# A Wide Band Modem Based on Impulse Modulation and Frequency Domain Signal Processing for Powerline Communication

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Abstract—We describe a powerline (PL) communication system that deploys wide band impulse modulation combined with direct sequence code division multiple access (DS-CDMA) to obtain a form of orthogonal modulation, and to allow for user multiplexing. Several novel frequency domain (FD) detection algorithms are proposed. They all have the capability of canceling the inter-code interference (ICI) and the multiple access interference (MAI) that is generated by the frequency selective PL channel. Practical estimation of the channel, and mitigation of impulse noise is also addressed. When channel coding is used, we also show that iterative techniques with feedback from the decoder better the channel estimation and detection performance. Simulation results prove that the scheme achieves high data rates in a PL channel in the presence of impulsive noise and MAI.

Keywords—Wide band powerline communication systems, frequency domain processing, impulse modulation, iterative processing, multiuser detection.

#### I. Introduction

We describe a powerline (PL) communication system that is based on the use of wide band impulse modulation. Indoor applications such as local area networks, peripheral office connectivity, and home/industrial control [1] are considered. Most of the current proposals deploy multicarrier modulation [2]. Instead, in this paper we investigate an alternative approach based on wide band (beyond 20 MHz) impulse modulation [1], [3]-[4]. The basic idea behind impulse modulation is to convey information by mapping an information symbol stream into a sequence of short duration pulses [5]-[6]. Pulses (referred to as monocycles) are followed by a guard time to cope with the channel time dispersion. The monocycle can be shaped to avoid the low frequencies where we experience higher levels of background noise. Several users are multiplexed via direct sequence code division multiple access (DS-CDMA) using signature waveforms that are a repetition of time delayed and weighted monocycles.

In our system the simplest receiver is the matched filter receiver that correlates the received signal with a template waveform. This requires estimation of the channel that can be complex if performed in the time domain [4]. Further, the channel frequency selectivity [7]-[8] introduces inter-code

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interference (ICI) (interference among the codes that are assigned to the same user) and multiple access interference (MAI) when multiple users access the network [3].

We propose a novel frequency domain (FD) detection approach which allows to improve the detection/estimation performance and to the keep the complexity at moderate levels. A FD approach was also proposed in [9] considering the wireless scenario, and in [10] for the powerline scenario. The specific contribution of this paper is about the description of several novel FD algorithms, in particular, a simplified FD joint detector, a FD iterative detector, and a FD interference decorrelator. They all include the capability of rejecting the ICI/MAI but have different level of performance and complexity which is lower than the optimal maximum likelihood joint detector. Further, channel coding is also considered and it is based on bit-interleaved convolutional codes. We focus on the practical estimation of the parameters. and we show that iterative techniques with feedback from the decoder allow to obtain improved channel estimation and detection performance. Finally, we consider impulsive noise, and we modify the Viterbi decoder to better the performance in this scenario. We also describe the key parameters of a PL impulse modulated system that has been used to assess performance and whose hardware prototype is described in [1]. To this respect, we propose the use of a wide band statistical channel model that allows to evaluate the system performance by capturing the ensemble of indoor PL grid topologies.

#### II. WIDE BAND IMPULSE MODULATED SYSTEM MODEL

We consider a system where a number of nodes (users) wish to communicate sharing the same PL network. Communication is from one node to another node, such that if other nodes simultaneously access the medium they are seen as potential interferers. Users' multiplexing is obtained in a CDMA fashion allocating the spreading codes among the users [10]. The signal transmitted by user u can be written as

$$s^{(u)}(t) = \sum_{k} \sum_{i \in C_u} b_k^{(u,i)} g^{(u,i)}(t - kT_f)$$
 (1)

where  $g^{(u,i)}(t)$  is the waveform (signature code) used to convey the *i*-th information symbol  $b_k^{(u,i)}$  of user u that is transmitted during the k-th frame. Each symbol belongs to the pulse amplitude modulation (PAM) alphabet, and it carries

 $\log_2 M_S$  information bits where  $M_S$  is the number of PAM levels, e.g., with 2-PAM  $b_k^{(u,i)}$  has alphabet  $\pm 1$ .  $T_f$  is the symbol period (frame duration).  $C_u$  denotes the set of signature code indices that are allocated to user u. Thus, user u can adapt its rate by transmitting  $C_u$  information symbols per frame. The signature code comprises the weighted repetition of  $L \ge 1$  narrow pulses (monocycles):

$$g^{(u,i)}(t) = \sum_{m=0}^{L-1} c_m^{(u,i)} g_M(t - mT)$$
 (2)

where  $c_m^{(u,i)} = \pm 1$  are the codeword elements (chips), and T is the chip period. The monocycle  $g_M(t)$  can be appropriately designed to shape the spectrum occupied by the transmission system. In this paper we consider the second derivative of the Gaussian pulse with duration D (Fig.1.A). An interesting property is that its spectrum does not occupy the low frequencies where we experience higher levels of man-made background noise (Fig.1.B). In typical system design we choose the chip period  $T \ge D$  and we further insert a guard time  $T_g$  between frames to cope with the channel time dispersion. Thus, the frame duration is  $T_f = LT + T_g$ .

