OFDM system identification based on *m*-sequence signatures in cognitive radio context

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***Abstract*—In the context of cognitive radio, system identification is a crucial step towards radio environment awareness. In this paper, we present a new OFDM system identification method based on *m*-sequence (MS) specific characteristics. Thanks to their good random properties, *m*-sequences are commonly used in existing standards (such as Wifi or WiMAX) to modulate pilot tones for channel estimation and/or for synchronization purposes. We demonstrate that such sequences show extra-properties relevant to distinguish systems from each other and therefore advocate to generalize their use in a cognitive context. MS signatures are indeed of interest since they are able to discriminate OFDM based systems that have the same modulation parameters (intercarrier spacing, cyclic prefix duration, etc.). In order to detect these signatures, we conduct a hypothesis test based on the MS high order statistics. Detailed numerical examples demonstrate the efficiency of the proposed identification criterion and especially show its benefits compared to classical correlation based methods.**

I. Introduction

The increasing demand of wireless services faced to the limited spectrum resources constrains wireless systems to evolve towards more embedded intelligence. The Cognitive Radio (CR) concept [1] appears as a key solution to make different systems coexist in the same frequency band. CR terminals have the ability to reconfigure themselves (i.e. to adapt the modulation parameters, carrier frequency, power, etc.) with regards to the surrounding radio environment and spectrum policy. Spectrum sensing and especially system identification is therefore a crucial step towards radio environment awareness. In this paper we focus on OFDM based systems as it becomes the physical layer for many wireless standards [2]–[5]. Identification of such systems has mainly been studied using various OFDM cyclostationary properties induced by the Cyclic Prefix (CP) [6]–[9]. The performance of this approach fully depends on the cyclic prefix duration and on the length of the multipath propagation channel. Note also that such a method is totally inefficient in the presence of a zero-padded OFDM system which may be relevant in a cognitive context [10]. Moreover, considering the increasing interest in OFDM by the wireless designers, cyclostationary properties of such systems are likely to become closer and closer. For instance 3GPP/LTE [5] and Mobile WiMAX [11] systems have already an intercarrier spacing only different from 4% which may prevent from getting an accurate system identification based on the intercarrier spacing estimation principle.

To overcome these limitations, methods that involve more particular signatures in OFDM systems are required. [12] suggested approaches using specific preambles or dedicated subcarriers with cyclostationary patterns. Preambles being usually intermittently transmitted and therefore difficult to intercept, the use of dedicated subcarriers is preferable. However, dedicating subcarriers to only embed signatures may have a cost as it adds overhead and thus reduces systems capacity. One way to address this issue is to jointly use pilot tones for channel estimation (their initial usage) as well as for system identification.

In this contribution, we develop a solution relying on the use of *m*-sequence (MS) modulated pilot tones to embed signatures in OFDM signals. MSs show specific high order statistics relevant for system identification and avoid any additional overhead as they meet the requirements of usual training sequences (such *m*-sequences are indeed already used in existing standards for channel estimation, see WiMAX [2] and Wifi [3]). Thus, we here suggest to take advantage of signatures created as a side-effect of existing MS structures to identify standards such as [2] and [3] and also advocate to generalize MSs use in a cognitive context.

The paper is organised as follows: Section II describes the MS useful properties. Section III introduces the OFDM identification scheme and especially the associated cost function based on MS signature characterization. In section IV the impact of synchronization impairments is analysed. Identification performance is assessed through simulations in Section V. Finally, conclusions are presented in Section VI.

II. MS properties

A maximum length sequence, commonly called *m*-sequence, is a type of pseudorandom binary sequence generated using maximal linear feedback shift registers and modulo 2 addition. A necessary and sufficient condition that a sequence be of maximal length (i.e. sequence of length 2^p-1 for length-p registers) is that its corresponding generator polynomial, denoted by P_{MS}, be primitive.

