IMPULSIVE NOISE DETECTION IN PLC WITH SMOOTHED L0-NORM

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ABSTRACT

Power-line communications (PLC) commonly employs orthogonal frequency-division multiplexing (OFDM) as the modulation technique, and impulsive noise has a significant negative impact on its performance. Using the property of null subcarriers in OFDM and the fact that impulsive noise is sparse, we formulate a minimization problem to detect and estimate the impulsive noise. In previous works, ℓ_1-norm minimization was employed to achieve this task. In this paper, we propose to use a smoothed ℓ_0-norm minimization algorithm for impulsive noise detection instead. Simulation results show that this approach is promising as it achieves comparable performance as ℓ_1-norm minimization but with much lower complexity.

Index Terms— PLC, OFDM, impulsive noise, smoothed ℓ_0-norm, ℓ_1-norm

1. INTRODUCTION

Power-line communications (PLC) is an alternative promising solution for providing a fast and reliable data transmission through power-lines for smart grid [1, 2]. The applications of PLC in smart grids range from those in high voltage networks to low voltage networks such as remote fault detection, monitoring the networks, automatic meter reading, and vehicle-to-grid communications [2, 3]. However, power-lines were originally designed for transmitting electricity power rather than data. Consequently, transmitting data through power-lines faces some impairments related to noise, impedance, and attenuation [4].

This paper focuses on solving the noise problem as it is the major concern in PLC. In particular, the noise in PLC consists of background, narrowband, and impulsive noise [5]. Narrowband noise is sometimes also regarded as part of the background noise [4, 6]. Background noise can be modeled as AWGN [4, 7, 8] while impulsive noise is often modeled as Bernoulli-Gaussian [8, 9].

Orthogonal frequency-division multiplexing (OFDM) is commonly adopted as the modulation technique in PLC. Although OFDM demodulator (i.e. discrete Fourier transform (DFT)) spreads the impulsive noise power in the frequency domain, high power of the impulsive noise still affects the data symbols [10]. Thus, an impulsive noise mitigation method is needed.

The impulsive noise mitigation can be conducted by first detecting the impulsive noise and if detected, further processing can be performed. The simplest impulsive noise detection is by using a threshold. If a sample exceeds a certain threshold, the sample is assumed to be contaminated by impulsive noise. Then, an appropriate nonlinear preprocessing (such as clipping) is employed [11, 12, 13]. However, this technique is prone to false alarm since OFDM has large peak-to-average power ratio (PAPR) [14, 15, 16].

On the other hand, OFDM systems often use some null subcarriers that do not carry information. In particular, more than half of the subcarriers are occupied by null subcarriers in some modern PLC standards [17]. For example, the PRIME standard uses 158 null subcarriers out of 256 subcarriers. With the aid of null subcarriers and the fact that impulsive noise is sparse, in [10], principles of compressive sensing [18, 19, 20] were used to detect and estimate the impulsive noise modeled as Bernoulli-Gaussian. An extension to bursty impulsive noise was proposed in [21]. The basic idea was to estimate the number of impulsive noise samples by minimizing the ℓ_0-norm. However, working on ℓ_0-norm directly is not easy as minimization of ℓ_0-norm is NP-hard. As a result, some previous works relaxed the minimization model by using the convex programming algorithm with ℓ_1-norm minimization.

In [22], an approximation of ℓ_0-norm, called smoothed ℓ_0-norm, along with its minimization algorithm were proposed. Different from the estimation using ℓ_1-norm minimization, using the minimization of smoothed ℓ_0-norm algorithm yielded a lower complexity while having the same (or better) accuracy. Its lower complexity motivates us to investigate its potential for impulsive noise detection in power-line communications.

In this paper, we propose to use the smoothed ℓ_0-norm minimization algorithm for detecting impulsive noise in power-line communications. In particular, we compare the impulsive noise detection performance of the proposed smoothed ℓ_0-norm minimization with the conventional one using ℓ_1-norm minimization. The proposed method yields lower complexity and simulation results show that similar (or better) accuracy to the conventional detection method can be achieved. In addition, we also present the effect of the number of null subcarriers on the detection performance for smoothed ℓ_0 and ℓ_1 algorithms. Simulation results show that the larger the number of null subcarriers, the better the detection accuracy.