Distinct codes are allocated to distinct users. In our design the codes are defined as follows:

$$c_m^{(u,i)} = c_{1,m}^{(u)} c_{2,m}^{(i)} \quad m = 0,...,L-1$$
 (3)

where  $\{c_{1,m}^{(u)}\}$  is a binary  $(\pm 1)$  random sequence of length L allocated to user u, while  $\{c_{2,m}^{(i)}\}$  is the i-th binary  $(\pm 1)$  Walsh-Hadamard sequence of length L. It should be noted that with this choice each node can use all L Walsh codes, which yields a peak data rate per user equal to  $R = L/T_f$  symb/s. It approaches  $\log_2 M_s/T$  bit/s with long codes. Clearly, while the signals of a given user are orthogonal, the ones that belong to distinct transmitting nodes are not. The random code  $\{c_{1,m}^{(u)}\}$  is used to randomize the effect of the MAI.

In the multiple access channel that we consider, the signals of distinct users propagate through distinct channels with impulse response  $h^{(u)}(t)$ . At the receiver of the desired node, we deploy a band-pass front-end filter with impulse response  $g_{FE}(t) = g_M(-t)$  that is matched to the transmit monocycle and that suppresses out of band noise and interference. Then, the output signal in the presence of  $N_I$  other users (interferers), reads

$$y(t) = \sum_{k} \sum_{i \in C_0} b_k^{(0,i)} g_{EQ}^{(0,i)}(t - kT_f) + i(t) + \eta(t)$$

$$i(t) = \sum_{k} \sum_{u=1}^{N_f} \sum_{i \in C_u} b_k^{(u,i)} g_{EQ}^{(u,i)}(t - kT_f - \Delta_u)$$
(4)

where the equivalent impulse response for user u and symbol i (equivalent signature code) is denoted as  $g_{EQ}^{(u,i)}(t) = g^{(u,i)} * h^{(u)} * g_{FE}(t)$ . It comprises the convolution of the signature code of indices (u,i) with the channel impulse

response of the corresponding user and the front-end filter. The index u=0 denotes the desired user.  $\Delta_u$  denotes the time delay of user u with respect to the desired user's frame timing.  $\eta(t)$  denotes the additive background noise. Distinct users experience distinct channels that we assume to introduce identical maximum time dispersion.

# A. Statistical Channel Model

The algorithms that we describe in the next section do not rely on a specific channel model. However, to evaluate performance we propose to use a statistical channel model. We start from the well-known band pass PL model in [7] where the frequency response is synthesized with  $N_P$  echoes as

$$H_{+}(f) = \sum_{n=1}^{N_{p}} g_{p} e^{-j\frac{2\pi d_{p}}{v} f} e^{-(\alpha_{0} + \alpha_{1} f^{\kappa})d_{p}} \quad 0 \le B_{1} \le f \le B_{2} \quad (5)$$

where  $|g_p| \le 1$  is the transmission/reflection factor for path p,  $d_p$  is the length of the path,  $v = c/\sqrt{\varepsilon_r}$  with c speed of light and  $\varepsilon_r$  dielectric constant. The parameters  $\alpha_0, \alpha_1, K$  are chosen to adapt the model to a specific network. This, model can realistically represent a true frequency response. Instead of using a specific channel response, it is beneficial to deal with a statistical model that allows to capture the ensemble of PL grid topologies. Thus, we propose to add some statistical property to it. In particular, we assume the reflectors (that generate the paths) to be placed over a finite distance interval. We fix the first reflector at distance  $d_1$  and we assume the other reflectors to be located according to a Poisson arrival process with intensity  $\Lambda$  [m<sup>-1</sup>]. The reflection factors  $g_p$  are assumed to be real, independent and uniformly distributed in [-1,1]. Finally, we appropriately choose  $\alpha_0, \alpha_1, K$  to a fixed value. If we further assume K=1, the real impulse response can be obtained in closed form. This allows to easily generate a channel realization (corresponding to a realization of the random parameters  $N_p, g_n, d_n$ ) as follows

