

# Soft Detection with Synchronization and Channel Estimation from Hard Quantized Inputs in Impulsive UWB Power Line Communications

Andrea M. Tonello<sup>(1)</sup> and Nicolangelo Palermo<sup>(2)</sup>

<sup>(1)</sup> DIEGM - Università di Udine

Via Delle Scienze 208 - 33100 Udine – Italy - e-mail: [tonello@uniud.it](mailto:tonello@uniud.it)

<sup>(2)</sup> Microtelecom s.r.l.

S.S. 352 km 3.6 - 33050 Pavia di Udine – Italy - e-mail: [nicopal@microtelecom.it](mailto:nicopal@microtelecom.it)

**Abstract**—We consider an Ultra Wide Band Power Line Communication system that deploys binary impulse modulation. We propose a simple matched filter receiver that uses one-bit quantized input samples for frame synchronization and soft channel estimation with data training. Data detection can still use unquantized (soft) inputs. The proposed algorithm has low complexity and it requires less memory and computational power than the unquantized maximum likelihood synchronization algorithm. It produces small excess noise w.r.t. the unquantized algorithm for low signal-to-noise ratios. Simulation results over highly frequency selective PLC channels confirm that also the bit-error-rate performance penalty is small.

**Keywords**—Channel estimation, synchronization, power line communications, ultra wide band.

## I. INTRODUCTION

Ultra Wide Band (UWB) communications have been almost entirely considered for wireless applications. However, UWB transmission is applicable also over power lines. Power Line Communications (PLC) are based on the idea of exploiting the existing power grid for communication purposes. The application scenarios include the outdoor (transmission over high, medium, and low voltage networks), and the indoor, i.e., in-home and in-vehicle (car, ship, airplane) communications. Commercial systems, e.g., the Home Plug, the CEPICA and the UPA systems for high speed in-home communications, use multicarrier modulation in the band from 1 to 30 MHz and reach a peak data rate of about 200 Mbps [1]. They can be classified as UWB systems because the ratio between the band and the central carrier is larger than 0.2. Increased data rates in the order of Gbps require the usage of wider bands. For instance, this is explored within the EU FP7 OMEGA project where PLC channel modeling and modulation techniques are developed for bandwidth beyond 30 MHz [2]. The PLC channel is a low pass medium with an attenuation that rapidly increases with frequency. Further, PLC systems have to respect stringent regulations to coexist with other technologies due to possible mutual radiation effects. These considerations suggest that the transmission band cannot indefinitely increase.

Although multicarrier modulation is the dominant transmission technology in both wireless and PLC, UWB in the form of impulse modulation has attracted considerable attention and it is a valid alternative both in wireless [3],

known as impulse radio (IR), and in PLC that we refer to as impulse PLC (I-PLC). We have investigated the use of I-PLC in [4]-[7]. However, in those papers we have focused on high data rate applications with optimal receiver algorithms that make the impulse modulation solution an attractive alternative to the orthogonal frequency division modulation (OFDM) solution. In this paper, instead, we target the moderate rate applications that require simple modulation and demodulation architectures. These simple transceivers can be used for PLC command/control systems and sensor networks as those used for in-home and industrial automation, or for in-vehicle device connectivity. Other applications that can be envisioned are energy monitoring and control in smart grids.

The basic idea behind impulse modulation, is to convey information by mapping an information bit stream into a sequence of short duration pulses [3]. No carrier modulation is required. Pulses (referred to as monocycles) are followed by a guard time in order to cope (at least in part) with the channel time dispersion. If the guard time is sufficiently long the inter-symbol interference is negligible at the receiver side such that detection simplifies to a matched filter (MF) receiver that basically correlates the received signal with a template waveform [4]. The monocycle can be appropriately designed to shape the spectrum occupied by the transmission system and in particular to avoid the low frequencies where we typically experience higher levels of man-made background noise. Further, the transmitted power spectral can be low such that notching for coexistence purposes is not required.

