the noise power if there is no interference or out of band signal intrusion on the subcarrier. In general, we can choose a few subcarriers with least signal powers for noise power estimation. Based on this idea, we propose the successive maximum to minimum energy comparison (SMMEC) method. The detection is based on the ratio of a subcarrier energy to the minimum subcarrier energy and a hard threshold.

**Algorithm 2:** Successive maximum to minimum energy comparison (SMMEC)

1. Compute the average received signal power
   \[ y(n) = \frac{1}{M} \sum_{i=0}^{M-1} |x_i(n)|^2, \quad n = 0, \ldots, N-1. \]

2. Reorder sequence \( y(n) \) into \( y_1(n) \) with descending order.

3. For \( p = 1, 2, \ldots, N \), if
   \[ y_1(N-p)/y_1(N-1) > \gamma, \]
   then \( K_v = p-1 \) and stop testing; otherwise, continue testing for \( p+1 \); where \( \gamma > 1 \) is a threshold.

4. Find the \( K_v \) subcarriers with lowest powers and define them as vacant subcarriers.

   Obviously, even if all the subcarriers are occupied, the algorithm will still report that at least one subcarrier is vacant. Fortunately, as discussed above, usually there are vacant subcarriers due to existence of null subcarriers.

   The threshold should be set such that, when all subcarriers are vacant, the algorithm makes a decision of “all subcarriers vacant” at a certain probability. Let \( P_{\text{target}} \) be the target probability of “all subcarriers vacant” decision when all subcarriers are vacant. Then the threshold should be set to satisfy

   \[ P_{\text{target}} = P(y_1(0) \leq \gamma y_1(N-1)). \tag{18} \]

   Note that \( y_1(0) \) and \( y_1(N-1) \) are the maximum and minimum of the \( N \) iid random variables (at the case of all subcarriers being vacant), respectively. Based on order statistics [13], it is possible to get the distribution of \( y_1(0) - \gamma y_1(N-1) \) and then find the theoretical value for \( \gamma \). However, a simple and
easy computable formula is yet to be found. Please see the Appendix for more on this.

Alternatively, the threshold can be found based on simulations. For example, we can conduct \( I \) Monte-Carlo tests at the case of all subcarriers being vacant. Let the values of \( y_1(0)/y_1(N-1) \) for all tests be \( \beta(i) \), \( i = 1, 2, \ldots, I \). Reorder \( \beta(i) \) into \( \beta_1(i) \) with ascending order. Then the threshold is set as

\[
\gamma = \beta_1(P_{\text{target}}). \tag{19}
\]

V. SIMULATIONS

In this section, we will give some simulation results based on randomly generated channels and powerline channels. The system parameters are chosen based on HomePlug 1.0 as follows:

1) \( N = 256 \);  
2) CP length 172;  
3) Channel length not larger than CP length.  
4) QPSK modulated signal.

To increase the data rate, without loss of generality, we use frequency from 0 to 30MHz.

We need some criteria to evaluate the performances of the methods. For this purpose, some notations are defined as follows:

1) Mean rank: the mean of detected number of occupied subcarriers;  
2) Variance: standard deviation of the detected number of occupied subcarriers.

Obviously, a good detection should have its mean rank approaching to the actual number of occupied subcarriers, and its variance as small as possible.

In the following, we choose \( M = 20 \). We need to set thresholds for the SMMEC and ED. As discussed above, we can use theoretic formula or simulation to achieve this by setting all subcarriers vacant. For SMMEC, the target detection probability of “all subcarriers vacant” is set as \( P_{\text{target}} = 0.9 \). For ED, the detection probability of “occupied” is set as \( 4 \times 10^{-5} \) for each subcarrier. The threshold for ED with 1dB noise uncertainty [12], [6], [7] is the same as that of ED, because in practice the receiver has no idea if there is noise uncertainty or not. Based on the thresholds, when all subcarriers are vacant, the SSIT, SMMEC, ED and ED-1dB (ED with 1dB noise uncertainty) have detected the number of occupied subcarriers (average on 200 tests) as 1.6770, 1.2560, 2.0450 and 5.8090, respectively, and have variances as 1.3358, 1.9525, 1.4342, and 7.7403, respectively. It is clear that SSIT, SMMEC and ED have a good detection, but ED-1dB has an unacceptable performance with large errors.