$$h^{(u)}(t) = 2 \operatorname{Re} \left\{ \sum_{p=1}^{N_p} g_p e^{-\alpha_0 d_p} \frac{\alpha_1 d_p + j2\pi (t - d_p / \nu)}{(\alpha_1 d_p)^2 + 4\pi^2 (t - d_p / \nu)^2} \right.$$

$$\times \left( e^{j2\pi B_1 (t - d_p / \nu) - \alpha_1 B_1 d_p} - e^{j2\pi B_2 (t - d_p / \nu) - \alpha_1 B_2 d_p} \right) \right\}.$$

$$(6)$$

We assume distinct users to experience independent channels. The impulse responses are assumed to be constant for the whole duration of the transmission between the nodes of a given network topology. They change for a new (randomly picked) topology. In Fig.1.C we plot an example of channel realization that has been obtained with  $B_1$ =0 and  $B_2$ =55 MHz. Having in mind an indoor environment where the number of paths is typically high, we fix for the underlying Poisson process an intensity  $\Lambda$ =1/15 m<sup>-1</sup>, i.e., one reflector every 15 m in average. The first one set at distance 30 m with  $g_1$ =1. The maximum path distance is set at 300 m, and we fix K=1,  $\alpha_0$ =10<sup>-5</sup> m<sup>-1</sup>,  $\alpha_1$ =10<sup>-9</sup> s/m. In Fig.1.D we plot the equivalent channel response  $g_{EO}(t) = g_M * h^{(u)} * g_{FE}(t)$ . It is

significantly compressed because the monocycle filters out the low frequency components that are responsible for the longer channel delays according to the model (5).

# III. FREQUENCY DOMAIN RECEIVER

Detection can be accomplished in a symbol by symbol fashion by using a matched filter receiver. This baseline correlation receiver is optimal when the background noise is white Gaussian and there is perfect orthogonality among the received signature codes. To implement the correlation receiver we need to estimate the channel. Time-domain channel estimation [4] is complicated by the large time dispersion of the PL channel that implies that  $g_{EQ}^{(0,i)}(t)$  is an involved function of the channel and the transmitted waveform. Furthermore, the correlation receiver may suffer from the presence of inter-code interference (ICI) and multiple access interference (MAI) that is generated by the dispersive PL channel and the presence of multiple users.

Motivated by the above considerations, following some of the ideas in [9], we propose a frequency domain (FD) receiver approach. We assume discrete-time processing such that the received signal is sampled to obtain

$$y(nT_c) = \sum_{k} \sum_{i \in C_0} b_k^{(0,i)} g_{EQ}^{(0,i)}(nT_c - kT_f) + z(nT_c)$$
 (7)

with  $T_c = T_f/M$ , M equal to the number of samples per frame, and where  $z(nT_c) = i(nT_c) + \eta(nT_c)$  is the interference plus noise term. If we acquire frame synchronization with the desired user and we assume that the guard time is sufficiently long not to have inter-frame interference, i.e., interference among the symbols of adjacent frames, we can write

$$y_k(nT_c) = \sum_{i \in C_c} b_k^{(0,i)} g_{EQ}^{(0,i)}(nT_c - kT_f) + z_k(nT_c) \quad n = 0, ..., M - 1 \quad (8)$$

with 
$$y_k(nT_c) = y(kMT_c + nT_c)$$
,  $z_k(nT_c) = z(kMT_c + nT_c)$ .

To derive the proposed receiver we model the interference plus noise has a discrete time, zero mean, colored Gaussian process (non necessarily stationary) with correlation function  $r(nT_c, lT_c) = E[z(nT_c)z(lT_c)]$ . Then, using Parseval theorem it can be shown that the maximum-likelihood receiver can be implemented in the frequency domain (the derivation is omitted for space limitations).

