Two vertical handcover metrics toward an IEEE 802.11N network

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ABSTRACT

This paper deals with two metrics for vertical handover toward an IEEE 802.11n network, estimated from the physical layer instead of the MAC layer. For this reason we don't need to be connected to the network to estimate them. The first metric is related to the channel occupancy rate, and is estimated by the mean of a likelihood function of the observed samples. The second one is related to the collision rate. Using an information theoretic criterion and taking advantage of the OFDM structure of the signal, we avoid the channel length estimation and decide if a collision occured or not.

Index Terms— Vertical handover, channel occupancy rate, IEEE 802.11n, collision detection.

1. INTRODUCTION

Wireless devices took a vital and consequent place in our daily life. As a consequence, the number of wireless services and users are steadily increasing. These devices are used for a wide range of multimedia applications that are sensitive to different aspects of communication performance; like delay, bandwidth and reliability. For this reason a high QoS (quality of service) is continually required by the higher layer applications.

As the number of wireless networks increases, many standards of communication coexist and the emerging mobile stations will be equipped with multiple network interfaces to access different wireless networks. Thus, taking advantage of this diversity, to maintain its network connection and the QoS required by the higher layers, a mobile station should roam freely from one interface to an other, this is known as *the vertical handover*.

Since in heterogeneous environment the networks have different system characteristics, to decide which network offers better performance, the signal to noise ratio is not the best indicator to trigger a vertical handover, and new metrics must be found.

Within this framework, we focus on metrics that could be used for vertical handover toward an IEEE 802.11 network based on a physical layer sensing, drawing from methods that relied on MAC (media access control) layer listening.

For example, in [1, 2] it has been highlighted that the usage of the channel bandwidth in a WiFi system can be approximated as the ratio between the time in which the channel status is busy according to the NAV (Network Allocation Vector) settings and the considered time interval. Indeed, prior to transmitting a frame, a station calculates the amount of time necessary to send the frame based on the frame's length and data rate. The station places a value representing this time in the duration field in the header of the frame. From the above description we can see that the NAV busy state can well reflect the traffic load. Higher the traffic is larger the NAV busy occupation will be, and vice versa. So, once we observe a NAV value during a certain time window, the available bandwidth and access delay can be estimated given a certain packet length [3].

The matter with this method is that it requires to be connected to the access point in order to have access to the NAV duration from the header, this may increases the decision time if many standards or Access Point (AP) are detected.

In this paper, we propose a method that requires no connection to the AP, and no NAV duration reading. This method is based on a physical layer sensing : Considering that the medium is free when only noise is observed and occupied when signal plus noise samples are observed (data frame), we use a likelihood function that can distinguish the signal plus noise samples from the one corresponding to noise only. Once we get the number of signal plus noise samples, a simple ratio processing can inform us on the network occupancy rate.

In the same context, IEEE 802.11 uses a contention-based access mechanism where all the stations listen to the channel before competing for the access to avoid collision between the frames. Unfortunately, as the number of competing stations increases the collision probability increases and the throughput decreases affecting the QoS. Then, the collision rate is a good metric for both horizontal handover where many access points are available, or also vertical handover if we wish to handoff from any standard to a WiFi access point.

Within this framework, we propose a second method for collisions detection. Once the data frame are detected thanks to the first method we use an information theoretic criterion to get the rank of the autocorrelation matrix of the observed frame. Unfortunately to estimate the number of sources, the channel length is necessary. We propose to exploit the OFDM signals properties in order to be able to estimate the number of sources without a prior knowledge on the channel length, and decide if a collision occurred or not (number of sources greater than 1).

2. MODEL STRUCTURE

In the rest of the paper, we assume that IEEE 802.11n access points are detected. An IEEE 802.11 communication is based on a collision avoidance medium access protocol. Between two consecutive frames we have different inter frame spacing (IFS) intervals. Which guarantee different type of priority. At the receiver side, the observed signal is a succession of frames of noise samples corresponding to the IFS intervals or idle periods and of data frames.

For clarity reason, we assume in this section that we have only one data frame in the observation duration (N_s samples) and explain the proposed algorithm to locate it in section 3.

Consider that our receiver is doted of N antennas and let $\mathbf{y}_i = [y_i(1), \ldots, y_i(N_s)]$ be a set of N_s observations on the i^{th} antenna such that :

$$\begin{cases} y_i(n) = w_i(n) & 1 < n < n_1 - 1 \\ y_i(n) = x_i(n) & n_1 < n < n_2 \\ y_i(n) = w_i(n) & n_2 + 1 < n < N_s \end{cases} \tag{1}$$

where $x_i(n)$ is the based band sample being received on the i^{th} antenna at the instant n, expressed as :

$$x_i(n) = \sum_{j=1}^{M} \sum_{k=0}^{L-1} h_{ij}(k) s_j(n - n_1 - k) + w_i(n) \tag{2}$$

where M is the number of source signals transmitted, $s_j(n)$ denotes the n^{th} transmitted symbol from the j^{th} source. $h_{ij}(k)$ is the channel response from source signal j to the i^{th} antenna. L is the order of the channel, and $\sum_0^{L-1} \sigma^2_{h_{ij}(k)} = 1$. $w_i(n)$ is a complex additive white gaussian noise with zero mean and variance σ_w^2.