Frequency domain processing at the receiver for I-PLC was proposed in [7]. In this paper, we consider a time domain MF receiver. The MF has to be matched to the equivalent impulse response that comprises the transmission waveform, and the channel impulse response. Accurate frame synchronization and channel estimation is required. This task is complex because of the high channel frequency selectivity [8]. Maximum likelihood synchronization and channel estimation approaches were described in [4],[9]. Those approaches are based on the idea of sending a training sequence and run a correlation at the receiver side to estimate both the frame timing and the channel impulse response. This approach is conceptually simple. However, it poses non negligible implementation problems

since it requires high processing power and large memory to store the high resolution samples (referred to unquantized samples in the following). Thus, in this paper we first describe the unquantized ML synchronizer (Section III) and then we propose a simplified synchronization and soft channel estimation algorithm (Section IV) that is based on processing one-bit quantized samples. The performance analysis is also reported (Section V). We point out that in wireless applications the analog-to-digital converter (ADC) introduces major technical difficulties due to the required extremely high sampling speed. Therefore, the performance of digital receivers with low resolution ADC has been studied, e.g., in [10]. The objective of this paper is, instead, to derive a low complexity synchronizer that provides soft estimates of the channel response requiring simple processing on one-bit samples. Then, data detection uses either soft (unquantized) or one-bit (hard quantized) ADC samples.

## II. IMPULSE MODULATED SYSTEM MODEL

The signal transmitted by a given node can be written as

$$s(t) = \sum_k b_k g(t - kT_f) \quad (1)$$

where  $g(t)$  is the narrow pulse (monocycle) used to convey information. The information symbol  $b_k$  is transmitted during the  $k$ -th frame. We assume the symbols to belong to the alphabet  $\{\pm 1\}$ .  $T_f$  is the symbol period (frame duration). The monocycle  $g(t)$  can be appropriately designed to shape the spectrum occupied by the transmission system. In this paper we consider the conventional second derivative of the Gaussian pulse with duration  $D$  [7] (Fig. 1). An interesting property is that its spectrum does not occupy the low frequencies where we experience higher levels of man-made background noise. We insert a guard time  $T_g$  between frames to cope with the channel time dispersion and limit the inter-frame interference. The frame has duration  $T_f = D + T_g$ .

The transmitted signal has low average power spectral density (PSD). In the example of Fig. 1 we have assumed  $D \approx 75\text{ns}$ ,  $T_f = 2\mu\text{s}$ , and a PSD below  $-80\text{ dBm/Hz}$ . We further, plot the typical value of background noise PSD in PLC scenarios that equals  $-120\text{ dBm/Hz}$ . Current commercial PLC systems [1] transmit with a PSD of  $-50\text{ dBm/Hz}$  and they deploy notching with a mask at  $-80\text{ dBm/Hz}$  to grant coexistence with broadcast and radio amateur signals. Therefore, in our I-PLC system notching is not required.

We further assume a packet transmission where each packet is composed of a number of bits that are used for training and identification purposes and are followed by the information bits. Direct sequence data spreading can also be used [7]. The training frames can have longer duration than the data frames to allow for accurate channel estimation [6].

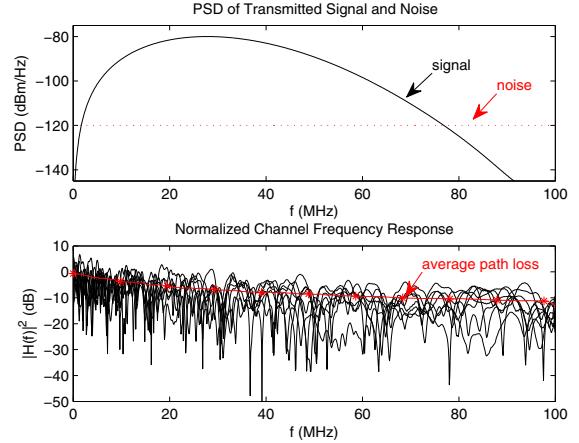


Fig. 1. Power spectral density of the transmitted signal and the noise (top plot). Normalized channel frequency response for 9 realizations and average path loss (bottom plot).

### A. Received Signal

The signal transmitted by a given node propagates through a channel with impulse response  $h(t)$  such that the received signal at another given node can be written as

$$y(t) = \sum_k b_k g_{EQ}(t - kT_f - \Delta) + w(t) \quad (2)$$

where the equivalent impulse response is denoted as  $g_{EQ}(t) = g^* h(t)$ .  $\Delta$  denotes the time delay.  $w(t)$  denotes the additive noise that is assumed to be white Gaussian with zero mean and correlation  $N_0 / 2\delta(t)$ .

