

Improving Performance of the MH-Iterative IN Mitigation Scheme in PLC Systems

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Abstract—We call the Häring-iterative scheme with the clipping-nulling scheme as the preprocessing impulsive noise (IN) mitigation scheme: Mengi-Häring (MH)-iterative scheme. In this paper, we report two ideas that can significantly improve its performance. The first idea is to use the replacement-nulling scheme as the preprocessing IN mitigation scheme. The second idea is to use the output vector of the preprocessing IN mitigation scheme in all iterations. To show the performance comparison between the MH-iterative scheme and our proposed scheme, we conduct some simulations in the simplified model of the Middleton's additive white class A noise model and present performance in terms of the bit-error rate as a function of the signal-to-noise ratio.

Index Terms—Impulsive noise, iterative impulsive noise mitigation scheme, orthogonal frequency-division multiplexing (OFDM).

I. INTRODUCTION

THE USE of the power-line channel (PLC) as a communication medium is an interesting idea. However, the PLC is not a friendly channel for information delivery. It has many problems, such as signal attenuation, narrowband interference, and also impulsive noise (IN). We present a solution for handling degradation in performance of orthogonal frequency-division multiplexing (OFDM)-based transmission caused by the presence of IN.

The research direction of the IN mitigation schemes for OFDM is basically divided into two categories: 1) parametric and 2) nonparametric IN mitigation schemes. The parametric scheme requires the knowledge of IN parameters, while the nonparametric does not require any knowledge of the IN parameters. Thus, the benefit of the nonparametric IN mitigation scheme over the parametric scheme is that it can be used on different IN channel models.

The basic idea of a parametric scheme, which is a threshold-based approach, can be divided into two parts: 1) determining the threshold value to be used and 2) determining the action to be taken. Only the first part—the determination of the threshold value to be used—requires the full [1] or partial [2] knowledge of the IN parameters. The second part, on the other hand, requires no knowledge of the IN parameters. Therefore, when the

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first part of a parametric scheme is designed to not depend on the IN parameters, the parametric scheme has been turned into a nonparametric scheme. Some recent publications on the nonparametric IN mitigation schemes for OFDM systems are in [3]–[5].

The two categories of the IN mitigation schemes mentioned before can be further divided into two types: 1) iterative and 2) noniterative schemes. The difference between these two types is the use of a feedback mechanism that allows iterative IN mitigation processes: an output of the i th IN mitigation process is used as an input of the $(i+1)$ th mitigation process. An iterative scheme uses the feedback mechanism whereas a noniterative scheme does not use it.

This paper focuses on ideas to improve a known iterative IN mitigation scheme for an OFDM system, called the Mengi-Häring (MH)-iterative scheme [1]. The MH iterative scheme is an extension of the Häring (H)-iterative scheme [6], where the clipping-nulling (CN) scheme [7] is added as a preprocessing IN mitigation scheme. The use of the preprocessing IN mitigation scheme is to increase the reliability of the first noise estimate by reducing IN power. This simple idea is an interesting idea since it improves the performance of the H-iterative scheme while maintaining low complexity in the receiver design. However, we notice that the structure of the MH-iterative scheme allows the use of unreduced IN power in the IN iterative mitigation process, which reduces the reliability of the noise estimate in the following iterations.

In this paper, we show two ideas that can improve the performance of the MH-iterative scheme significantly. First, there is the modification of the MH-iterative scheme structure, so that the IN power is reduced in all IN iterative mitigation processes and, therefore, good reliability of the noise estimate can be preserved in all iterations. Second, we show that the use of the replacement-nulling (RN) scheme, such as the preprocessing IN mitigation scheme, instead of the CN scheme, will bring additional performance improvement.

The rest of this paper is organized as follows. Section II explains the system model used. In Section III, the MH-iterative scheme will be explained, whereas in Section IV, we present the proposed ideas. Sections V and VI report the simulation results and conclude this paper.

II. SYSTEM MODEL

An OFDM system is a pair of inverse discrete Fourier transforms (IDFTs) and discrete Fourier transforms (DFTs). The IDFT is commonly used at the transmitter side, while the DFT is used at the receiver side.