The rest of this paper is organized as follows. In Section 2 we discuss the impulsive noise detection algorithm. In Section 3 we present the simulation results. And the conclusions are given in Section 4.

2. IMPULSIVE NOISE DETECTION ALGORITHM

2.1. System Model and Problem Formulation

Fig. 1 shows the equivalent complex baseband PLC system model. The QPSK modulated data vector, $\mathbf{X} = [X_0, X_1, \cdots, X_{N-1}]^T$, is passed to the N-point inverse discrete Fourier transform (IDFT)

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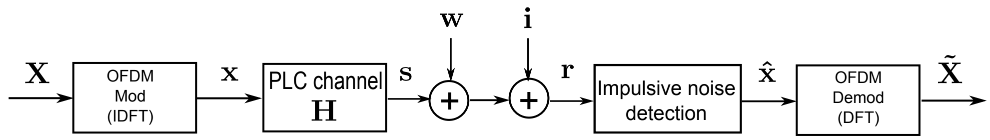

Fig. 1. System model.

block to form an OFDM symbol. $\mathbf{x} = [x_0, x_1, \cdots, x_{N-1}]^T = \mathbf{F}^H\mathbf{X}$ is then the OFDM symbol, where $\mathbf{F}$ is the $N \times N$ unitary DFT Vandermonde matrix, $(\cdot)^T$ and $(\cdot)^H$ are transpose and Hermitian transpose operator, respectively. Assume that there are K data subcarriers and $N-K$ null subcarriers. Without loss of generality, we normalize the OFDM signal power.

The OFDM signal is appended by a cyclic prefix (not shown in the figure) and passed to the PLC channel and contaminated by AWGN, $\mathbf{w}$, and impulsive noise, $\mathbf{i}$. By assuming that the length of the cyclic prefix is long enough to deal with interblock interference (IBI), the received signal after dropping the cyclic prefix is given by

$$\mathbf{r} = \mathbf{H}\mathbf{x} + \mathbf{w} + \mathbf{i}, \tag{1}$$

where $\mathbf{H}$ is an $N \times N$ column circulant channel matrix with the first column being normalized discrete-time channel impulse response [21]. The AWGN has variance $2\sigma_w^2$. The impulsive noise is modeled as Bernoulli-Gaussian as follows [9]

$$\mathbf{i} = \mathbf{b} \circ \mathbf{g}, \tag{2}$$

where $\circ$ is Hadamard product operator, $\mathbf{b}$ is the Bernoulli sequence of 1 and 0 with probabilities p and $1-p$, respectively, and $\mathbf{g}$ is a random variable with Gaussian distribution with mean 0 and variance $2\sigma_g^2$. As a result, we have signal-to-(background) noise ratio $SNR = 1/2\sigma_w^2$ and signal-to-impulsive noise ratio $SINR = 1/2\sigma_g^2$. We also define $INR = SNR/SINR$.

The impulsive noise detection block is discussed in the following. Let $\mathcal{N}$ be the set of indices of null subcarriers and $\mathcal{N}^C$ its complement. We can construct an $(N-K) \times N$ parity matrix $\mathbf{F_1}$ where the $(N-K)$ rows are obtained from $\mathbf{F}$ that are in $\mathcal{N}$, i.e. $\mathbf{F_1} = \mathbf{F}(\mathcal{N}, :)$. We then have

$$\begin{aligned} \mathbf{S} &= \mathbf{F_1}\mathbf{r} \\ &= \mathbf{F_1}\mathbf{s} + \mathbf{F_1}\mathbf{w} + \mathbf{F_1}\mathbf{i} \\ &= \mathbf{F_1}\mathbf{i} + \tilde{\mathbf{w}}, \end{aligned} \tag{3}$$

where $\mathbf{s} = \mathbf{H}\mathbf{x}$, $\tilde{\mathbf{w}} = \mathbf{F_1}\mathbf{w}$, and $\mathbf{F_1}\mathbf{s} = \mathbf{0}$. Note that $\tilde{\mathbf{w}}$ is also AWGN and has the same mean and variance as $\mathbf{w}$. The objective is to find the sparsest solution of $\mathbf{i}$ as follows