### B. PLC Channel Model

PLC channels exhibit high frequency selectivity which translates in high delay spreads. Multipath models have been developed [8]. Differently from the wireless context, the channel cannot be realistically modeled with a small and sparse numbers of rays in the time domain. The model herein considered to report numerical results follows the statistical approach described in [7] and it synthesizes the frequency response with a finite number of multipath components [8],

$$G_{CH}^+(f) = A \sum_{i=1}^P g_i e^{-(\alpha_0 + \alpha_i f^k) d_i} e^{-j2\pi f(d_i/v_p)}, \quad 0 \leq f \leq B.$$

The number of such components  $P$  is drawn from a Poisson process. The attenuation factor is denoted with  $A$ . Further, the reflection factors  $g_i$  are considered to be uniformly distributed. The parameters have been chosen to fit responses obtained from measurements. They are the following:  $k = 1$ ,  $\alpha_0 = 0.3 \times 10^{-2}$ ,  $\alpha_i = 4 \times 10^{-10}$ ,  $v_p = 2 \times 10^8$ , average path rate equal to 0.2, maximum path length of 800 m. The channel has been generated in the band 0-100 MHz. Further, it has been truncated to  $2\mu\text{s}$  and normalized such that the average path loss at zero frequency is equal to 0 dB. Nine realizations are reported in Fig. 1, where we also show the average path loss profile.

### C. Matched Filter Receiver

We consider detection based on matched filtering [5],[7]. It operates in a symbol by symbol fashion by computing the correlation between the received signal frame  $y_k(t + \Delta) = y(t + kT_f + \Delta)$ ,  $0 \leq t < T_f$ , and the equivalent impulse response  $g_{EQ}(t)$  to obtain the decision metric

$$z_{DM}(kT_f) = \int_0^{T_f} y_k(t + \Delta) g_{EQ}(t) dt. \quad (3)$$

Then, a threshold decision is made to detect the  $k$ -th transmitted bit, i.e.,  $\hat{b}_k = \text{sign}\{z_{DM}(kT_f)\}$ .

To implement the MF receiver we need to acquire frame synchronization and estimate the channel. We consider a data aided approach, i.e., we send a known training bit sequence.

### III. ML SYNCHRONIZATION AND CHANNEL ESTIMATION

Maximum likelihood (ML) channel estimation [1]-[4] is based on finding the waveform  $\hat{g}_{EQ}(t)$  and the time phase  $\hat{\Delta}$  that minimizes the likelihood function [9]

$$\Lambda = \int_{-\infty}^{\infty} |y(t) - \sum_{k=0}^{N_{TR}} b_{TR,k} \hat{g}_{EQ}(t - kT_f - \hat{\Delta})|^2 dt.$$

To proceed we synthesize the channel with a FIR filter such that

$$g_{EQ}(t) = \sum_{p=0}^{N_p} \alpha_p g(t - pT_c) \quad (4)$$

with  $N_p T_c < T_g - D$ . Then, after some manipulation (details are not reported for space limitations)  $\Lambda$  can be written, neglecting constant additive terms, as

$$\begin{aligned} \Lambda &\sim \mathbf{a}^T \mathbf{R}_z^{-1} \mathbf{a} - \mathbf{a}^T \mathbf{x}(\hat{\Delta}) - \mathbf{x}(\hat{\Delta})^T \mathbf{a} \\ &= (\mathbf{a} - \mathbf{R}_z^{-1} \mathbf{x}(\hat{\Delta}))^T \mathbf{R}_z (\mathbf{a} - \mathbf{R}_z^{-1} \mathbf{x}(\hat{\Delta})) - \mathbf{x}(\hat{\Delta})^T \mathbf{R}_z^{-1} \mathbf{x}(\hat{\Delta}) \end{aligned} \quad (5)$$

where the *vector of channel taps* is

$$\mathbf{a} = [\alpha_0, \dots, \alpha_{N_p}]^T, \quad (6)$$

and the *vector of template correlations*

$$\mathbf{x}(\Delta) = [x(\Delta), x(\Delta + T_c), \dots, x(\Delta + N_p T_c)]^T \quad (7)$$

has elements obtained by correlating the received signal  $y(t)$  with the *template waveform*  $z(t)$  as follows

$$x(\tau) = \int_{-\infty}^{\infty} y(t) z(t - \tau) dt \quad (8) \quad z(\tau) = \sum_{k=0}^{N_{TR}} b_{TR,k} g(\tau - kT_f). \quad (9)$$