Any binary MS w_k generated by length p registers of polynomial $P_{MS}=\sum_{i=0}^{p}\alpha_i X^i$ verifies over GF(2)

$$w_k=\sum_{i=1}^{p}\alpha_i w_{k-i}\Leftrightarrow\sum_{i=0}^{p}\alpha_i w_{k-i}=0.$$

Moreover, let $\breve{w}_k = 1 - 2w_k$ be the BPSK associated sequence. Thanks to [13], one can see that

$$\lim_{M\to+\infty} \frac{1}{M} \sum_{k=0}^{M-1} \left(\prod_{i\in\mathcal{B}} \breve{w}_{k-i} \right) = \begin{cases} 1, & \text{if } \mathcal{B} = \mathcal{A} \\ 1/(1-2^p) & \text{otherwise} \end{cases} \tag{1}$$

where $\mathcal{B}$ is any subset of $\{0, \cdots, 2^p - 2\}$ and $\mathcal{A} = \{i \in \{0, \cdots, p\} | \alpha_i = 1\}$.

III. OFDM SYSTEM IDENTIFICATION ALGORITHM

A. System model

In order to facilitate the identification of OFDM systems, we suggest to generalize the use of *m*-sequence modulated pilot tones. Assuming that a transmitted OFDM symbol consists of N subcarriers and N_p comb-type pilot tones, the discrete-time baseband equivalent signal is given by

$$x(m) = \sqrt{\frac{E_s}{N}} \big[x_d(m) + x_r(m) \big], \tag{2}$$

where

$$x_d(m) = \sum_{k\in\mathbb{Z}} \sum_{\substack{n=0 \\ n\notin \mathsf{I_p}}}^{N-1} a_k(n) e^{2i\pi \frac{n}{N}[m-D-k(N+D)]} g[m-k(N+D)],$$

and

$$x_r(m) = \sum_{k\in\mathbb{Z}} \sum_{n\in \mathsf{I_p}} \breve{w}_k(n) e^{2i\pi \frac{n}{N}[m-D-k(N+D)]} g[m-k(N+D)].$$

E_s is the signal power, $a_k(n)$ are the transmit data symbols assumed to be independent and identically distributed (i.i.d), D is the CP length, $m \mapsto g(m)$ is the pulse shaping filter. $\mathsf{I_p}$ denotes the set of pilot subcarrier indexes. For each $n \in \mathsf{I_p}$, $\breve{w}_k(n)$ is a BPSK pilot symbols sequence associated with one *m*-sequence obtained by the generator polynomial $P_{MS}(n)$.

System signature is thus entirely characterized by $\mathsf{I_p}$ and $\{P_{MS}(n)\}_{n=0,\cdots,N_p-1}$. Notice that the number of primitive polynomials of degree p over GF(2) is given by $\phi(2^p - 1)/p$, where $\phi(.)$ is Euler's Totient function [14]. As an example, for $N_p = 1$ and $p \leq 11$, there are 335 different possible signatures which is much larger than the number of existing OFDM systems! Consequently each existing or future system may have its own system signature based on the knowledge of $\mathsf{I_p}$ and $\{P_{MS}(n)\}_{n=0,\cdots,N_p-1}$.

Now, we consider that the signal propagates through a multipath channel. Let $\{h(l)\}_{l=0,\cdots,L}$ be the base-band equivalent discrete-time channel impulse response of length L. The received samples of the OFDM signal are thus given by

$$y(m) = e^{-i(2\pi\varepsilon \frac{m-\tau}{N} + \theta)} \sum_{l=0}^{L-1} h(l) x(m - l - \tau) + \eta(m), \tag{3}$$

where ε is the carrier frequency offset (normalized by the intercarrier spacing), θ the initial arbitrary carrier phase, τ the timing offset and $\eta(m)$ a zero mean circularly-symmetric complex-valued white Gaussian noise of variance σ^2 per complex dimension.

The k-th received symbol on subcarrier n is therefore written as

$$Y_k(n) = \frac{1}{\sqrt{N}} \sum_{m=0}^{N-1} y[k(N+D) + D + m] e^{-2i\pi \frac{nm}{N}}.$$

In the case of perfect synchronization (i.e. $\varepsilon = 0$, $\tau = 0$ and $\theta = 0$) and for $n \in \mathsf{I_p}$, $Y_k(n)$ simplifies to

$$Y_k(n) = H_k(n) \breve{w}_k(n) \sqrt{E_s} + \mathfrak{N}_k(n)$$

where $H_k(n)$ and $\mathfrak{N}_k(n)$ are respectively the channel frequency response and the noise at subcarrier n of the k-th received symbol.