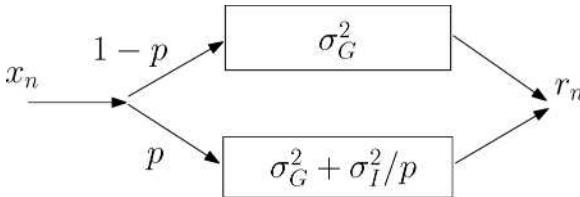


Fig. 1. Simplified model of the Middleton's additive white class A noise (AWCN) model. The transmitted signal is corrupted by the AWGN and the IN with probability p , and is corrupted by only the AWGN with probability $1 - p$. The variances of the AWGN and the IN are σ_G^2 and σ_I^2 , respectively.

The IDFT at the transmitter side is used to generate the time-domain OFDM samples x_n , or the complex baseband transmitted signal, from baseband symbols X_k as follows:

$$x_n = \frac{1}{\sqrt{N}} \sum_{k=0}^{N-1} X_k e^{j2\pi nk/N} \quad (1)$$

where N is the number of OFDM subcarriers, X_k is a baseband symbol, and x_n is the same length as X_k .

At the receiver side, the DFT is then used to transform the received time-domain OFDM samples r_n to its frequency-domain representation. It is obvious that if the received time-domain OFDM samples are noiseless, that is, $r_n = x_n + n_n$, where n_n is the additive noise sample and $n_n = 0$, then the output of the DFT is basically the transmitted baseband symbols X_k ,

$$X_k = \sum_{n=0}^{N-1} r_n e^{-j2\pi nk/N}. \quad (2)$$

If r_n is noisy, that is, $n_n \neq 0$, then an additional step such as, for example, maximum-likelihood (ML) estimation is needed to obtain the approximation U_k of the transmitted baseband symbols X_k .

The MH-iterative scheme and, thus, our proposed scheme uses the combination between IDFT, DFT, and the ML estimation to form the IN iterative mitigation process at the receiver side as will be discussed in Sections III and IV.

To simplify simulations and analysis, we use the simplified model of the Middleton's additive white class A noise (AWCN) model to describe the presence of the noise (Fig. 1). This model is also called *two-state IN channel model* and can be seen as a simplified PLC channel model (see also [9]). The AWCN model was also used in [1] and [6] and, therefore, it is sufficient to be used to show a fair comparison between the MH-iterative scheme and the proposed scheme.

III. MH-ITERATIVE SCHEME

Fig. 2 shows the blocks diagram of the MH-iterative scheme, which works as follows.

In the zeroth iteration, $l = 0$, the CN scheme is used to do preliminary IN mitigation. Its result, vector \tilde{r} , is then used as an input to the DFT. In the next iterations, $l > 0$, where the vector \tilde{r} is not used anymore, the following steps are applied.

In every iteration $l > 0$, the better approximation of the transmitted time-domain OFDM samples vector $r^{(l+1)}$ are transformed to the frequency-domain representation with the help

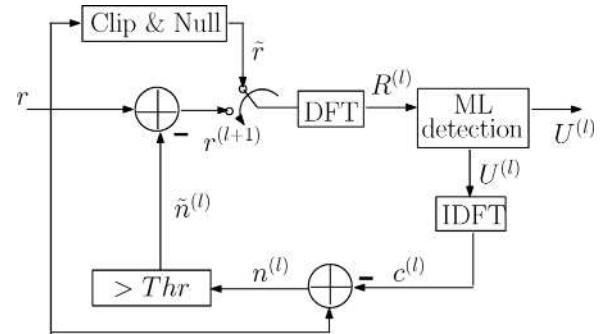


Fig. 2. MH-iterative scheme [1].

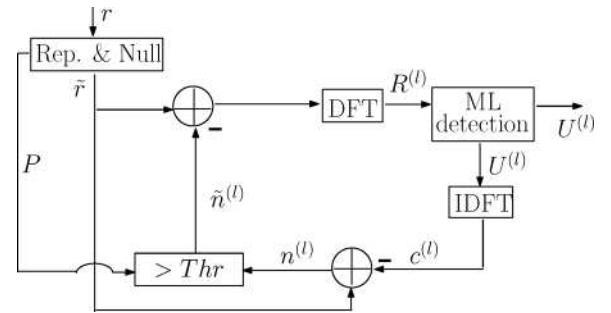


Fig. 3. Proposed modifications of the MH-iterative scheme.