Further, the *autocorrelation matrix of the template* is

$$\mathbf{R}_z = \begin{bmatrix} R_z(0) & \dots & R_z(N_p T_c) \\ \dots & \dots & \dots \\ R_z(N_p T_c) & \dots & R_z(0) \end{bmatrix} \quad (10)$$

$$\begin{aligned} R_z(\tau) &= \int_{-\infty}^{\infty} z(t) z(t + \tau) dt \\ &= \sum_{k,k'=0}^{N_{TR}} b_{TR,k} b_{TR,k'} R_g(\tau + kT_f - k'T_f) \\ &\stackrel{0 \leq \tau \leq T_g - D}{=} (N_{TR} + 1) R_g(\tau) \end{aligned} \quad (11)$$

$$R_g(\tau) = \int_{-\infty}^{\infty} g(t) g(t + \tau) dt. \quad (12)$$

Now, since (5) is the difference of two quadratic forms, the minimum is found in correspondence to

$$\hat{\Delta} = \arg \max_{\Delta} \{ \mathbf{x}(\Delta)^T \mathbf{R}_z^{-1} \mathbf{x}(\Delta) \} \quad (13) \quad \hat{\mathbf{a}} = \mathbf{R}_z^{-1} \mathbf{x}(\hat{\Delta}). \quad (14)$$

The practical realization is done assuming discrete time processing. Thus, if we sample (8) with period  $T_c$  we obtain

$$x(iT_c) = \sum_{k=0}^{N_{TR}} b_{TR,k} \chi(iT_c + kT_f) \quad (15)$$

with

$$\chi(\tau) = \int_{-\infty}^{\infty} y(t) g(t - \tau) dt. \quad (16)$$

It follows that the algorithm consists in filtering the received signal with the pulse  $g(-\tau)$  and in sampling the outputs at rate  $1/T_c$  to obtain  $\chi(iT_c)$ . Then, we construct the vector  $\mathbf{x}(iT_c)$  by correlating the filter output signal with the training bit pattern. Finally, the frame timing is obtained by finding the argument  $\Delta = mT_c$  that maximizes the quadratic form (13), while the channel amplitudes are obtained from (14) once the frame timing is determined. The matrix inversion can be avoided if we make the approximation that  $R_g(iT_c) = V_0 \delta_i$  (with  $\delta_i$  being the Kronecker delta) since in such a case  $\mathbf{R}_z$  is diagonal and we obtain the simplified metrics

$$\hat{\Delta} = \arg \max_{\Delta} \{ \| \mathbf{x}(\Delta) \|^2 \} \quad (17)$$

$$\hat{\mathbf{a}} = \mathbf{x}(\hat{\Delta}) / R_z(0) = \mathbf{x}(\hat{\Delta}) / (V_0 (N_{TR} + 1)). \quad (18)$$

Nevertheless, this algorithm is rather complex. In fact, just to compute  $x(iT_c)$  in (15) we need to run  $N_{TR}$  floating point sums at rate  $1/T_c$ . If for instance  $N_{TR} = 100$ , and  $T_c = 10\text{ns}$ , we need to run 10 Giga floating point sums per second. Further, the memory requirement is equal to  $N_p N_{TR} = 240\text{kbits}$  to store the input samples assuming a 12 bits ADC and  $N_p = T_f / T_c = 2 \times 10^{-6} / 20 \times 10^{-9} = 200$ . This motivates the development of a simplified algorithm. A possible simplified approach consists in reducing the length of the training sequence and/or reduce the sampling speed of the ADC. Another approach is to simplify the synchronization metric as described in the following.

### IV. SIMPLIFIED HARD QUANTIZED ALGORITHM

If we operate with binary samples the hardware implementation of the synchronization and channel estimation algorithm can be deeply simplified. Thus, we propose to hard quantize the samples at the receiver analog filter output  $\chi(iT_c)$ , to obtain

$$\chi_Q(iT_c) = \text{sign}\{\chi(iT_c)\} = \begin{cases} 1 & \chi(iT_c) \geq 0 \\ -1 & \chi(iT_c) < 0 \end{cases}. \quad (19)$$

Then, we consider the following synchronization signal

$$q(iT_c) = \sum_{k=0}^{N_{TR}} b_{TR,k} \underbrace{\chi_Q(iT_c + kT_f)}_{B_k(iT_c)}. \quad (20)$$