Based the threshold set above, we now simulate the methods when some of the subcarriers are occupied at different signal-to-noise ratios (SNRs). Here, the SNR is defined as the average received signal power on all subcarriers to the noise power, that is,

\[
\text{SNR} = \frac{\sum_{n=0}^{N-1} |s_i(n)|^2}{\sum_{n=0}^{N-1} |\gamma_i(n)|^2}. \tag{20}
\]

Without loss of generality, it is assumed that \( q \) subcarriers are in use by another user with equally transmitted power on each subcarrier. The channel (time domain) from the user to the detector is denoted by \( h(l) \). First, randomly generated multipath channel is considered, where the channel has 128 taps with exponential power profile:

\[
E(|h(l)|) = \exp(-0.5l), \quad l = 0, 1, \cdots, 127. \tag{21}
\]

The taps \( h(l) \) are generated as Gaussian random numbers and different for different Monte Carlo realizations. Simulation results for \( q = 160 \) are shown in Figure 2 and 3. Secondly, a fixed powerline channel based on the model in [14] is used. The detection results are given in Figure 4 and 5 for \( q = 100 \).

Simulations show that SSIT, SMMEC and ED give reasonable good detections. Although ED with exact noise power performs well, when there is noise uncertainty in practical applications, performance of ED degrades dramatically. In fact, ED with 1dB noise uncertainty is much worse than other methods.

For SSIT, SMMEC and ED, the detected rank (number of occupied subcarriers) approaches to the actual rank and the variance is smaller than 3 for all cases at SNR higher than 15 dB. However, the detected rank usually is not exactly the same as the actual rank. It means that there could be few wrongly
classified subcarriers. We can combine the subcarrier sensing result with other information, such as subchannel allocation (in many applications, subcarriers are grouped into subchannels and a user can either use a subchannel or does not use any subcarriers in it), to finally determine the occupied subcarriers.

VI. CONCLUSIONS

In this paper, a new system structure has been proposed for PLC based on the concept of cognitive radio. A major advantage of the new structure is that users can share the same channel opportunistically on different subcarriers without a centralized control. Subcarrier sensing is the key to realize the system. Two subcarrier sensing methods have been proposed and verified. The methods are also applicable to other decentralized OFDMA systems.

APPENDIX : THRESHOLD SETTING FOR SMMEC

When all subcarriers are vacant, \( x_1(n) = n_1(n) \) are iid noise samples. Since \( y_1(0) \leq \gamma y_1(N - 1) \) if and only if \( y_1(0)/c \leq \gamma y_1(N - 1)/c \), where \( c \) is any constant larger than 0, we know that the noise power will not affect the threshold. Hence, we can assume that \( n_1(n) \) is complex Gaussian with mean 0 and variance 1. Then it is easy to verify that \( y(n) \) has mean 1 and variance \( 1/M \). In general, the distribution of \( y(n) \) is the Chi-square distribution with \( 2M \) degrees of freedom. For large \( M \), based on central limit theorem, we can approximate the distribution by a Gaussian distribution. Thus the probability density function (PDF) of \( y(n) \) is approximated as

\[
f(t) = \frac{\sqrt{M}}{\sqrt{2\pi}} \exp \left( -\frac{(t-1)^2}{2/M} \right)
\]

The cumulative density function (CDF) can be expressed as

\[
F(t) = \int_{-\infty}^{t} f(u) \, du
\]

Based on order statistics, the joint distribution (PDF) of \((y_1(0), y_1(N - 1))\) is

\[
g(u, v) = \begin{cases} 
N(N - 1)f(u)[F(v) - F(u)]^{N-2}f(v), & u < v \\
0, & u \geq v
\end{cases}
\]

Thus we have

\[
P_{\text{target}} = P(y_1(0) \leq \gamma y_1(N - 1)) = N \int_{0}^{+\infty} f(u)[F(\gamma u) - F(u)]^{N-1} \, du.
\]

The values of the function on the right hand side is not related to noise power and signal property. Hence it can be computed off-line and stored. However, for easy computation, a more simplified expression is yet to be found. Based on this, the threshold should be chosen by inverting the function.

REFERENCES