of the DFT. After that, the ML estimation is used to approximate transmitted baseband symbols $U^{(l)}$. The noise vector $n^{(l)}$ in the received samples vector r (or $r^{(0)}$) is defined as $n^{(l)} = r^{(0)} - c^{(l)}$, where $c^{(l)}$ is the representation of $U^{(l)}$ in the time domain. The detection of the components in $n^{(l)}$, which are the IN $\tilde{n}^{(l)}$, is done in the time domain with the help of a threshold Thr as follows:

$$\tilde{n}_i^{(l)} = \begin{cases} 0, & \text{for } |n_i|^{(l)} \leq Thr \\ n_i^{(l)}, & \text{for } |n_i|^{(l)} > Thr \end{cases}. \quad (3)$$

The input vector for the next iteration is defined as $r^{(l+1)} = r^{(0)} - \tilde{n}^{(l)}$.

Having the mechanism explained, the scheme is expected to improve $U^{(l)}$ (or $c^{(l)}$) in every iteration, so that the approximation of the noise $n^{(l)}$ becomes more accurate.

As can be noticed, the structure of the MH-iterative scheme allows the use of unreduced IN power in the IN iterative mitigation process. This leads to a reduction in the reliability of the noise estimate in the following iterations, since the IN variance strongly influences the calculation of the threshold Thr . The detailed discussion on this topic is covered in Section V-B. Therefore, in the next section, we propose a modification to the MH-iterative scheme structure as a solution to this problem. We also explain the motivation of replacing the CN scheme with the RN scheme as the preprocessing IN mitigation scheme.

IV. PROPOSED MODIFICATION

The proposed modifications of the MH-iterative scheme are described using Fig. 3.

A. First Modification: We Use the RN Scheme as the Preprocessing IN Mitigation Scheme

In [3], we introduced the replacement (R) scheme and showed that it delivers better performance than the C scheme. Therefore, our first proposed modification is to use the combination between the R scheme and the N scheme, forming the replacement-nulling (RN) scheme, instead of the combination between the C scheme and the N scheme, as the preprocessing IN mitigation scheme. The decision of the RN scheme is as follows:

$$\tilde{r}_n = \begin{cases} r_n, & \text{for } |r_n| \leq T_{\text{rep}} \\ |\bar{x}| e^{j \arg r_n}, & \text{for } T_{\text{rep}} < |r_n| \leq T_{\text{null}} \\ 0, & \text{for } |r_n| > T_{\text{null}} \end{cases} \quad (4)$$

where \tilde{r}_n is the sample that is obtained after the mitigation process, and $|\bar{x}|$ is the average magnitude of the OFDM noiseless samples

$$|\bar{x}| = \sqrt{\frac{\pi * \sigma_S^2}{4}} \quad (5)$$

where σ_S^2 is the variance of the transmitted signal. The replacement threshold and the nulling threshold are defined as T_{rep} and T_{null} , respectively.

B. Second Modification: We Use \tilde{r} in All Iterations

The second modification is to use the vector \tilde{r} in all iterations instead of only in the zeroth iteration as the MH-iterative scheme does. In this way, we limit the power spectral density (PSD) of the IN σ_I^2 in the received samples vector r that will be used in all iterations.

Now, we discuss the basic reason of using a preprocessing IN mitigation scheme in the zeroth iteration, $l = 0$, and its relation to the next iterations $l > 0$. When a sample r_i is detected as being corrupted by the IN, then the preprocessing IN mitigation scheme changes the magnitude of the corrupted samples to a ‘better’ magnitude based on its rule: for the R scheme, the ‘better’ magnitude is $|\bar{x}|$ whereas for the N scheme it is zero. The ‘better’ magnitude can be further improved by replacing it with the output of the IDFT on every iteration, $c_i^{(l)}$. We assume that $c_i^{(l)}$, which is the approximation of the transmitted OFDM noiseless samples in iteration l , gets better from iteration to iteration. Therefore, in the set of positions P where the preprocessing IN mitigation scheme has been applied, we set $Thr = 0$. As a result, $\tilde{r}_i^{(l+1)} = \tilde{r}_i^{(0)} - \hat{n}_i^{(l)} = c_i^{(l)}$, where $i \in P$. For other positions $k \notin P$ in which the preprocessing IN mitigation scheme has not been applied, the following situations occur:

1) $c_k^{(l)}$ Is the Correct Estimate of the Transmitted Sample: Let x_k be the correct transmitted sample and $\tilde{r}_k^{(0)} = x_k + n_k$, where n_k is a noise component. Thus, in this case the $n_k^{(l)} = \tilde{r}_k^{(0)} - c_k^{(l)}$ contains only the underlying background noise or the IN. The input vector for the next iteration $\tilde{r}^{(l+1)}$ is then decided as follows:

$$\tilde{r}_k^{(l+1)} = \begin{cases} \tilde{r}_k^{(0)}, & \text{for } |n_k|^{(l)} \leq Thr \\ c_k^{(l)}, & \text{for } |n_k|^{(l)} > Thr \end{cases} \quad (6)$$

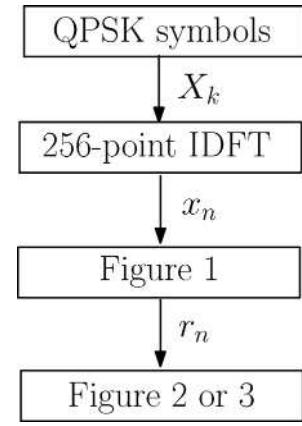


Fig. 4. Simulation block.

It is important to notice that when $|n_k|^{(l)} \leq Thr$, the basic iterative algorithm takes the corrupted transmitted sample $\tilde{r}_k^{(0)}$ instead of taking the correct transmitted sample itself $c_k^{(l)}$. This means it might degrade the performance at high SNR.

2) $c_k^{(l)}$ Is the Incorrect Estimate of the Transmitted Sample: In this case, there is additional noise $e_k^{(l)} = x_k - c_k^{(l)}$ which is called wrong decision noise. The input vector for the next iteration $\tilde{r}^{(l+1)}$, on the other hand, remains the same as given in (6).

V. SIMULATIONS AND DISCUSSIONS

We simulate QPSK-256OFDM uncoded transmission (see Fig. 4) with variance of the transmitted signal $\sigma_S^2 = 1$. The two-state IN channel model as explained in Section II is used. When a preprocessing IN mitigation scheme, such as the CN or the RN scheme is used, the threshold setting is $T_{\text{clip}} = 2.2\sigma_S^2$ and $T_{\text{null}} = 1.4T_{\text{clip}}$ [1]; $T_{\text{rep}} = T_{\text{clip}}$.

In [6], the threshold used to detect the location of the IN in $n^{(l)}$ is defined as $Thr = c \cdot \sigma_e$, where c is a constant factor and σ_e^2 is the variance of the statistical-independent noise caused by wrong decisions made by the detect operator. However, by using a threshold, which is a function of *only*, the wrong decision variance is not practical, since it requires the knowledge of the transmitted samples (see Section IV.B.2). Therefore, in simulations, we consider the threshold Thr which is a function of the noise variance in each iteration l , $Thr = c \cdot \sigma_n^{(l)}$, and it can be calculated from the vector $n^{(l)}$. The constant factor $c \geq 1$ itself is a subject to be optimized with the help of a brute-force search with respect to the BER.

A. Simulation 1: Is the Use of the RN Scheme as the Preprocessing IN Mitigation Scheme a Good Idea?

This simulation is to show the performance of the Häring-iterative scheme when the output of a preprocessing IN mitigation scheme is used in the zeroth iteration only (Mengi’s idea [1]). Two different simple IN mitigation schemes will be considered, the clipping-nulling (CN) scheme (the MH-iterative scheme idea) and the replacement-nulling (RN) scheme (our first idea, see Section IV-A).

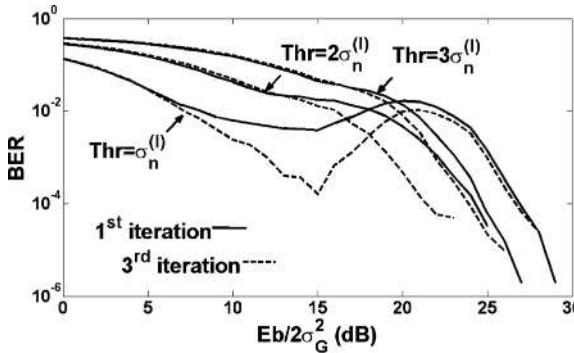


Fig. 5. Performance of the Härting-iterative scheme with the CN scheme as the preprocessing IN mitigation scheme. Different values of the threshold Thr are considered. The IN parameters are: $p = 0.1$, $\sigma_i^2 = 100\sigma_G^2$.