We start by running an *M*-point discrete Fourier transform (DFT) over the *M* samples of the *k*-th frame to obtain

$$Y_{k}(f_{n}) = \sum_{i \in C_{0}} b_{k}^{(0,i)} G_{EQ}^{(0,i)}(f_{n}) + I_{k}(f_{n}) + N_{k}(f_{n})$$
(9)

where  $Y_k(f_n)$ ,  $G_{EQ}^{(0,i)}(f_n)$ ,  $I_k(f_n)$ ,  $N_k(f_n)$ , for  $f_n = n/(MT_c)$ , n = 0,...,M-1, are respectively the DFT outputs of: the received frame samples, the *i*-th equivalent signature code  $g_{EQ}^{(0,i)}(nT_c)$ , the interference samples, and the noise samples. The MAI term is a function of the users' time delay, transmitted waveform, and channel. Assuming the transmitted symbols of all users to be i.i.d. and equally likely, the DFT outputs  $Z_k(f_n) = I_k(f_n) + N_k(f_n)$  are complex Gaussian with

zero mean. The impairment multivariate process  $\mathbf{Z}_k$  defined as  $\mathbf{Z}_k = [Z_k(f_0),...,Z_k(f_{M-1})]^T$ , has *time-frequency* correlation matrix equal to

$$\mathbf{R}_{k,m} = E[\mathbf{Z}_k \mathbf{Z}_m^{\dagger}] = \mathbf{F} \mathbf{K}_{k,m} \mathbf{F}^{\dagger} \tag{10}$$

where  $\mathbf{K}_{k,m}$  is the  $M \times M$  matrix with entries r(kM+n, mM+l) for n, l=0,..., M-1, and  $\mathbf{F}$  is the M-point DFT orthonormal matrix. (.)<sup>T</sup> denotes the transpose operator while (.)<sup>†</sup> denotes the conjugate and transpose operator.

Now, let us collect the M elements  $Y_k(f_n)$  and  $G_{EQ}^{(0,i)}(f_n)$  in the vectors  $\mathbf{Y}_k$  and  $\mathbf{G}_{EQ}^{(0,i)}$ . Then, the FD maximum likelihood receiver searches the sequence of data symbols  $\{b_k^{(0,i)}\}$  (belonging to the desired user) that maximizes the log-likelihood function

$$\Lambda(\{b_k^{(0,i)}\}) =$$

$$= -\sum_{k=-\infty}^{\infty} \sum_{m=-\infty}^{\infty} [\mathbf{Y}_k - \sum_{i \in C_0} b_k^{(0,i)} \mathbf{G}_{EQ}^{(0,i)}]^{\dagger} \mathbf{R}_{k,m}^{-1} [\mathbf{Y}_m - \sum_{n \in C_0} b_m^{(0,n)} \mathbf{G}_{EQ}^{(0,n)}].$$
(11)

In (11)  $\mathbf{R}_{k,m}^{-1}$  denotes the  $M \times M$  block of indices (k,m) of  $\mathbf{R}^{-1}$ , where  $\mathbf{R}^{-1}$  is the inverse of the matrix  $\mathbf{R}$  whose  $M \times M$  block of indices (k,m) is  $\mathbf{R}_{k,m}$ . If  $\mathbf{R}$  is block diagonal, e.g., when we neglect the impairment correlation across frames as we do in the next section,  $\mathbf{R}_{k,k}^{-1}$  is equal to the inverse of the k-th block, i.e., equal to  $(\mathbf{R}_{k,k})^{-1}$ .

In (11) detection is jointly performed for the desired user's symbols, while all signals belonging to the other nodes are treated as interference whose FD correlation is included in the matrix  $\mathbf{R}_{k,m}$  together with the noise correlation.

# A. Simplified FD Joint Detector

In order to simplify the algorithm complexity we neglect the temporal correlation of the interference (MAI+noise) vector  $\mathbf{Z}_k$ , i.e., we assume  $\mathbf{R}_{k,m} = 0$  for  $k \neq m$ , and we denote  $\mathbf{R}_{k,k}$  with  $\mathbf{R}_k = E[\mathbf{Z}_k\mathbf{Z}_k^{\dagger}]$ . Indeed, the MAI correlation across frames is zero when the users are synchronous and have identical frame length. Then, by dropping the terms that do not depend on the information symbols  $\mathbf{b}_k^{(0)} = \{b_k^{(0,i)}, i \in C_0\}$  of the desired user, the log-likelihood function simplifies into

$$\Lambda(\mathbf{b}_{k}^{(0)}) \sim \text{Re} \left\{ \sum_{i \in C_{0}} b_{k}^{(0,i)} \mathbf{G}_{EQ}^{(0,i)\dagger} \mathbf{R}_{k}^{-1} \right[ \mathbf{Y}_{k} - \frac{1}{2} \sum_{n \in C_{0}} b_{k}^{(0,n)} \mathbf{G}_{EQ}^{(0,n)} \right\}. \quad (12)$$

The decision on the transmitted symbols of frame k is made as

$$\hat{\mathbf{b}}_{k}^{(0)} = \arg\max_{\mathbf{b}_{k}^{(0)}} \left\{ \Lambda(\mathbf{b}_{k}^{(0)}) \right\}. \tag{13}$$

According to (12)-(13) the FD receiver operates on a frame by frame basis and it exploits the frequency correlation of the MAI+noise. Note that detection is jointly performed for all symbols that are simultaneously transmitted in a frame by the desired node. To obtain (12) we need to estimate  $\mathbf{G}_{EO}^{(0,i)}$ . The

attractive feature is that the matched filter frequency response at a given frequency depends only on the channel at that frequency. This greatly simplifies the channel estimation task.