B. Identification cost function

Thanks to Eq. (1), systems described in Eq. (2) can be discriminated by using the following criterion J

$$J = \sum_{n\in\mathsf{I_p}} \left| \lim_{M\to+\infty} \frac{1}{M} \sum_{k=0}^{M-1} \left(\prod_{i\in\mathcal{A}(n)} \breve{w}_{k-i}(n) \right) \right|^2$$

where $\mathcal{A}(n)$ is the set of indexes associated with the non-null components of $P_{MS}(n)$. For the sake of simplicity, we consider that the same MS generator polynomial is used for all pilot subcarriers. Consequently $\mathcal{A}(n)$ and $P_{MS}(n)$ are independent of n. Moreover, we limit P_{MS} to trinomials of the form $1 + X^l + X^p$ $(p > l)$. [1]

J can now be written as

$$J = \sum_{n\in\mathsf{I_p}} \left| \lim_{M\to+\infty} \frac{1}{M} \sum_{k=0}^{M-1} \breve{w}_k(n) \breve{w}_{k-l}(n) \breve{w}_{k-p}(n) \right|^2.$$

In practice, J cannot be computed and the sequence $\breve{w}_k(n)$ is only accessible via the observations $Y_k(n)$. Thus, the cost function is based on the following estimate

$$\hat{J} = \sum_{n\in\mathsf{I_p}} |Z(n)|^2, \tag{4}$$

where $Z(n)$ is defined as

$$Z(n) = \frac{1}{M-p} \sum_{k=p}^{M-1} \tilde{Y}_k(n) \tilde{Y}^*_{k-l}(n) \tilde{Y}_{k-p}(n). \tag{5}$$

M is the number of available OFDM symbols and the superscript "*" stands for complex conjugation which is added on the second term to mitigate the influence of the frequency offset ϵ on $\hat{J}$ (for more details, see Section IV). Moreover, in order to get the criterion $\hat{J}$ independent of the received signal gain, each term $Y_k(n)$ in Eq. (5) is normalized so that

$$\tilde{Y}_k(n) = \frac{Y_k(n)}{\sqrt{\widehat{\mathrm{Var}}\,[Y(n)]}}, \tag{6}$$

where Var[.] denotes the variance and

$$\widehat{\mathrm{Var}}\,[Y(n)] = \frac{1}{M} \sum_{k=0}^{M-1} |Y_k(n)|^2. \tag{7}$$

[1] Limiting P_{MS} to trinomials reduces the number of possible signatures but does not call the validity of the concept into question. For instance, there are still 19 different possible signatures for $N_p = 1$ and $p \leq 11$.

C. Decision statistics

In this section we assume perfect synchronization (i.e. $\varepsilon = 0$, $\tau = 0$ and $\theta = 0$). Synchronization impairments are studied in Section IV.

Our identification problem described in the previous subsection boils down to a standard detection problem for which we have to select the most likely hypothesis between the following two hypotheses

$$\begin{cases} \mathcal{H}_0 & : \ y(m) \text{ writes as in Eq. (3) without MS structure or with MS structure for tones in } \mathsf{I_p} \text{ associated with } P'_{MS} = 1 + X^{l'} + X^{p'} \text{ and } (l', p') \neq (l, p) \\ \mathcal{H}_1 & : \ y(m) \text{ writes as in Eq. (3) with MS structure for tones in } \mathsf{I_p} \text{ described by } P_{MS} = 1 + X^{l} + X^{p}. \end{cases} \quad (8)$$

To decide the most likely hypothesis, we propose a detection test constrained by the asymptotic false alarm probability similar to what is suggested in [9]. The decision is made by comparing $\hat{J}$ to a positive threshold such that

$$\hat{J} \underset{\mathcal{H}_0}{\overset{\mathcal{H}_1}{\gtrless}} \Lambda,$$

with Λ defined as

$$\mathcal{F}_{\hat{J}|\mathcal{H}_0}(\Lambda) = 1 - P_{fa}. \quad (9)$$

$\mathcal{F}_{\hat{J}|\mathcal{H}_0}$ is the cumulative distribution of $\hat{J}$ when $\mathcal{H}_0$ holds and P_{fa} is the tolerated false alarm probability.