$$(P_0)\ \mathbf{i_p} = \arg\min_{\mathbf{i}} \|\mathbf{i}\|_0 \text{ subject to } \|\mathbf{F_1}\mathbf{i} - \mathbf{S}\|_2 \leq \epsilon, \tag{4}$$

where $\|\mathbf{i}\|_0$ is the smoothed ℓ_0-norm of $\mathbf{i}$ and ϵ is any positive number. Note that we will use (P_0) to denote the smoothed ℓ_0-norm algorithm. The amplitude of the estimated impulsive noise, $\mathbf{i_p}$, is then refined to get a better estimate. The refined estimated impulsive noise, $\hat{\mathbf{i}}_\mathbf{p}$, is then subtracted from the received signal to get the clean signal, i.e. $\hat{\mathbf{x}} = \mathbf{r} - \hat{\mathbf{i}}_\mathbf{p}$. The signal is then passed to the OFDM demodulator (i.e. the DFT).

2.2. The Smoothed ℓ_0-Norm and Minimization Algorithm

Let us consider how to find the sparsest solution for $\mathbf{A}\mathbf{y} = \mathbf{z}$ by minimizing the $\|\mathbf{y}\|_0$. In contrast to [22] where only real numbers are considered, we are dealing with complex numbers so we use the smoothed ℓ_0-norm for complex numbers [23].

We define the ℓ_0-norm of $\mathbf{y} = [y_0, y_1, \cdots, y_{n-1}]^T$ as the number of nonzero elements of $\mathbf{y}$ or

$$\|\mathbf{y}\|_0 = \sum_{i=0}^{n-1} \nu(y_i), \tag{5}$$

where

$$\nu(y) = \begin{cases} 1, & |y| \neq 0, \\ 0, & |y| = 0. \end{cases} \tag{6}$$

We can developing an approximation of (6) by using a continuous (smoothed) function, such as

$$f_\sigma(y) = e^{-\frac{|y|^2}{2\sigma^2}}. \tag{7}$$

As a result, we have

$$\lim_{\sigma \to 0} f_\sigma(y) = \begin{cases} 1, & |y| = 0, \\ 0, & |y| \neq 0. \end{cases} \tag{8}$$

or [24]

$$f_\sigma(y) \approx \begin{cases} 1, & |y| \ll \sigma, \\ 0, & |y| \gg \sigma. \end{cases} \tag{9}$$

We define

$$F_\sigma(\mathbf{y}) = \sum_{i=0}^{n-1} f_\sigma(y_i). \tag{10}$$

Using (10), we can rewrite (5) as

$$\|\mathbf{y}\|_0 \approx n - F_\sigma(\mathbf{y}) \tag{11}$$

for small σ. Note that when $\sigma \to 0$, $\|\mathbf{y}\|_0$ is close to the true solution (5). From (11), we can minimize $\|\mathbf{y}\|_0$ by maximizing $F_\sigma(\mathbf{y})$ subject to $\mathbf{A}\mathbf{y} = \mathbf{z}$.

A small value σ results in a lot of local maxima. When σ is large, the function becomes smoother and contains less local maxima, thereby easier to solve. As the algorithm requires $\sigma \to 0$, one strategy is to use a decreasing σ sequence, e.g. by using a gradient algorithm. We start the algorithm by finding $\hat{\mathbf{y}}_0$, i.e. the solution for $\sigma \to \infty$. This solution has been given in [22, 23, 24], as follows

Theorem 1 *The solution of the problem*

$$\max F_\sigma(\mathbf{y}) \textit{ subject to } \mathbf{A}\mathbf{y} = \mathbf{z}, \tag{12}$$

where $\sigma \to \infty$ *is the minimum* ℓ_2*-norm solution of* $\mathbf{A}\mathbf{y} = \mathbf{z}$*, that is,* $\mathbf{y} = \mathbf{A}^\dagger\mathbf{z}$*, where* $\mathbf{A}^\dagger = \mathbf{A}^H(\mathbf{A}\mathbf{A}^H)^{-1}$ *is the pseudo-inverse of* $\mathbf{A}$.