Further, if we define

$$\beta(\tau) = \sum_{p=0}^{N_p} \alpha_p R_g(\tau - pT_c) \quad (21)$$

we can write

$$\begin{aligned} B_k(iT_c) &= b_{TR,k} \text{sign}\{\sum_k b_k \beta(iT_c + kT_f - k'T_f - \Delta) \\ &\quad + \eta(iT_c + kT_f)\} \\ &= \text{sign}\{\beta(iT_c - \Delta) + \sum_{k' \neq 0} b_{TR,k} b_{k-k'} \beta(iT_c + k'T_f - \Delta) \\ &\quad + b_{TR,k} \eta(iT_c + kT_f)\}. \end{aligned} \quad (22)$$

In correspondence to the exact frame timing and for  $0 \leq iT_c < T_f$  we obtain

$$B_k(iT_c + \Delta) = \text{sign}\{\beta(iT_c) + b_{TR,k} \eta(iT_c + kT_f + \Delta)\}. \quad (23)$$

For  $0 \leq iT_c < T_f$ , and  $\ell \neq 0$  we obtain

$$\begin{aligned} B_k(iT_c + \Delta + \ell T_f) &= \text{sign}\{b_{TR,k} b_{k+\ell} \beta(iT_c) \\ &\quad + b_{TR,k} \eta(iT_c + kT_f + \ell T_f + \Delta)\}. \end{aligned} \quad (24)$$

Now, the random variables  $B_k(iT_c + \Delta + \ell T_f)$  are for distinct  $\ell$  i.i.d. with alphabet  $\pm 1$ . They have probability  $\frac{1}{2}$  for  $\ell \neq 0$ , while for  $\ell = 0$  they have probability

$$P[B_k(iT_c + \Delta) = \pm 1] = \frac{1}{2} \left( 1 \pm \text{erf}\left(\frac{\beta(iT_c)}{\sqrt{N_0 R_g(0)}}\right) \right) \quad (25)$$

since the noise samples  $\eta(iT_c + \ell T_f + \Delta)$  are Gaussian, with zero mean, and correlation  $N_0 / 2R_g(iT_c)$ . The error function is defined as  $\text{erf}(x) = 2 \int_0^x e^{-a^2} da / \sqrt{\pi}$ .

It follows that  $q(iT_c)$  in (20) is the sum of i.i.d. binary random variables. Thus, it has a binomial distribution that for long training sequences approaches a Gaussian distribution with mean and variance

$$m_q(iT_c) = (N_{TR} + 1) \text{erf}\left(\frac{\beta(iT_c)}{\sqrt{N_0 R_g(0)}}\right) \quad (26)$$

$$\sigma_q^2(iT_c) = (N_{TR} + 1) \left( 1 - \text{erf}^2\left(\frac{\beta(iT_c)}{\sqrt{N_0 R_g(0)}}\right) \right) \quad (27)$$

in correspondence to the exact timing, otherwise it has zero mean. Therefore, we propose to estimate the frame timing as follows

$$\hat{\Delta} = T_c \arg \max_i \{\|\mathbf{q}(iT_c)\|^2\} \quad (28)$$

$$\mathbf{q}(iT_c) = [q(iT_c), q(iT_c + T_c), \dots, q(iT_c + N_p T_c)]^T \quad (29)$$

since  $\|\mathbf{q}(iT_c)\|^2 \equiv \sum_{p=0}^{N_p} m_q(iT_c + pT_c)^2$  is maximum in correspondence to the exact frame timing.

It should be noted that the real time hardware realization of (20) is significantly simplified w.r.t. (13) because the sums and multiplications are applied on binary values.

Furthermore, after having acquired frame synchronization, since  $m_q(iT_c) \equiv q(iT_c)$ , an unquantized (soft) estimate of the channel taps can be obtained from the hard quantized analog filter output as

$$\hat{\mathbf{a}} = \underbrace{(\mathbf{K}^T \mathbf{K})^{-1} \mathbf{K}^T}_{\mathbf{R}_K} \hat{\mathbf{p}} \quad (30)$$

$$\mathbf{K} = \begin{bmatrix} R_g(0) & \dots & R_g(-N_p T_c) \\ \dots & \dots & \dots \\ R_g(M T_c) & \dots & R_g(M T_c - N_p T_c) \end{bmatrix}, \quad M = T_f / T_c \quad (31)$$

$$\hat{\mathbf{p}} = [\hat{\beta}(0), \dots, \hat{\beta}((M-1)T_c)]^T \quad (32)$$

where the elements of (32) can be obtained from (26) as

$$\hat{\beta}(iT_c) = \sqrt{N_0 R_g(0)} \text{erf}^{-1}\left(\frac{q(iT_c + \hat{\Delta})}{N_{TR} + 1}\right) \quad (33)$$

where  $\text{erf}^{-1}(\cdot)$  is the inverse error function.