#### B. Iterative FD Joint Detector

The complexity of the *Simplified FD Joint Detector* is still high because it increases exponentially with the number of symbols that are simultaneously transmitted by the desired user in a frame (equal to the number of assigned spreading codes). A possible way to simplify complexity is to search the maximum of the metric in an iterative fashion. That is, we first detect symbol  $\hat{b}_k^{(0,0)}$  by setting to zero all other symbols in  $\Lambda(\mathbf{b}_k^{(0)})$ . Then, we detect symbol  $\hat{b}_k^{(0,1)}$  by setting  $b_k^{(0,0)} = \hat{b}_k^{(0,0)}$  in  $\Lambda(\mathbf{b}_k^{(0)})$ . We detect new symbols using past decisions. Once all symbols are detected, we re-run an iterative detection pass. This is similar in spirit to interference cancellation in CDMA systems [11] but it operates in the frequency domain.

# C. FD Full Decorrelator

Another possibility is to perform detection of the symbols that belong to the desired node in a symbol by symbol fashion. That is, when we detect one symbol we treat as interference both the other users signals and all signals that are associated to all other codes that belong to the desired user. Thus, the decision metric for the *i*-th symbol of user 0 becomes

$$\Lambda(b_k^{(0,i)}) \sim \text{Re}\left\{b_k^{(0,i)}\mathbf{G}_{EQ}^{(0,i)\dagger}(\mathbf{R}_k^{(0,i)})^{-1}\left[\mathbf{Y}_k - \frac{1}{2}b_k^{(0,i)}\mathbf{G}_{EQ}^{(0,i)}\right]\right\} (14)$$

where  $\mathbf{R}_{k}^{(0,i)}$  is the correlation matrix of the noise plus ICI and MAI that is seen by the symbol associated to the *i*-th signature code of frame k, i.e.,

$$\mathbf{R}_{k}^{(0,i)} = E[\mathbf{E}_{k}^{(0,i)}\mathbf{E}_{k}^{(0,i)\dagger}] \qquad \mathbf{E}_{k}^{(0,i)} = \mathbf{Z}_{k} + \sum_{c \in C_{0}, c \neq i} b_{k}^{(0,c)}\mathbf{G}_{EQ}^{(0,c)}.$$
(15)

This algorithm requires a matrix inversion for each code. Assuming that all codes are assigned, its complexity is lower than the FD joint detector when the channel and interference remain static for a long time, such that the inverse matrices can be computed once. A way to reduce further its complexity is to use a rank reduction approach, i.e., we process only the frequency bins that exhibit sufficiently high energy.

#### IV. CHANNEL CODING

We consider the use of bit interleaved convolutional codes. A block of information bits is coded, interleaved, and then modulated as described in Section II. Interleaving spans a packet of N frames that we refer to as super-frame. Decoding is done with the soft Viterbi algorithm using soft bit statistics from the FD detection stage. To improve the performance in the presence of impulsive noise, we can modify the Viterbi channel decoder by puncturing the trellis sections that are associated with bits that are hit by impulsive noise. We erase the coded bits that belong to a frame that is partially or fully hit by impulsive noise. To implement this algorithm we need to know where the noise spikes occur. The location of these frames is estimated by making a comparison between the average received signal energy computed over a super-frame

 $E_{SF} = \sum_{k=1}^{N} \mathbf{Y}_{k}^{\dagger} \mathbf{Y}_{k} / N / M$  and the energy computed over a frame  $E_{F}(k) = \mathbf{Y}_{k}^{\dagger} \mathbf{Y}_{k} / M$ . Then, in the decoding stage we disregard the frames of index k for which  $E_{F}(k) / E_{SF} > E_{th}$  for a given threshold  $E_{th}$ .