3. FRAME LOCALISATION

As presented in the previous section, the vector $\mathbf{y}_i$ can be divided into three parts : noise , signal+noise and noise. Starting from the set of observation $\mathbf{y}_i$ we want to find which samples correspond to noise and which ones correspond to signal plus noise. Since the samples are supposed to be independent in the noise areas, and correlated in the signal plus noise area we propose to use a likelihood function that informs us on the independance of the processed sample.

Let now $\mathbf{Y}_i(u)$ denotes the following set of observations :

$$\mathbf{Y}_i(u) = [y_i(u), \ldots, y_i(N_s)] \qquad 1 \leq u < N_s \tag{3}$$

And let us define $f_Y(\mathbf{Y}_i(u))$ the probability density function of $\mathbf{Y}_i(u)$. If $\mathbf{Y}_i(u)$ is composed of only noise samples : $f_Y(\mathbf{Y}_i(u)) = \prod_{m=u}^{N_s} f_w(y_i(m))$, where f_w is the probability density function of a complex normal law centered and variance σ_w^2. σ_w^2 is assumed to be known or at least estimated by a subspace-based algorithm [4].

The log-likelihood that the vector $\mathbf{Y}_i(u)$ is formed of $(N_s - u)$ noise independent samples is expressed as :

$$\mathcal{L}_i(u) = \log \left[\prod_{m=u}^{N_s} f_w(y_i(m)) \right] \tag{4}$$

Computing the mean of the N log-likelihood functions expressed on each sensor, we get a criterion $\mathcal{J}(u)$ that informs us on the nature of the processed samples :

$$\begin{aligned} \mathcal{J}(u) &= \frac{1}{N} \sum_{i=1}^{N} \mathcal{L}_i(u) \\ &= -(N_s - u) \log(\pi \sigma_w^2) - \frac{1}{N \sigma_w^2} \sum_{i=1}^{N} \sum_{m=u}^{N_s} |y_i(m)|^2 \end{aligned} \tag{5}$$

As u varies in the interval $[1, n_1)$, the number of noise samples composing $\mathbf{Y}_i(u)$ decreases and so does $\mathcal{J}(u)$ until it reaches a minimum bound at n_1.

However, for u varying from n_1 to n_2 the number of signal plus noise samples decreases, therefore the ratio noise samples over signal plus noise samples increases and by the way $\mathcal{J}(u)$ increases. It reaches its maximum value while $\mathbf{Y}_i(u)$ contains only noise samples, i.e when $u = n_2$.

Finally for $n_2 < u < N_s$, $\mathcal{J}(u)$ decreases again for the sames reasons than the one explained for $1 < u < n_1$.

4. ESTIMATION OF THE CHANNEL OCCUPANCY RATE

We propose to get the channel occupancy rate by a physical layer sensing. Indeed, while observing a set of N_s samples, if we can estimate the number of samples corresponding to signal+noise (i.e the length of the data frame), we can easily estimate the channel occupancy rate.

When we have only one data frame in the observed window the occupancy rate can easily be estimated thanks to the previous criterion by $\frac{n_2 - n_1}{N_s}$. However, the assumption to have only one frame in the duration window is too restrictive. In practice we may get a signal as shown in figure 1 or with more frames.

Based on the behavior of $\mathcal{J}(u)$, we can clearly see (fig 1) that the slope of $\mathcal{J}(u)$ is positive when u corresponds to the index of a signal plus noise sample and negative when u corresponds to the index of a noise sample. Therefore, we can take advantage of the gradient of $\mathcal{J}(u)$ to distinguish the nature of our observed samples. Introducing the function $\Phi(u)$ such that :

$$\Phi(u) = \frac{1}{2}\left[\text{sign}\{\nabla(\mathcal{J}(u))\} + 1\right] \tag{6}$$

Here we denote by ∇ the gradient of $\mathcal{J}(u)$ processed using the central difference method, such that the derivative for any point of index $u \notin \{1, N_s\}$ is processed as :

$$\nabla(\mathcal{J}(u)) = \frac{1}{2}\left(\mathcal{J}(u+1) - \mathcal{J}(u-1)\right)$$

For the first point, we use the a forward finite difference such that :

$$\nabla(\mathcal{J}(1)) = \mathcal{J}(2) - \mathcal{J}(1)$$

Finally, at the left end element a backward difference is used :

$$\nabla(\mathcal{J}(N_s)) = \mathcal{J}(N_s) - \mathcal{J}(N_s - 1)$$

sign$\{.\}$ denotes the sign operator. According to this, $\Phi(u)$ equals 1 when signal plus noise samples are present and zero when it is only noise.