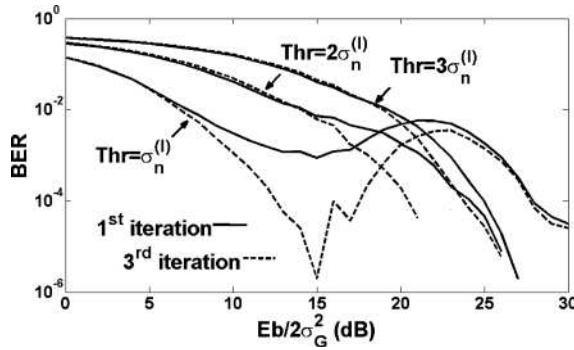


Fig. 6. Performance of the H-iterative scheme with the RN scheme as the preprocessing IN mitigation scheme. Different values of the threshold Thr are considered. The IN parameters are $p = 0.1$, $\sigma_i^2 = 100\sigma_G^2$.

The threshold setting for T_{clip} , T_{rep} and T_{null} follows the explanation in Section V. The threshold Thr , which is used to detect the location of the IN, is optimized with the help of a brute-force search (see Figs. 5 and 6). As can be seen, regardless of the type of preprocessing IN mitigation scheme, $Thr = \sigma_n^{(l)}$ is a good threshold for mitigating the IN.

Additional important information that we can see (Fig. 7) is that the use of the RN scheme as the preprocessing IN mitigation scheme shows that it is a good idea to mitigate the IN. In the high-SNR region, however, due to the use of the replacement threshold T_{rep} , which is not good for high SNR [3], the RN scheme delivers worse performance. We will see later (Section V-C), that the high-SNR region problem can be eliminated when we apply our second proposed idea.

B. Simulation 2: Is the Use of the Output of a Preprocessing IN Mitigation Scheme in All Iterations a Good Idea?

First of all, we discuss what actually happens when the output of a preprocessing IN mitigation scheme is used only in the zeroth iteration $l = 0$ and when it is used in all iterations $l \geq 0$.

In the MH-iterative scheme, where the output of the CN scheme is used only in the zeroth iteration, the noise variance in each iteration, $\sigma_n^{2(l)}$, depends on the wrong decision variance σ_e^2 , the AWGN variance σ_G^2 and the IN variance σ_i^2 . In our proposed scheme, however, due to the use of the output of the preprocessing IN mitigation scheme in all iteration l , the noise variance $\sigma_n^{2(l)}$ depends mainly on the wrong decision variance

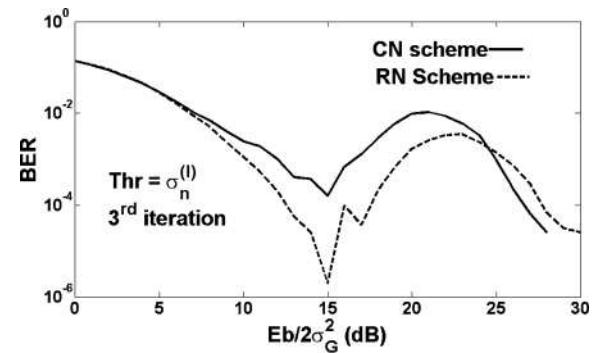


Fig. 7. Performance comparison of the H-iterative scheme when the RN scheme and the CN scheme are used as the preprocessing IN mitigation scheme. The IN parameters are: $p = 0.1$, $\sigma_i^2 = 100\sigma_G^2$.

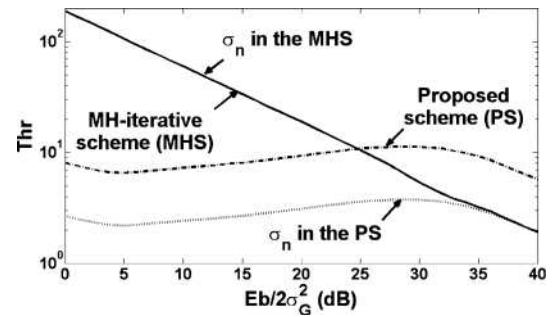


Fig. 8. The value of the threshold Thr as a function of SNR. The threshold Thr values for the MH-iterative scheme and our proposed scheme are $\sigma_n^{(l)}$, and $3\sigma_n^{(l)}$, respectively. The depicted noise variance is an average noise variance from iteration 1 to iteration 3. Both systems use the clipping-nulling (CN) scheme as the preprocessing IN mitigation scheme. The IN parameters are: $p = 0.1$, $\sigma_i^2 = 1000\sigma_G^2$.