Next step is to choose a sequence of σ, $[\sigma_1, \sigma_2, \cdots, \sigma_J]$, where σ_1 can be chosen two to four times of $\max_i |y_i|$ [24]. The next values of σ can be calculated by $\sigma_j = c\sigma_{j-1}$, where c is the σ decreasing factor and $j = 2, 3, \cdots, J$. For each value of σ_j, we maximize F_σ on $\boldsymbol{\mathcal{Y}} = \{\mathbf{y}|\mathbf{A}\mathbf{y} = \mathbf{z}\}$ by using M iterations of the steepest ascent algorithm. For every iteration, we calculate $\mathbf{y} \leftarrow \mathbf{y} + (\mu\sigma^2)\nabla F_\sigma = \mathbf{y} - \mu\boldsymbol{\delta}$, where μ is a decreasing step-size parameter and $\boldsymbol{\delta} \triangleq -\sigma^2\nabla F_\sigma = [y_0 e^{-\frac{|y_0|^2}{2\sigma^2}}, y_1 e^{-\frac{|y_1|^2}{2\sigma^2}}, \cdots, y_{n-1} e^{-\frac{|y_{n-1}|^2}{2\sigma^2}}]^T$.

The last step is to project back $\mathbf{y}$ to the feasible set $\boldsymbol{\mathcal{Y}}$, i.e. by calculating $\mathbf{y} \leftarrow \mathbf{y} - \mathbf{A}^\dagger(\mathbf{A}\mathbf{y} - \mathbf{z})$. The final answer is $\mathbf{y}^\mathbf{0} = \mathbf{y}_J$.

The above algorithm is summarized as follows:

1. Initialization
   (a) Choose a solution for $\mathbf{A}\mathbf{y} = \mathbf{z}$, i.e. $\mathbf{v}_0 = \mathbf{A}^\dagger\mathbf{z}$.
   (b) Choose a decreasing sequence of $\sigma = [\sigma_1, \sigma_2, \cdots, \sigma_J]$, where σ_1 can be chosen as two to four times of $\max\{\mathbf{v}_0\}$.
2. For $j = 1, 2, \cdots, J$
   (a) Set $\sigma = \sigma_j$.
   (b) Maximize the F_σ on feasible set $\boldsymbol{\mathcal{Y}}$ using U iterations as follows:
      i. Set $\mathbf{y} = \mathbf{v}_{j-1}$.
      ii. For $u = 1, 2, \cdots, U$
         A. Calculate $\boldsymbol{\delta} = [y_0 e^{-\frac{|y_0|^2}{2\sigma^2}}, y_1 e^{-\frac{|y_1|^2}{2\sigma^2}}, \cdots, y_{n-1} e^{-\frac{|y_{n-1}|^2}{2\sigma^2}}]^T$.
         B. Calculate $\mathbf{y} \leftarrow \mathbf{y} - \mu\boldsymbol{\delta}$.
         C. Project $\mathbf{y}$ back onto feasible set $\boldsymbol{\mathcal{Y}}$: $\mathbf{y} \leftarrow \mathbf{y} - \mathbf{A}^\dagger(\mathbf{A}\mathbf{y} - \mathbf{z})$.

         End for
   (c) Set $\mathbf{v}_j = \mathbf{y}$.

   End for
3. Output: $\mathbf{y}^\mathbf{0} = \mathbf{v}_J$.

Now consider the noisy case $\mathbf{z} = \mathbf{A}\mathbf{y} + \tilde{\mathbf{n}}$, where $\tilde{\mathbf{n}}$ is the AWGN. The minimization problem can be formulated as follows

$$\mathbf{y_p} = \arg\min_{\mathbf{y}} \|\mathbf{y}\|_0 \text{ subject to } \|\mathbf{A}\mathbf{y} - \mathbf{z}\|_2 \leq \epsilon. \tag{13}$$

Note that the previous (noiseless) algorithm can also be applied to this noisy case. However, in this case the accuracy of the estimated $\mathbf{y}$ is bounded by noise power [24].