The difficulty is to estimate the channel occupency rate accurately for low signal to noise ratio. In fact, there are fluctuations that can mislead the decision for a given sample. To fix this problem, we propose to use a smoothing window. As the SIFS (for Short IFS) is the smallest inter frame gap, theoretically we can't get a set of succesive noise samples of a length less than a SIFS. Then, if it happens this means that the algorithm took the wrong decision and $\Phi(u)$ will be forced to 1. Practically, to avoid confusion it is judicious to choose a smoothing window less than a SIFS. Thus we get the smoothed $\Phi(u)$ and the channel occupency rate is estimated by :

$$\widehat{Cor} = \frac{1}{N_s}\sum_{u=1}^{N_s}\Phi(u) \tag{7}$$

5. COLLISION DETECTION

A collision occur when two or more stations attempt to transmit a packet across the network at the same time. Thanks to the first technique we can now determine when a data frame starts and ends. We propose here to use a theoretical information criterion on those samples to detect the number of sources present in it and determine if a collision happened or not. The model presented in equation (2) can be written as follow :

$$\mathbf{x}(n) = \sum_{k=0}^{L-1}\mathbf{H}(k)\mathbf{s}(n - n_1 - k) + \mathbf{w}(n) \tag{8}$$

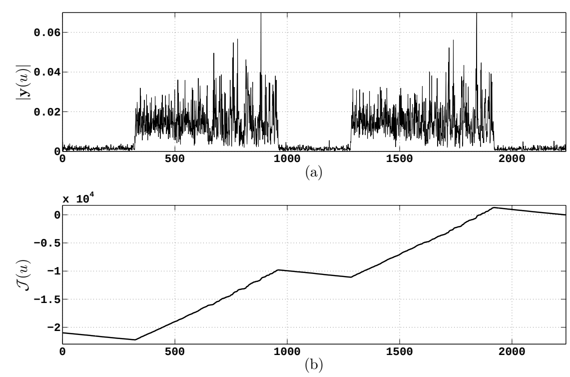

Fig. 1. (a) Absolute value of a wifi signal, (b) corresponding behavior of the criterion $\mathcal{J}(u)$

where $\mathbf{x}(n) = [x_1(n), x_2(n), \ldots, x_N(n)]^T$, $\mathbf{s}(n) = [s_1(n), \ldots, s_M(n)]$. The s_i are supposed to be stationary independent and uncorrelated with the noise $\mathbf{w}(n)$. $\mathbf{H}(k)$ is a $N \times M$ matrix that models the channel effect.

Now, considering an observation window of d samples and defining :

$$\mathbf{x}_d(n) = \begin{bmatrix} \mathbf{x}^T(n), & \ldots, & \mathbf{x}^T(n-d+1) \end{bmatrix}^T \tag{9}$$

$$\mathbf{s}_i(n) = [s_i(n), \ldots, s_i(n-d-L+1)]^T \tag{10}$$

$$\mathbf{w}_d(n) = \begin{bmatrix} \mathbf{w}^T(n), & \ldots, & \mathbf{w}^T(n-d+1) \end{bmatrix}^T \tag{11}$$

we get :

$$\mathbf{x}_d(n) = \boldsymbol{\mathcal{H}}\mathbf{s}_d(n) + \mathbf{w}_d(n) \tag{12}$$

where the $\boldsymbol{\mathcal{H}}$ is $Nd \times M(L+d)$ Sylvester matrix. and $\mathbf{s}_d(n) = [\ \mathbf{s}_1(n), \ \ldots, \ \mathbf{s}_N(n)\ ]$. Define the statical covariance matrices of the signals and noise as :

$$\mathbf{R}_x = \mathbb{E}\left[\mathbf{x}_d(n)\mathbf{x}_d(n)^H\right] \tag{13}$$

$$\mathbf{R}_s = \mathbb{E}\left[\mathbf{s}_d(n)\mathbf{s}_d(n)^H\right] \tag{14}$$

$$\mathbf{R}_w = \mathbb{E}\left[\mathbf{w}_d(n)\mathbf{w}_d(n)^H\right] \tag{15}$$

We verify that :

$$\mathbf{R}_x = \boldsymbol{\mathcal{H}}\mathbf{R}_s\boldsymbol{\mathcal{H}}^H + \sigma_w^2\mathbf{I}_{Nd} \tag{16}$$

Where $\mathbf{I}_{Nd}$ is the idendity matrix of order Nd and $(.)^H$ is the transpose conjugate.