# V. PRACTICAL IMPLEMENTATION OF THE FD ALGORITHMS

The practical implementation of the above algorithms requires the estimation of the frequency response of the desired user channel and the impairment correlation matrix. We propose to use a pilot channel (a Walsh code). In particular assuming packet transmission of duration N frames (superframe) the pilot channel spans N frames, i.e., it corresponds to a training sequence of length N symbols that we assume to have  $\pm 1$  alphabet. In order to better sound the channel, we propose to change the assigned Walsh code (pilot code) at each new frame. If we assume full rate transmission, i.e., a user is allocated to all L-1 Walsh codes, channel sounding is done in a cyclic manner as follows. The pilot channel uses the Walsh code 1 in the first frame of the super-frame, while the remaining L-1 codes are used for data transmission. Then, it uses code 2 in the second frame, and so on in a cyclic manner.

To improve the performance of the estimators we consider the use of an iterative approach where first we take into account only the knowledge of the pilot symbols. Then, after detection/channel decoding we re-run an estimation pass by exploiting the knowledge of all detected symbols.

We implement FD channel estimation independently over the DFT output sub-channels (frequency bins) using a one-tap recursive least square (RLS) algorithm. We approximate the equivalent channel frequency response for the *i*-th code of the desired user as

$$\hat{G}_{EO}^{(0,i)}(f_n) \approx W^{(0,i)}(f_n)\hat{H}(f_n) \quad i = 0,...,L-1$$
 (16)

where  $W^{(0,i)}(f_n)$  denotes the M-point DFT (at frequency  $f_n$ ) of the pilot signature code that comprises the front-end filter. The channel estimate  $\hat{H}(f_n)$  is obtained via a one-tap RLS algorithm that uses the following error signal for the k-th frame

$$e_k(f_n) = Y_k(f_n) - \hat{H}_{k-1}(f_n) W^{(0, \text{mod}(k, L))}(f_n) b_{TR, k}$$
 (17)

where  $b_{TR,k}$ , k=0,...,N-1, is the known training symbol that is transmitted in the k-th frame by the desired user,  $\hat{H}_k(f_n)$  is the channel estimate for the k-th iteration, and  $\operatorname{mod}(\cdot,\cdot)$  denotes the remainder of the integer division (recall that the Walsh code that is associated to the pilot channel is cyclically updated frame after frame).

Once we have obtained an estimate of the equivalent signature code frequency response  $\hat{\mathbf{G}}_{EQ}^{(0,i)}$ , the MAI-plus-noise correlation matrix that is required in the algorithm (12) can be estimated via time-averaging the error vector as follows

$$\hat{\mathbf{R}} = \frac{1}{N} \sum_{k=0}^{N-1} \hat{\mathbf{E}}_k \hat{\mathbf{E}}_k^{\dagger} \qquad \hat{\mathbf{E}}_k = \mathbf{Y}_k - b_{TR,k} \hat{\mathbf{G}}_{EQ}^{(0, \text{mod}(k, L))}.$$
(18)

With independent zero mean symbols, and MAI

uncorrelated from the desired user signal, the correlation of the interference that is seen by the *i*-th signature code of the desired user can be written as  $\mathbf{R}^{(0,i)} = \mathbf{R} + \mathbf{R}^{(0,i)}_{ICI}$ . That is, as the sum of the correlation matrix of the MAI-plus-noise and the correlation matrix of the ICI experienced by the *i*-th code of the desired user. After channel estimation, we can obtain an estimate of the ICI correlation matrix as follows

$$\hat{\mathbf{R}}_{ICI}^{(0,i)} = \sum_{c \in C_0, c \neq i} \hat{\mathbf{G}}_{EQ}^{(0,c)} \hat{\mathbf{G}}_{EQ}^{(0,c)\dagger}.$$
 (19)

#### A. Iterative Estimation with Feedback from the Decoder

The estimators can be improved by using a data decision aided approach. That is, we can iteratively refine the estimation as data decisions are made. At the first pass we estimate the channel and the correlation matrix assuming knowledge of only the pilot symbols. In a second pass, we re-run estimation of the channel and the correlation matrix using the data decisions made at the first pass. If we assume to have detected all symbols in a super-frame of length N frames, we can re-run RLS channel estimation using the error signal

$$e_k(f_n) = Y_k(f_n) - \hat{H}_{k-1}(f_n) \sum_{c \in C_0} W^{(0,c)}(f_n) \hat{b}_k^{(0,c)}$$
 (20)

where  $\{\hat{b}_k^{(0,c)}, c \in C_0\}$  are all detected symbols plus the pilot symbol that are transmitted in the k-th frame by the desired user. To re-estimate the correlation matrix of the MAI-plusnoise we can implement (18) using the following error vector

$$\hat{\mathbf{E}}_{k} = \mathbf{Y}_{k} - \sum_{c \in C_{0}} \hat{b}_{k}^{(0,c)} \hat{\mathbf{G}}_{EQ}^{(0,c)}$$
(21)

where  $\hat{\mathbf{G}}_{EO}^{(0,c)}$  are the new channel estimates.