If for simplicity we assume the pulse autocorrelation matrix (31) to be diagonal, then  $\hat{\mathbf{a}} = \hat{\mathbf{p}} / R_g(0)$ .

## V. PERFORMANCE ANALYSIS

### A. SNR at the ML Estimator Output

The ML unquantized channel tap vector estimate is given by

$$\hat{\mathbf{a}} = \mathbf{R}_z^{-1} \mathbf{x}(\Delta) = \mathbf{a} + \mathbf{n}_1 \quad (34)$$

where  $\mathbf{n}_1$  is a Gaussian vector that has components with zero mean and variance  $N_0 / 2R_z^{-1}(0)$ , where the diagonal element of  $\mathbf{R}_z^{-1}$  is denoted with  $R_z^{-1}(0)$ . Thus, we can define the signal-to-noise ratio (SNR) between the  $i$ -th tap estimate and the noise as

$$\text{SNR}_{ML}(i) = 2\alpha_i^2 / (N_0 R_z^{-1}(0)). \quad (35)$$

Since  $R_z(iT_c) = (N_{TR} + 1)R_g(iT_c)$  according to (11), we obtain

$$\text{SNR}_{ML}(i) = 2(N_{TR} + 1)\alpha_i^2 / (N_0 R_g^{-1}(0)) \quad (36)$$

where  $R_g^{-1}(0)$  is the diagonal element of the square matrix  $\mathbf{R}_g^{-1}$ . If we define the SNR at the receiver filter output as

$$\text{SNR}_{RX}(i) = 2\alpha_i^2 / (N_0 R_g^{-1}(0)) \quad (37)$$

we have that

$$\text{SNR}_{ML}(i) = (N_{TR} + 1)\text{SNR}_{RX}(i). \quad (38)$$

Therefore, the SNR at the correlator output increases linearly with the training sequence length. If we further, assume that

$$R_g(iT_c) = V_0 \delta_i, \text{ then } \text{SNR}_{RX}(i) = 2V_0 \alpha_i^2 / N_0.$$

### B. SNR at the One-Bit Estimator Output

When we quantize the filter outputs, the SNR at the correlator output can be defined as

$$SNR_Q(i) = \frac{(m_q(iT_c))^2}{\sigma_q^2(iT_c)} = \frac{(N_{TR}+1)}{2} \frac{\text{erf}^2(\sqrt{SNR_{RX}(i)})}{1 - \text{erf}^2(\sqrt{SNR_{RX}(i)})}. \quad (39)$$

Exploiting the MacLaurin series expansion  $\text{erf}^{-1}(2x/\sqrt{\pi}) = x + 1/3x^3 + \dots$ , and assuming  $R_g(iT_c) = V_0 \delta_i$ , we can approximate the tap estimate at low SNRs as follows

$$\alpha(iT_c) \approx \sqrt{\pi N_0 / R_g(0)} q(iT_c) / (2N_{TR} + 2). \quad (40)$$

Therefore, the SNR in (39) represents the  $i$ -th estimated tap SNR, i.e.,  $SNR_\alpha(i) = \alpha^2(iT_c) / \sigma_\alpha^2$ , and we can conclude that for low input SNR we have that

$$SNR_\alpha(i) \approx SNR_Q(i) \approx 2(N_{TR}+1)SNR_{RX}(i) / \pi. \quad (41)$$

Thus, for low input SNR the one-bit quantized channel estimator exhibits a penalty of only 1.96 dB over the ML unquantized version.

In Fig. 2 we report a numerical simulation of  $SNR_\alpha(i)$  as a function of the input SNR. The figure shows that for low input SNRs the penalty is 1.96, indeed. For very large SNRs the quantized estimator diverges since the inverse error function in (33) goes to infinity. The estimation error can be limited by adding some dithering noise at the input to randomize the effect of quantization, or simply by clipping the estimator output.

### C. BER Performance

In Fig. 3 we report a comparison in terms of bit-error-rate between the MF receiver with ML channel estimation (labelled with Unquant.) and with the one-bit quantized soft channel estimator (labelled with Quant. Soft). We also show the performance when we use quantized estimation and quantized (one-bit) input samples to the MF (labelled with Quant. Hard). The performance of the ideal MF is also shown (labelled with Ideal MF).