σ_e^2 and the AWGN variance σ_G^2 . This can be seen clearly from Fig. 8: in the low-SNR region, where the influence of the IN is strong, the average noise variance in the MH-iterative scheme is high, whereas our proposed system produces almost a flat average noise variance.

The benefit of having the flat average noise variance is that the optimized threshold Thr value, which is a function of the noise variance, can work fine for all SNR. The optimization of the threshold Thr value used in the MH-iterative scheme on the other hand, needs an accurate approximation of the SNR: a different SNR needs a different constant factor c . This is a high complexity task and therefore becomes unattractive from a practical point of view.

In this simulation, as it is mentioned in Section V, we use a brute-force search to find a good constant factor c with respect to the BER that will be used in the MH-iterative scheme and our proposed scheme. We find the constant factor $c = 1$ for the MH-iterative scheme while for our proposed scheme, the constant factor $c = 3$. This indicates that the threshold Thr value used in the MH-iterative scheme depends *only* on the noise variance and therefore it leads to the following consequences: in the low-SNR, the threshold Thr value is too high and in the high-SNR it is too low.

When the threshold Thr value is too high in the low-SNR, then we allow more noisy received samples vector r to enter the next iteration. In the high-SNR, on the other hand, when

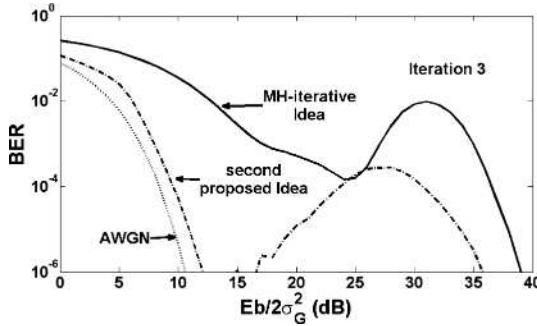


Fig. 9. Performance comparison between the original MH-iterative scheme and the proposed scheme. Both schemes use the clipping-nulling (CN) scheme as the preprocessing IN mitigation scheme. The IN parameters are: $p = 0.1, \sigma_I^2 = 1000\sigma_G^2$.

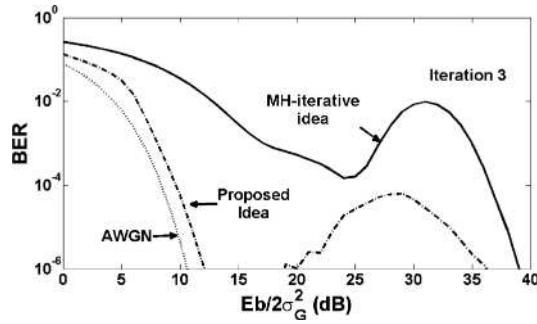


Fig. 10. Performance comparison between the original MH-iterative scheme and the proposed scheme. The MH-iterative scheme uses the clipping-nulling (CN) scheme as the preprocessing IN mitigation scheme, whereas our proposed scheme uses the replacement-nulling (RN) scheme as the preprocessing IN mitigation scheme. The IN parameters are: $p = 0.1, \sigma_I^2 = 1000\sigma_G^2$.

the threshold Thr value is too low then we allow more approximated transmitted samples vector $c^{(l)}$, which might contain decision errors made by the ML estimation, to enter the next iteration. Based on these two consequences, the MH-iterative scheme is expected to be worse in performance compared to the performance of our proposed scheme (Fig. 9).

C. Simulation 3: Does the Combination of the First and the Second Proposed Ideas Brings the Best Performance?

In our simulations so far, we look at the performance brought by our first idea only and second idea only. We see that each idea provides a positive contribution. In this simulation, we provide the performance of our proposed scheme when both ideas are used. By comparing Fig. 9, in which only the second idea is used, to Fig. 10 where we combine the first and the second ideas, we can see that additional gain can be achieved. We see also that the high-SNR problem introduced by the use of the RN scheme with an inappropriate T_{rep} as the preprocessing IN mitigation scheme (see Section V.A) is not noticeable.