Similarly, we can re-estimate the correlation matrix of the ICI-plus-noise according to (19) using however the new channel estimates.

The data decisions that are used in the above algorithms can be provided by the detector, or better, by the channel decoder. In the latter case we just need to use a standard soft-input hard-output Viterbi decoder followed by interleaving and re-encoding. Further, to minimize the correlation with previous estimates we can partition the super-frame in two parts: we estimate the channel and correlation matrix for the first part using data decisions of the second part and vice versa.

# VI. PERFORMANCE RESULTS

We assume a frame duration  $T_f$ =4.096  $\mu$ s and a monocycle of duration  $D\approx 126$  ns (Fig.1). The guard time is  $T_g$ =2.048  $\mu$ s. The front-end filter output signal is sampled with period  $T_c$ =16 ns. Thus, we collect M=256 samples per frame and we use an FFT of size 256. The spreading codes have length L=16 with a chip period T=128 ns. The codes are obtained by the chip by chip product of the 16 Walsh codes and a random code for each user to be multiplexed. One code is reserved for training. We consider binary data symbols. A bit interleaved convolutional code of rate  $\frac{1}{2}$  and memory 4 is used. The transmission rate is adjusted according to the number of codes that are allocated to each user. The super-frame spans N=540 frames over which block interleaving is applied. The uncoded

data rate ranges from 244 kbit/s to 3.66 Mbit/s, while the net rate with coding is half of that. It can be increased with higher level PAM or longer codes.

To test performance we have used the statistical channel model of Section II.A and we have truncated the impulse responses to 4  $\mu$ s. However, we use a guard time of only 2.048  $\mu$ s. The performance degradation that is due to the inter-frame interference generated by the tail of the channel is negligible.

In Fig.2 we report BER performance. The additive background noise is white Gaussian. We point out that we normalize the channel such that the received bit-energy is constant for all channel realizations. This choice removes the fading effect which is appropriate in the PL context differently, for instance, from the mobile wireless context. A single full rate user that deploys all available 16 Walsh codes is present. With practical channel estimation (plot B) we are close to the ideal curves (plot A). The curves labeled with EST.IT=2 assume two channel estimation passes using hard feedback from the decoder. With 3 iterative detection passes we are within 0.5 dB from the Single Code Bound that corresponds to single code transmission and ideal channel estimation. The simplified F-DEC is within 0.5 dB from the iterative detector.

In Fig.3.A we assume the presence of impulsive noise and practical channel estimation. In this paper we model the impulsive noise with the two terms Gaussian model [12]. The position of the noise spikes within a super-frame is estimated. The impulsive noise occurrence probability is  $\varepsilon = 0.01$ , the second term has power  $\sigma_2^2 = 100\sigma_1^2$ , and the duration of the impulsive noise when it occurs is equal to 4 frames. The results show that a performance degradation is introduced compared to the AWGN case. However, with the proposed modified Viterbi algorithm (curves labeled with Erasure) the performance comes close to that of the single code in AWGN. A second channel estimation pass with feedback from the decoder results beneficial and yields near ideal performance.

Multiplexing can be done by partitioning the Walsh codes among the users. To stress the system we have assumed all users at full rate, i.e., they deploy all 16 codes. In Fig. 3.B four total users are transmitting with a random starting phase. The overall interferers power equals the desired user power. Fig.3.B shows that although there is some penalty compared to single code single user case due to the MAI, the FD detection algorithms allow to keep such a penalty small. This can be explained by the fact the random codes on top of the Walsh codes, and the multiple access channel diversity, introduce some degrees of freedom that can be exploited in the frequency domain by the interference cancellation algorithms.

The practical estimation (Fig. 3.B) of the channel introduces a BER floor at the first estimation pass (curves labeled with EST.IT=1). Further, herein we assume to first run detection and channel decoding without performing MAI cancellation. For the JD-IT scheme we run 3 iterations. Then, for the curves labeled with EST.IT=2 we re-run a second channel estimation pass followed by practical estimation of the MAI correlation matrix using hard feedback from the convolutional decoder. The iterative detector with 3 iterations performs better than the simplified full decorrelator. An error floor appears, although it

is reduced with further iterations. Although not shown, the practical curves are within 1 dB from those with ideal channel/correlation estimation.