The BER is reported as a function of the training sequence length for 4 values of average channel attenuation at zero frequency that is equal to 48, 45, 42, 39 dB. The transmitted signal has a frame duration of  $2\mu\text{s}$ , and an average PSD below -80 dBm/Hz (Fig. 1). The noise is assumed to be white Gaussian with a PSD of -120 dBm/Hz. The receiver filter output is sampled at rate 100 MHz. Therefore, we collect 200 sample per frame.

For low SNR even the use of quantized samples for matched filtering yields reasonably good performance. With high SNRs the MF with hard inputs provides a significant performance loss. However, the soft synchronizer with one-bit inputs combined with soft unquantized matched filtering yields performance close to the ML unquantized estimator.

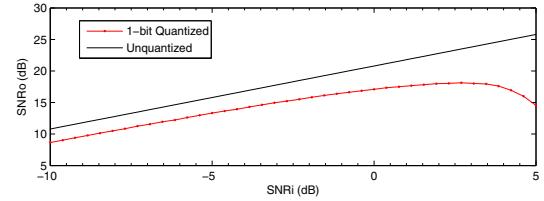


Fig.2. Output SNR as a function of input SNR for the unquantized and quantized estimators. Training sequence of length 120 bits.

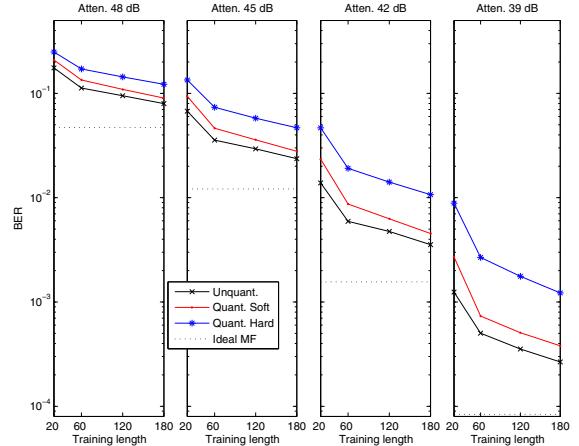


Fig.3. BER as a function of the training sequence length for 4 values of average channel attenuation at zero frequency.

## VI. CONCLUSIONS

We have proposed the use of a simple synchronization and soft channel estimation algorithm from hard quantized inputs in I-PLC systems. It has low complexity and performs close to the optimal ML estimator at moderate and low SNRs.

## VII. REFERENCES

- [1] State of the art, application scenario and specific requirements for PLC, Deliv. D3.1, FP7 OMEGA Project, <http://www.ict-omega.eu>.
- [2] FP7 ICT Project OMEGA, Home Gigabit Networks, <http://www.ict-omega.eu>.
- [3] M. Win, R. Scholtz, "Impulse radio: how it works", *IEEE Comm. Letters*, vol. 2, pp. 10-12, January 1998.
- [4] A. M. Tonello, R. Rinaldo, M. Bellini, "Synchronization and channel estimation for wide band impulse modulation over power line channels", *Proc. of ISPLC 2004*, Zaragoza, Spain, March 2004.
- [5] A. M. Tonello, R. Rinaldo, L. Scarel, "Detection algorithms for wide band impulse modulation over power line channels", *Proc. of ISPLC 2004*, Zaragoza, Spain, March 2004.
- [6] G. Mathisen, A. M. Tonello, "WIRENET: An experimental system for in-house powerline communication," *Proc. of IEEE ISPLC 2006*, Orlando, US, March 2006.
- [7] A. M. Tonello, "Wide band impulse modulation and receiver algorithms for multiuser power line communications," *EURASIP Journ. on Advanc. in Signal Processing*, Vol. 2007, pp. 1-14, 2007.
- [8] M. Zimmermann, K. Dostert, "A multipath model for the powerline channel", *IEEE Trans. on Comm.*, vol. 50, pp. 553-559, April 2002.
- [9] M. Win, R. A. Scholtz, "Characterization of ultra-wide bandwidth wireless indoor channels: a communication-theoretic view", *IEEE JSAC*, pp. 1613-1627, December 2002.
- [10] J. Tang, Z. Xu, B. M. Sadler, "Digital receiver for TR-UWB systems with inter-pulse interference," *Proc. of SPAWC 2005*, New York, June 2005.