As implied in (8), $\mathcal{H}_0$ embodies two different sub-hypotheses respectively named $\mathcal{H}_0^a$ and $\mathcal{H}_0^b$. $\mathcal{H}_0^a$ represents the case where $y(m)$ does not have any MS structure that is to say that $y(m)$ is any signal such that $Y_k(n)$, $Y^*_{k-l}(n)$ and $Y_{k-p}(n)$ are mutually independent and $\mathbb{E}[Y_k(n)] = 0$. As for $\mathcal{H}_0^b$, it corresponds to the case where the tones of $y(m)$ belonging to the set $\mathsf{I_p}$ follow a MS structure with generator polynomial $P'_{MS} = 1 + X^{l'} + X^{p'} (\neq P_{MS})$ where $l' \neq l$ and/or $p' \neq p$. Thanks to the random, independent and centered nature of the vast majority of digital modulated signals, we can make the reasonable assumption that $\mathcal{H}_0 = \mathcal{H}_0^a \cup \mathcal{H}_0^b$.

In order to find the relevant threshold Λ, we hereafter analyse the asymptotic statistical behavior of $\hat{J}$ under both hypotheses $\mathcal{H}_0^a$ and $\mathcal{H}_0^b$.

1) Asymptotic probability density function of $\hat{J}$ under $\mathcal{H}_0^a$: As shown in Eq.(6), $\tilde{Y}_k(n)$ is expressed as a ratio of two random variables. The variance estimator introduced in Eq.(7) being consistent, it converges almost surely to a constant denoted v_n so that, thanks to the asymptotic theory developped in [15], $\tilde{Y}_k(n)$ converges in distribution to $Y(n)/\sqrt{v_n}$. Moreover, $Z(n)$ being a sum of i.i.d random variables when $\mathcal{H}_0^a$ holds, we deduce that $Z(n)|\mathcal{H}_0^a$ is asymptotically normal with

$$\begin{aligned} \mathbb{E}\left[Z(n)|\mathcal{H}_0^a\right] &= 0, \\ \mathrm{Var}\left[Z(n)|\mathcal{H}_0^a\right] &= \frac{\left(\mathbb{E}\left[|H_k(n)|^2\right]\rho(n) + \sigma^2/N\right)^3}{(M-p)v_n^3}. \end{aligned}$$

where $\rho(n)$ is the signal power of subcarrier n. If we consider the multipath channel as static over the observation window (impacts of channel variation are discussed in section V) then $v_n = |H(n)|^2 \rho(n) + \sigma^2/N$ and $\mathrm{Var}\left[Z(n)|\mathcal{H}_0^a\right]$ simplifies to

$$\mathrm{Var}\left[Z(n)|\mathcal{H}_0^a\right] = \frac{1}{M-p}.$$

Therefore, the asymptotic probability density function of $\hat{J}$ under $\mathcal{H}_0^a$ is given by

$$2(M-p)\hat{J} \sim \chi^2_{2N_p},$$

where χ^2_d denotes a chi-square distribution with d degrees of freedom.

2) Asymptotic probability density function of $\hat{J}$ under $\mathcal{H}_0^b$: According to Eq. (1),

$$\lim_{M\to+\infty} \frac{1}{M} \sum_{k=0}^{M-1} \breve{w}_k(n)\breve{w}_{k-l}(n)\breve{w}_{k-p}(n) = \frac{1}{1-2^{p'}}$$

when $\mathcal{H}_0^b$ holds. Following the same approach described in Sec. III-C1, we then have

$$\begin{aligned} \mathbb{E}\left[Z(n)|\mathcal{H}_0^b\right] &= \frac{|H(n)|^2 H(n)\rho(n)^{\frac{3}{2}}}{(1-2^{p'})v_n^{\frac{3}{2}}}, \\ \mathrm{Var}\left[Z(n)|\mathcal{H}_0^b\right] &= \frac{1}{(M-p)^2 v_n^3} \sum_{i,j=0}^{M-p-1} [C]_{i,j}. \end{aligned}$$