# VII. CONCLUSIONS

We have considered a wide band impulse modulated approach for PL communications with a simple time domain transmitter and a frequency domain receiver. We have derived several novel FD receiver algorithms that include the capability of rejecting the ICI/MAI but have different level of performance and implementation complexity. In particular, the FD full decorrelator has the lowest complexity.

Algorithms for the FD estimation of the channel and the interference correlation are also described. Iterative estimation and detection with hard feedback from the decoder proves to be effective.

Simulation results show that the scheme allows to achieve high data rates and it is robust to frequency selectivity, MAI, and impulsive noise. This is due to the exploitation of the wide band channel frequency diversity and the time diversity provided by spreading each data symbol both in frequency (through the wide band pulse), and in time (via the spreading code, and the bit interleaved convolutional code).

#### REFERENCES

- G. Mathisen, A. Tonello, "Wirenet: An Experimental System for In-House Power Line Communications" *Proc. of ISPLC 2006*, Orlando, FL, pp. 137-142, March 2006.
- [2] M. K. Lee, R. E. Newman, H. A. Latchman, et al. "HomePlug 1.0 Powerline Communication LANs – Protocol Description and Performance Results version 5.4", *Int. Jour. of Comm. Syst.*, John Wiley, 2000.
- [3] A. Tonello, R. Rinaldo, L. Scarel, "Detection Algorithms for Wide Band Impulse Modulation over Power Line Channels", *Proc. of ISPLC 2004*, Zaragoza, Spain, pp. 367-372, March 2004.
- [4] A. Tonello, R. Rinaldo, M. Bellin, "Synchronization and Channel Estimation for Wide Band Impulse Modulation over Power Line Channels", Proc. of ISPLC 2004, Zaragoza, pp. 206-211, March 2004.
- [5] M., R. Scholtz, "Impulse Radio: How It Works", IEEE Comm. Letters, vol. 2, pp. 10-12, January 1998.
- [6] G. Durisi, S. Benedetto, "Performance Evaluation and Comparison of Different Modulation Schemes for UWB Multiple Access", Proc. of IEEE ICC 2003, Anchourage, USA.
- [7] M. Zimmermann, K. Dostert, "A Multipath Model for the Powerline Channel", *IEEE Trans. on Comm.*, vol. 50, pp. 553-559, April 2002.
- [8] E. Biglieri, "Coding and Modulation for a Horrible Channel", IEEE Comm. Magazine, pp. 92-98, May 2003.
- [9] A. Tonello, R. Rinaldo, "A Time-frequency Domain Approach to Synchronization, Channel Estimation, and Detection for DS-CDMA Impulse Radio Systems", *IEEE Tr. on Wireless Comm.*, pp. 3005-3017, Nov. 2005.
- [10] A. Tonello, "An Impulse Modulation based PLC System with Frequency Domain receiver Processing", *Proc of. IEEE ISPLC 2005*, Vancouver, pp. 241-245, April 2005.
- [11] R. M. Buehrer, A. Kaul, B. D. Woerner, "Analysis of DS-CDMA parallel interference cancellation with phase and timing errors", *IEEE JSAC*, vol. 14, pp. 1522-1535, October 1996.
- [12] H. Dai, H. V. Poor, "Advanced Signal Processing Algorithms for Powerline Communications", *IEEE Comm. Mag.*, pp. 100-107, May 2003.

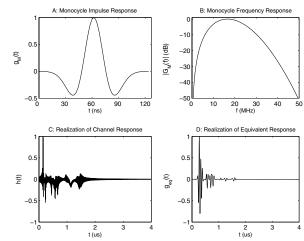


Fig. 1. Gaussian monocycle impulse response (plot A) and frequency response (plot B). Example of statistical channel realization (plot C) and of equivalent impulse response (plot D).

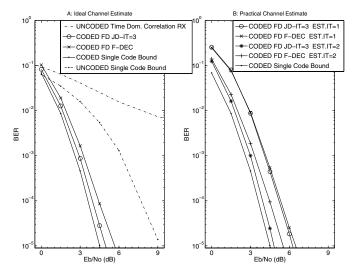


Fig. 2. One full rate user with ideal and practical channel estimation.

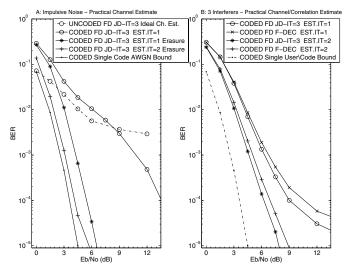


Fig. 3. One full rate user with impulsive noise (plot A), and with three full rate interferers (plot B) without impulsive noise.