For impulsive noise detection, our problem formulation of (4) is similar to (13) by simply replacing the parameters as follows: $\{\mathbf{A}, \mathbf{y}, \mathbf{z}\} \rightarrow \{\mathbf{F_1}, \mathbf{i}, \mathbf{S}\}$.

2.3. Postprocessing

We conduct postprocessing to the amplitude of raw estimated impulsive noise to get $\hat{\mathbf{i}}_\mathbf{p}$. The procedure is as follows [10, 21]:

1. Solve (4) to get the raw estimated values $\mathbf{i_p}$.
2. Estimate the support $\mathcal{I}_p = \{j : |i_{p(j)}| > th\}$, where $th = k \times \sqrt{2\sigma_w^2}$ and k is the multiplication constant given by $k = \sqrt{2\ln\left((1-p)/p \cdot \sigma_g/\sigma_w\right)}$ [25].
3. Recalculate the amplitude of $\mathbf{i_p}$ by using least-square (LS) or MMSE as follows. We construct an $N \times m$ selection matrix $\mathbf{S_m}$, where m is the cardinality of estimated impulsive noise samples, $m = |\mathcal{I}_p|$. The elements of the matrix is $S_m(i, j)$=1 for $i \in \mathcal{I}, j = 1, 2, \cdots, m$ and 0 otherwise. Finally, we calculate
   (a) LS
   $$\hat{\mathbf{i}}_\mathbf{p} = \mathbf{B}^{-1}\mathbf{S}_\mathbf{m}^H\mathbf{F}_\mathbf{1}^H\mathbf{S}, \tag{14}$$
   or
   (b) MMSE
   $$\hat{\mathbf{i}}_\mathbf{p} = [(2\sigma_w^2/2\sigma_g^2)\mathbf{I} + \mathbf{B}]^{-1}\mathbf{S}_\mathbf{m}^H\mathbf{F}_\mathbf{1}^H\mathbf{S}, \tag{15}$$
   where $\mathbf{B} = \mathbf{S}_\mathbf{m}^H\mathbf{F}_\mathbf{1}^H\mathbf{F_1}\mathbf{S_m}$.

3. SIMULATION RESULTS

We simulate an OFDM system with QPSK modulation, $N = 256$ and $N - K = 128$ (19% lower than PRIME) to show the ability of (P_0) algorithm[1] to recover the impulsive noise samples. Impulsive noise occurrence is rare (at most a few impulsive samples in every OFDM block) in practical systems [10]. In this paper, without loss of generality, we assume that every OFDM symbol is contaminated with three or five impulsive noise samples with random positions, i.e. $p \approx 0.01$ or $p \approx 0.02$, respectively. The channel impulse response is as in [15] and we set $SNR = 20$ dB, $INR = 30$ dB. Moreover, the parameters for (P_0) algorithm are as follows: $\mu = 2.5$, $\sigma_J = 0.3 \times \sqrt{2\sigma_w^2}$, σ decreasing factor 0.5, and $U = 3$.

As a baseline, we compare (P_0) with (P_1), which uses the conventional ℓ_1-norm minimization as follows

$$(P_1)\ \mathbf{i_p} = \arg\min_{\mathbf{i}} \|\mathbf{i}\|_1 \text{ subject to } \|\mathbf{F_1}\mathbf{i} - \mathbf{S}\|_2 \leq \epsilon, \tag{16}$$

where $\|\cdot\|_1$ is the ℓ_1-norm and $\|\cdot\|_2$ is the ℓ_2-norm. Following [19, 21], we set a threshold, ϵ, such that $\|\tilde{\mathbf{w}}\|_2 \leq \epsilon$ with probability ξ. To be feasible we choose $\xi = 0.95$. Note that $\|\tilde{\mathbf{w}}\|_2^2$ is a chi-squared distribution with $2(N-K)$ degrees of freedom, $\chi^2_{2(N-K)}$. We, then, have $\epsilon^2 = \chi^2_{2(N-K)}(0.95)2\sigma_w^2$, where $\chi^2_{2(N-K)}(0.95)$ is the 95th percentile of $\chi^2_{2(N-K)}$. The postprocessing steps are similar to those in Section 2.3, except that we use $k = 1$ in the second step. We use ℓ_1-magic with a log-barrier algorithm for (16) [26]. From now on, we will use the terms (P_1) and ℓ_1-magic (with a log-barrier algorithm) interchangeably.