$[C]_{i,j}$ are the elements of the covariance matrix defined as

$$C = \mathbb{E}\left[(\Upsilon - \mathbb{E}\{\Upsilon\})(\Upsilon - \mathbb{E}\{\Upsilon\})^H\right]$$

where the superscript ^{H} stands for transpose conjugate and

$$\begin{aligned} \Upsilon = [&Y_k(n)Y^*_{k-l}(n)Y_{k-p}(n), Y_{k+1}(n)Y^*_{k-l+1}(n)Y_{k-p+1}(n), \\ &\cdots, Y_{k+M-p}(n)Y^*_{k+M-p-l}(n)Y_{k+M-2p}(n)]. \end{aligned}$$

By developing each product term of the covariance matrix and assuming that $M \leq 2^{p'} - 1$, we get

$$[C]_{i,j} = \begin{cases} \left(|H(n)|^2\rho(n) + \sigma^2/N\right)^3 - \frac{|H(n)|^6\rho(n)^3}{(1-2^{p'})^2}, & i = j \\ \frac{\sigma^2|H(n)|^4\rho(n)^2}{N(1-2^{p'})} - \frac{|H(n)|^6\rho(n)^3 2^{p'}}{(1-2^{p'})^2}, & |i-j| = p \\ -\frac{|H(n)|^6\rho(n)^3 2^{p'}}{(1-2^{p'})^2}, & \text{otherwise.} \end{cases}$$

In a realistic scenario, the probability density function of $\hat{J}$ under $\mathcal{H}_0^b$ cannot be easily estimated as it depends on $H(n)$, $\rho(n)$, σ^2 and p' which are unknown by the receiver. However, in practice MS degrees can be chosen large enough (e.g., $p = 11$ in [2] and [4]) to consider the covariance matrix C as diagonal. In that case, $Z(n)|\mathcal{H}_0^b$ is asymptotically normal and $\mathrm{Var}\left[Z(n)|\mathcal{H}_0^b\right]$ is well approximated by $1/(M-p)$. Furthermore, if we assume that $M \ll 2^{p'} - 1$ then $\left|\mathbb{E}\left[Z(n)|\mathcal{H}_0^b\right]\right| \ll \mathrm{Var}\left[Z(n)|\mathcal{H}_0^b\right]$.

Therefore, we can consider that $\hat{J}$ follows the same cumulative distribution under both hypotheses $\mathcal{H}_0^a$ and $\mathcal{H}_0^b$, that is

$$\mathcal{F}_{\hat{J}|\mathcal{H}_0}(x) = \frac{\gamma\left(N_p, (M-p)\,x\right)}{(N_p-1)!}$$

where $\gamma(a, x)$ is the incomplete gamma function.

IV. Effect of synchronization impairments

Timing missynchronization ($\tau \neq 0$) and/or frequency offset ($\varepsilon \neq 0$) damage the observations $Y_k(n)$ as inter-symbol (ISI) and inter-carrier (ICI) interferences occur [16]. In addition to interference, ε modifies the phase of $Y_k(n)Y^*_{k-l}(n)Y_{k-p}(n)$ and consequently makes $\mathbb{E}[Z(n)|\mathcal{H}_1]$ decrease (note that the complex conjugation in Eq.(5) mitigates the phase variation speed). Therefore, as illustrated in Figure 1, the identification algorithm performance decreases dramatically in the case where $\varepsilon \neq 0$ and/or $\tau \neq 0$.

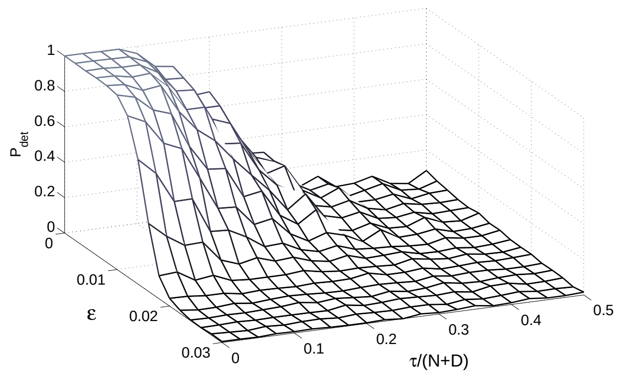

Fig. 1. Effect of ε and τ on the correct detection probability ($SNR = 0$ dB, $M = 50$, $P_{MS} = 1 + X^9 + X^{11}$, $N_p = 8$, $P_{fa} = 0.01$).