Another simulation result that we will discuss is the performance of both schemes when the IN power spectral density (PSD) is reduced: we change the IN PSD from $\sigma_I^2 = 1000\sigma_G^2$ to $\sigma_I^2 = 100\sigma_G^2$. As can be seen in Fig. 11, our proposed scheme performance is still better than the MH-iterative scheme in terms of the BER. However, when we compare the performance of our proposed scheme depicted in Figs. 10 and 11, it is interesting to see that for $10 < SNR \leq 20$ —the SNR-region in which the

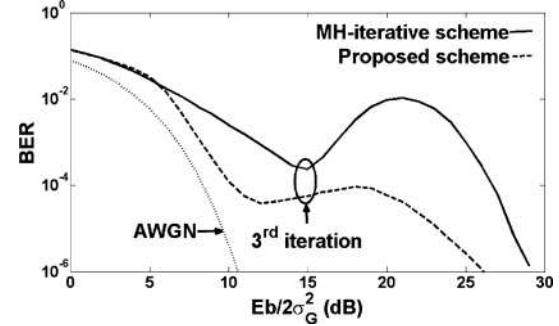


Fig. 11. Performance comparison between the original MH-iterative scheme and the proposed scheme. The MH-iterative scheme uses the clipping-nulling (CN) scheme as the pre-processing IN mitigation scheme, whereas our proposed scheme uses the replacement-nulling (RN) scheme as the pre-processing IN mitigation scheme. The IN parameters are: $p = 0.1, \sigma_I^2 = 100\sigma_G^2$. The threshold Thr values for the MH-iterative scheme and the proposed scheme are $Thr = \sigma_n^{(l)}$ and $Thr = 3\sigma_n^{(l)}$, respectively.

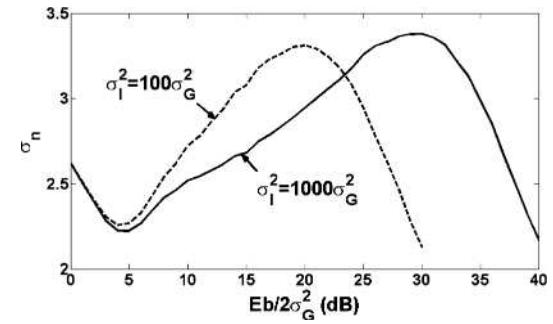


Fig. 12. Average noise variance from iteration 1 to iteration 3 in the proposed scheme (both proposed ideas are used) as a function of SNR for two different IN variances. The IN occurrence probability $p = 0.1$.

influence of the IN is still strong—the reduction in the IN PSD is not followed by the reduction in the BER. This is because the number of received samples corrupted by the IN, whose magnitudes are lower than the thresholds used in the preprocessing IN mitigation scheme, increases. As a result, the threshold Thr value used in our proposed scheme is more influenced by the IN variance (see Fig. 12). Therefore, the increase in the BER is expected.

D. Simulation 4: How Does the Performance of Both Schemes in a Weakly Disturbed Channel Look Like?

In three previous simulations, we discuss the performance of the MH-iterative scheme and our proposed scheme when $p = 0.1$ —the probability of occurrence of IN in a heavily disturbed channel. In this simulation, we look at the performance of both schemes in a weakly disturbed channel ($p = 0.01$).

In a weakly disturbed channel, the received samples in both schemes are mostly corrupted by the AWGN. The IN in this channel is modelled to have a large PSD. Hence, we can expect improved detection for the preprocessing IN mitigation scheme. This condition implies that there is no need to detect the IN further with the help of the threshold Thr . Therefore, the use of a high threshold Thr value which allows more received samples r_i , instead of the approximated transmitted samples $c_i^{(l)}$, to enter the next iteration is preferable. The brute-force search to find a good threshold Thr value used in our proposed scheme

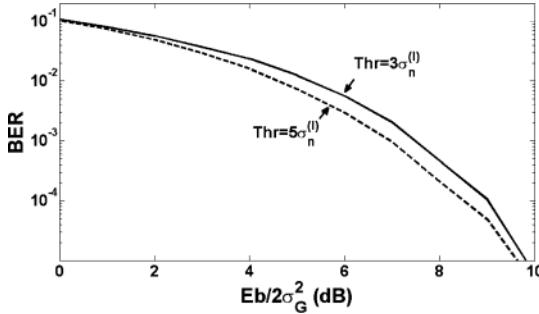


Fig. 13. Performance of the proposed scheme in a weakly disturbed channel for two different threshold Thr values in the first iteration. The replacement-nulling (RN) scheme is used as the preprocessing IN mitigation scheme. The IN parameters are $p = 0.01$, $\sigma_t^2 = 100\sigma_G^2$.