Fig. 2 shows the amplitude parts of the impulsive noise samples for original and estimated values using (P_0) and (P_1) algorithm before the postprocessing for one random OFDM symbol. It can be seen that the impulsive noise by using (P_0) is recovered better than (P_1). The amplitude values are then refined by using LS as discussed in Section 2.3.

To analyze the capability of impulsive noise detection, we introduce the residual interference-plus-(background)-noise signal as follows [10, 21]

$$\boldsymbol{\rho} = \mathbf{i} - \hat{\mathbf{i}}_\mathbf{p} + \mathbf{w} \tag{17}$$

The normalized variance of (17) is $\theta = \mathrm{var}(\boldsymbol{\rho})/\mathrm{var}(\mathbf{w})$. Furthermore, the mean-error square (MSE) of the estimated samples is $MSE = \|\mathbf{i} - \hat{\mathbf{i}}_\mathbf{p}\|_2$ and the "signal-to-noise" ratio is

[1] We use the publicly available program code for ℓ_0-norm minimization from `http://ee.sharif.edu/~SLzero`.

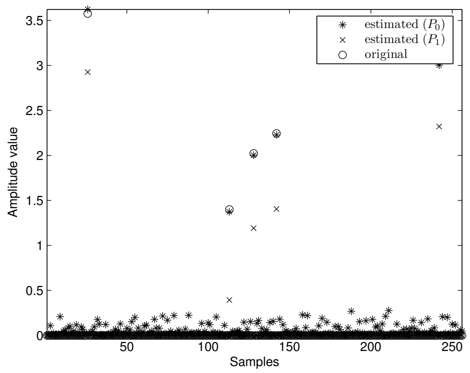

Fig. 2. Recovery of impulsive noise using (P_0) and (P_1) algorithms.

Table 1. Statistical performance comparison of (P_0) compared to (P_1) minimization.

m	θ_{avg}		$MSE_{avg}(\times 10^{-3})$		η_{avg} (dB)	
	(P_0)	(P_1)	(P_0)	(P_1)	(P_0)	(P_1)
3	1.06	1.08	0.837	1.09	25.8	24.1
5	1.06	1.14	1.09	1.81	25.9	23.6

$\eta(\text{dB}) = 20\log\|\mathbf{i}\|_2/\|\mathbf{i}-\hat{\mathbf{i}}_\mathbf{p}\|_2$. We then performed the experiments and repeated 100 times. The average statistical performance comparison of those parameters is shown in Table. 1. Note that if the estimated samples are the same as the original samples we have $\theta_{avg} = 1$. In addition, the number of experiments that yielded η larger than 20 dB was 91 ($m = 3$) and 95 ($m = 5$) among 100 runs for (P_0). However, it was just 76 ($m = 3$) and 73 ($m = 5$) for (P_1). It is clear that (P_0) algorithm outperforms (P_1) algorithm, by having lower MSE and higher η.

We also present the average F-measure, precision of recovery, and recall of support recovery for the estimated samples after post-processing as shown in Table. 2. F-measure is $F = (2PR)/(R+P)$, the precision of recovery is defined as $P = |\mathcal{I}_p \cap \mathcal{I}|/|\mathcal{I}_p|$, and the recall of support recovery is $R = |\mathcal{I}_p \cap \mathcal{I}|/|\mathcal{I}|$ [27].

Next, we compare the complexity in terms of the CPU processing time. The average processing time for one run was 2.56 milliseconds for (P_0) and 1.15 seconds for (P_1). It shows that the estimated value using (P_0) minimization can represent the original value better while having three orders of magnitude faster in running time than ℓ_1-magic.

Fig. 3 depicts the η_{avg} performance vs. the number of null subcarriers for (P_0) and (P_1) algorithms with $m = 3$ and $m = 5$. Consistent with the nature of compressive sensing, the larger the number of null subcarriers the better the detection accuracy. Furthermore, for a large number of null subcarriers, the η_{avg} values for both $m = 3$ and $m = 5$ are almost the same.