To overcome this issue, ϵ and τ can be estimated as

$$[\hat{\varepsilon}, \hat{\tau}] = \underset{(\varepsilon,\tau)}{\operatorname{argmax}}\, \hat{J}. \tag{10}$$

The direct use of the identification cost function $\hat{J}$ to estimate (ε, τ) implies to change the detection threshold Λ. In the specific case where Eq. (10) is solved using a grid of K points and assuming that the different $\hat{J}$ on this grid are mutually independent, Λ is given by

$$\left(\mathcal{F}_{\hat{J}|\mathcal{H}_0}(\Lambda)\right)^K = 1 - P_{fa}.$$

V. Simulations

In the following, all the results are averaged over 1000 Monte Carlo runs. The system to be recognized is the Fixed WiMAX described in [2]. WiMAX embeds MS structures of polynomial $P_{MS} = 1+X^9+X^{11}$. We recall that $N = 256$ and $N_p = 8$. Unless otherwise stated, $N/D = 32$. The subcarriers are equipowered. The asymptotic false alarm probability P_{fa} is fixed to 0.01. The Signal-to-Noise Ratio (SNR) is defined as SNR(dB) $= 10\log_{10}\left(E_s/\sigma^2\right)$.

In Figure 2, we plot the correct detection probability versus SNR in the context of AWGN channel. Different synchronization assumptions and various M are considered. We show that the performance of the MS criterion is significantly improved when the observation window increases. Moreover, we observe the impact of the synchronization method based on Eq. (10). We see that the loss due to missynchronization decreases when M increases. For the simulation, uniformly distributed random ε and τ were generated with $-0.5 \leq \varepsilon \leq 0.5$ and $-0.5(N+D) \leq \tau \leq 0.5(N+D)$. ε and τ were estimated by maximizing $\hat{J}$ over a grid with a step of 4.10^{-3} over ε and $0.1(N+D)$ over τ.

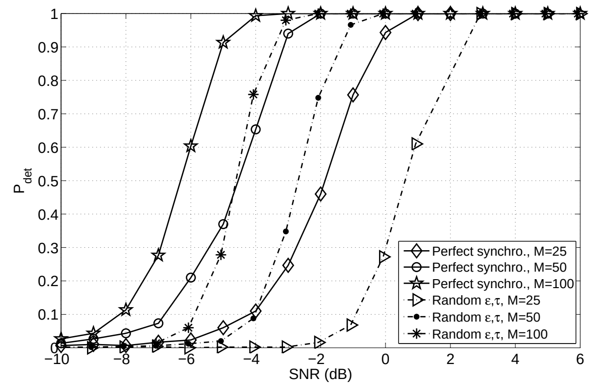

Fig. 2. Effect of SNR, M, ε and τ on the correct detection probability.

We hereafter consider a time-invariant discrete-time channel $\{h(l)\}_{l=0,\cdots,L}$ with $L = D$ and an exponential decay profile for its non-null component (i.e., $\mathbb{E}[|h(l)|^2] = Ge^{-l/\beta}$ for $l = 0, \cdots, L$ and G is chosen such that $\sum_{l=0}^{L} \mathbb{E}[|h(l)|^2] = 1$). Notice that β corresponds approximately to the root mean square (RMS) delay spread.

In Figure 3, we display the correct detection probability versus SNR for various RMS delay spread. We observe that the more frequency-selective the channel is, the better the performance is. This is due to the fact that Var$[|h(l)|^2]$ decreases as the RMS delay spread increases.