Under hypothesis that the channels have no common zeros, and for an observation window of a size d large enough, we establish that the rank of $\mathbf{R}_x$ is :

$$r = min\{M(d+L), dN\} \tag{17}$$

Using an information theoretic criterion, like AIC or MDL [5] it is possible to get an estimate of r, and therefore, according to the equation (17) the number of sources M is determined as being the nearest integer to $\frac{r}{d+L}$. Unfortunately, we have no access to the channel length L, and to get M we must estimate it using any available technique in the literature.

To avoid this step, we propose to exploit the properties of the WiFi signals. Since they are OFDM signals, we know that the length of the cyclic prefix is always chosen in such a way to be greater than L. So, if we choose the smoothing factor d as equal to the cyclic prefix, we are sure that $L < d$.

Starting from the hypothesis that only one station is emitting : $r = d + L$, and $L = r - d$. If this value is less than d, it means that there is indeed one source, otherwise more than one source is present and a collision occure.

6. SIMULATIONS

IEEE 802.11n signals are simulated. We recall that the IEEE 802.11n are 64 subcarriers OFDM signals with a cyclic prefix of length 16. The channel is a set of $L = 7$ complex random variables $\sim \mathcal{NC}(0, 1)$. A complex additive white gaussian noise corrupts the emitted symbols. As said previously the gradient is processed using the central difference method,

6.1. Channel occupancy rate

As treated previously, the Channel occupancy rate is function of the behavior of $\mathcal{J}(u)$. In figure 2, we show the NMSE (Normalized Mean Square Error) of the estimation of the channel occupancy rate versus the SNR. The results are averaged over $K = 500$ Monte Carlo runs, and the NMSE is here defined as $\frac{1}{K}\sum_1^K \left(\widehat{Cor}_k - Cor\right)^2 / Cor^2$, where $\widehat{Cor}_k$ is the channel occupancy rate estimated at the k^{th} realization and Cor is the real channel occupancy rate. We can clearly observe that for a high SNR the error tends to zero, and thus we achieve a good estimation. The proposed method is compared to the hard threshold denoising method proposed by Donoho [6], and to the energy detector proposed by Urkowitz [7], with a probability of false alarm $Pfa = 10^{-4}$, these methods are also smoothed as described in section 4. The cognitive terminal is supposed to be doted of $N = 2$ antennas.

6.2. Collision detection

Figures 3, shows the performances of the proposed method versus SNR, we clearly show that for both AIC and MDL we get a good probability of detection for a SNR greater than 10 dB, which is the usual operating range of the WiFi. The simulations were done with 800 samples observed, we observe that AIC behave better than MDL.

7. CONCLUSION

In this paper, we proposed new methods for estimating two metrics for vertical handoff based on a physical layer sensing,

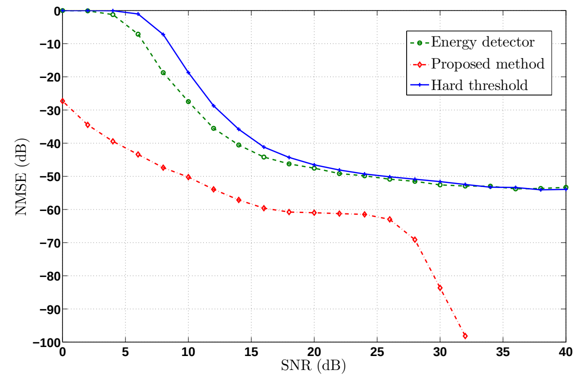

Fig. 2. NMSE of the channel occupancy rate versus SNR

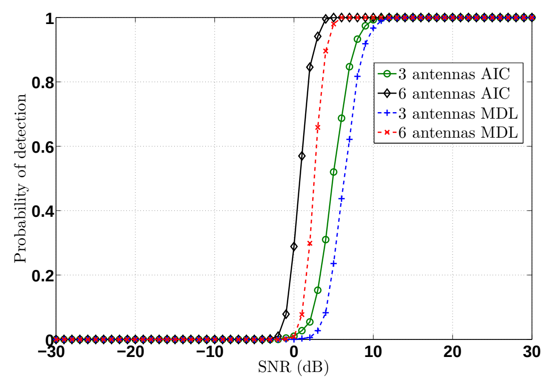

Fig. 3. Probabilty of detection with AIC and MDL versus SNR

without any need of connection to the access point. The first one, is related to the channel occupancy rate and the second one to the collision rate. These two metrics inform us on the MAC-layer QoS condition of the network, such as available bandwidth and access delay, which are good informations to perform a vertical handover. Computer simulation showed good results for the WiFi SNR operating range.

8. REFERENCES

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