Table 2. F-measure F, precision of recovery P, and recall of support R performance comparison of (P_0) compared to (P_1) minimization.

m	F_{avg}		P_{avg}		R_{avg}	
	(P_0)	(P_1)	(P_0)	(P_1)	(P_0)	(P_1)
3	0.971	0.924	0.970	0.975	0.980	0.897
5	0.970	0.940	0.965	0.988	0.980	0.906

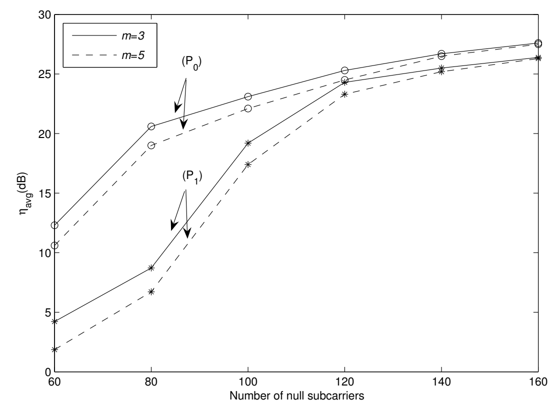

Fig. 3. Performance of η_{avg} vs. the number of null subcarriers.

4. CONCLUSIONS

We have investigated the use of smoothed ℓ_0-norm minimization algorithm for detecting impulsive noise in OFDM-based PLC. The impulsive noise can be considered as a sparse signal that is to be recovered by using compressive sensing approach by utilizing the property of null subcarriers in OFDM systems. We have compared the performance of the smoothed ℓ_0-norm minimization algorithm with that of the ℓ_1-norm minimization conventional recovery algorithm (using the ℓ_1-magic tool with a log-barrier algorithm). Simulation results have shown that the proposed method yields lower complexity in terms of CPU processing time and provides a good estimate.

5. REFERENCES

[1] S.-G. Yoon, S. Jang, Y.-H. Kim, and S. Bahk, "Opportunistic routing for smart grid with power line communication access network," *IEEE Trans. Smart Grid*, vol. 5, no. 1, pp. 303–311, 2014.

[2] Stefano Galli, A. Scaglione, and Z. Wang, "For the grid and through the grid: The role of power line communications in the smart grid," *Proceedings of the IEEE*, vol. 99, no. 6, pp. 998–1027, 2011.

[3] A. Cataliotti, D. D. Cara, R. Fiorelli, and G. Tiné, "Power-line communication in medium-voltage system: Simulation model and onfield experimental tests," *IEEE Trans. Power. Del.*, vol. 27, no. 1, pp. 62–69, 2012.

[4] H. Meng, Y. L. Guan, and S. Chen, "Modeling and analysis of noise effects on broadband power-line communications," *IEEE Trans. Power Del.*, vol. 20, no. 2, pp. 630–637, 2005.

[5] T. M. Lukusa, K. Ouahada, and H. C. Ferreira, "Frequency mappings with hadamard transform for power line communications channel," in *Int. Symp. Power Line Communications and Its Applications*, 2011.

[6] M. Zimmermann and K. Dostert, "Analysis and modeling of impulsive noise in broad-band powerline communications,"

IEEE Trans. Electromagn. Compat., vol. 44, no. 1, pp. 249–258, 2002.

[7] G. Ndo, P. Siohan, M-H. Hamon, and J. Horard, "Optimization of turbo decoding performance in the presence of impulsive noise using soft limitation at the receiver side," in *Proc. IEEE Global Telecom. Conf.*, 2008, pp. 1–5.

[8] G. Ndo, P. Siohan, and M-H. Hamon, "Adaptive noise mitigation in impulsive environtment: Application to power-line communications," *IEEE Trans. Power Del.*, vol. 25, no. 2, pp. 647–656, 2010.

[9] M. Ghosh, "Analysis of the effect of impulse noise on multicarrier and single carrier QAM systems," *IEEE Trans. Commun.*, vol. 44, no. 2, pp. 145–147, 1996.

[10] G. Caire, T. Y. Al-Naffouri, and A. K. Narayanan, "Impulse noise cancellation in OFDM: An application of compressed sensing," in *Proc. IEEE Int. Symp. Information Theory*, 2008, pp. 1293–1297.