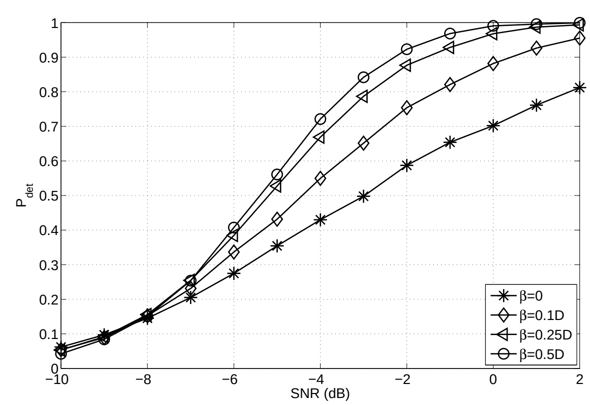

Fig. 3. Effect of β on the correct detection probability ($M = 50$).

In Figure 4, we compare the correct detection probability versus SNR between the proposed MS criterion and the standard correlation based method for $\beta = 0.5D$ and the various CP lengths handled by the WiMAX system.

To compare both methods, we consider that the correlation

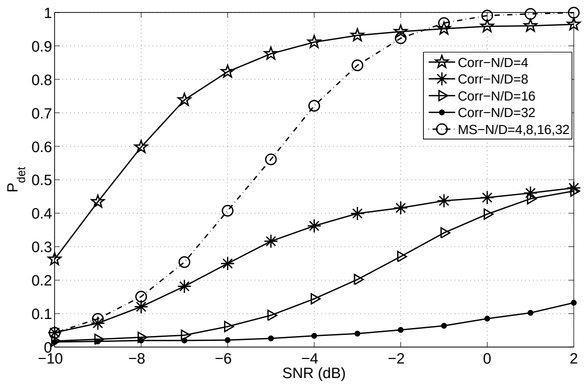

Fig. 4. Comparison between correlation based method and MS criterion ($M = 50$, $\beta = 0.5D$).

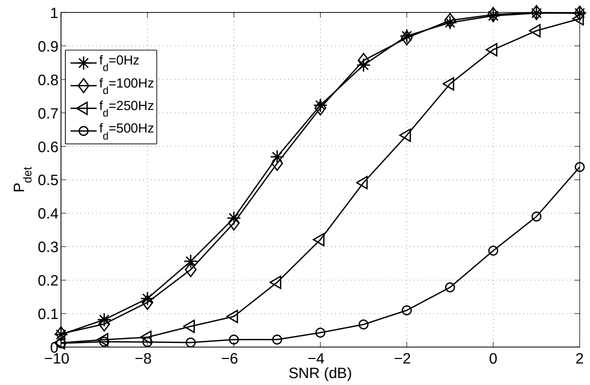

Fig. 5. Effect of Doppler spread on the correct detection probability ($M = 50$, $\beta = 0.5D$).

based detection is correct when

$$N-\delta/2 \leq \underset{v\in[v_{min},v_{max}]}{\operatorname{argmax}} \left| \sum_{m=0}^{M'-v-1} y(m)y^*(m+v) \right| \leq N+\delta/2$$

where $M' = M(N+D)$, $v_{min} = 32$ and $v_{max} = 2048$ which corresponds to searching systems from 32 to 2048 subcarriers, and where δ is the tolerated error on the subcarrier spacing. We choose δ to be conditioned by the P_{fa} under the white gaussian noise hypothesis such that $\delta = (v_{max} - v_{min})P_{fa}$. We observe that the proposed algorithm is not dependent on the CP length and outperforms the correlation based method as soon as $N/D \geq 8$. Moreover, for a fair comparison, it is important to remind that as long as the MSs are different, our method can discriminate systems with the same intercarrier spacing whereas the correlation algorithm cannot.

In Figure 5, we plot the correct detection probability versus SNR when the frequency-selective channel becomes time-variant. Various values of maximum Doppler frequencies f_d have been inspected. We see that our algorithm is quite robust to Doppler spread below 100Hz (at 3GHz, this corresponds to a relative velocity of 36kph) whilst above this frequency, performance degrades significantly.

VI. Conclusion

In this paper, we developed a new method based on *m*-sequence properties to embed signatures in OFDM systems without adding any overhead to standard pilot tones. We also studied the MS identification cost function and showed that this method exhibits excellent performance and is quite robust to channel impairements. Moreover, simulation results indicate that in addition to stronger discriminating properties, MS identification outperforms classical correlation based method in some relevant contexts.

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