[11] F. H. Juwono, Q. Guo, D. Huang, and K. P. Wong, "Deep clipping for impulsive noise mitigation in OFDM-based powerline communications," *IEEE Trans. Power Del.*, vol. 29, no. 3, pp. 1335–1343, 2014.

[12] S. V. Zhidkov, "Performance analysis and optimization of OFDM receiver with blanking nonlinearity in impulsive noise environment," *IEEE Trans. Veh. Technol.*, vol. 55, no. 1, pp. 234–242, 2006.

[13] S. V. Zhidkov, "Analysis and comparison of several simple impulsive noise mitigation schemes for OFDM receivers," *IEEE Trans. Commun.*, vol. 56, no. 1, pp. 5–9, 2008.

[14] C-H. Yih, "Iterative interference cancellation for OFDM signals with blanking nonlinearity in impulsive noise channels," *IEEE Signal Processing Letters*, vol. 19, no. 3, pp. 147–150, 2012.

[15] F. H. Juwono, Q. Guo, D. Huang, and K. P. Wong, "Joint peak amplitude and impulsive noise clippings in OFDM-based power line communications," in *Proc. Asia Pacific Conf. Communications*, 2013, pp. 567–571.

[16] K. M. Rabie and E. Alsusa, "Improving blanking/clipping based impulsive noise mitigation over powerline channels," in *Proc. Int. Symp. Personal Indoor and Mobile Radio Communications*, 2013, pp. 3413–3417.

[17] J. Lin, M. Nassar, and B. L. Evans, "Non-parametric impulsive noise mitigation in OFDM systems using sparse bayesian learning," in *Proc. IEEE Global Communications*, 2011, pp. 289–301.

[18] E. J. Candès, J. Romberg, and T. Tao, "Robust uncertainty principles: Exact signal reconstruction from highly incomplete frequency information," *IEEE Trans. Inf. Theory*, vol. 52, no. 2, pp. 489–509, 2006.

[19] E. J. Candès and P. A. Randall, "Highly robust error correction by convex programming," *IEEE Trans. Inf. Theory*, vol. 54, no. 7, pp. 2829–2840, 2006.

[20] T. Y. Al-Naffouri, A. A. Quadeer, and G. Caire, "Impulse noise estimation and removal for OFDM systems," *IEEE Trans. Commun.*, vol. 62, no. 3, pp. 976–989, 2014.

[21] L. Lampe, "Bursty impulse noise detection by compressed sensing," in *Proc. Int. Symp. Power Line Communications and Its Applications*, 2011, pp. 29–34.

[22] G. H. Mohimani, M. Babaie-Zadeh, and C. Jutten, "Fast sparse representation based on smoothed l_0 norm," in *Proc. 7th Int. Conf. Independent Component Analysis and Signal Separation (ICA)*, 2007, pp. 389–396.

[23] G. H. Mohimani, M. Babaie-Zadeh, and C. Jutten, "Complex-valued sparse representation based on smoothed ℓ^0 norm," in *Proc. Int. Conf. Acoustics, Speech, Signal Processing (ICASSP)*, 2008, pp. 3881–3884.

[24] H. Mohimani, M. Babaie-Zadeh, and C. Jutten, "A fast approach for overcomplete sparse decomposition based on ℓ^0 norm," *IEEE Trans. Signal Process.*, vol. 57, no. 1, pp. 289–301, 2009.

[25] H. Zayyani and M. Babaie-Zadeh, "Thresholded smoothed-ℓ^0 (sl0) dictionary learning for sparse representation," in *Proc. Int. Conf. Acoustics, Speech, and Signal Processing*, 2009, pp. 1825–1828.

[26] E. Candes and J. Romberg, "ℓ_1-magic: Recovery of sparse signals via convex programming," online, available at www.acm.caltech.edu/l1magic/downloads/l1magic.pdf, 2005.

[27] P. Ghosh, M. E. Sargin, and B.S. Manjunath, "Robust dynamical model for simultaneous registration and segmentation in a variational framework: A Bayesian approach," in *Proc. The 12th IEEE Int. Conf. Computer Vision*, 2011, pp. 709–716.