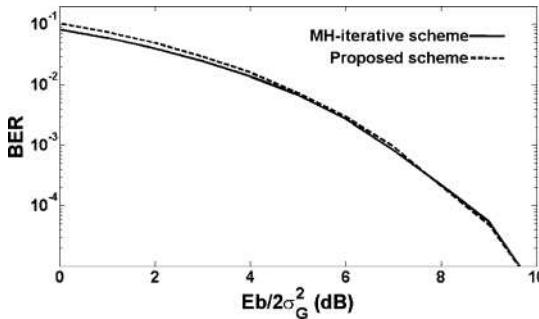


Fig. 14. First iteration performance comparison between the MH-iterative scheme and the proposed scheme in a weakly disturbed channel. The MH-iterative scheme uses the CN as the preprocessing IN mitigation scheme whereas our proposed scheme uses RN. The threshold Thr values for the MH-iterative scheme and our proposed scheme are $Thr = \sigma_n^{(l)}$ and $Thr = 5\sigma_n^{(l)}$, respectively. The IN parameters are $p = 0.01$, $\sigma_t^2 = 100\sigma_G^2$.

confirms this situation: we have to increase the threshold Thr value from $Thr = 3\sigma_n^{(l)}$ to $Thr = 5\sigma_n^{(l)}$ in order to have better performance (Fig. 13). In the MH-iterative scheme, however, it cannot be confirmed. The brute-force search gives the same threshold Thr value, $Thr = \sigma_n^{(l)}$. Fortunately as it is explained in Section V.B, in the low-SNR region, the threshold Thr value used in the MH-iterative scheme is already good— Thr is high. Therefore, we could expect a comparable performance of both schemes in this region. In the high-SNR region, for an almost AWGN channel, we expect that both schemes should also deliver comparable performance (Fig. 14).

VI. CONCLUSION

The MH-iterative scheme is an iterative IN mitigation scheme for OFDM-based transmission which delivers good performance with low complexity in the receiver design. In this paper, we report two ideas to improve its performance. The first idea is to use the RN scheme as the preprocessing IN mitigation scheme instead of the CN scheme. The second idea is to use the output vector \tilde{r} of the preprocessing IN mitigation scheme in all iterations instead of only in the zeroth iteration.

The performance comparison in terms of the BER between the MH-iterative scheme and the proposed scheme is made with the help of simulations of uncoded QPSK-256OFDM transmission in the two-state IN channel model. The results show that

the proposed scheme brings better performance than the MH-iterative scheme.

REFERENCES

- [1] A. Mengi, "On combined coding and modulation," Ph.D. dissertation, Inst. Experimental Math., Univ. Duisburg-Essen, Essen, Germany, 2010.
- [2] D.-F. Tseng, R.-B. Yang, T.-R. Tsai, Y. S. Han, and W. H. Mow, "Efficient clipping for broadband power line systems in impulsive noise environment," in *Proc. IEEE Int. Symp. Power Line Commun. Appl.*, Beijing, China, Mar. 2012, pp. 362–367.
- [3] V. N. Papilaya and A. J. H. Vinck, "Investigation on a new combined impulsive noise mitigation scheme for OFDM transmission," in *Proc. IEEE Int. Symp. Power Line Commun. Appl.*, Johannesburg, South Africa, Mar. 2013, pp. 86–91.
- [4] E. Alsusa and K. M. Rabie, "Dynamic peak-based threshold estimation method for mitigating impulsive noise in power-line communication systems," *IEEE Trans. Power Del.*, vol. 28, no. 4, pp. 2201–2208, Oct. 2013.
- [5] J. Lin, M. Nassar, and B. L. Evans, "Impulsive noise mitigation in power-line communications using sparse bayesian learning," *IEEE J. Sel. Area Commun.*, vol. 31, no. 7, pp. 1172–1183, Jul. 2013.
- [6] J. Haering and A. J. H. Vinck, "OFDM transmission corrupted by impulsive noise," in *Proc. IEEE Int. Symp. Power Line Commun. Appl.*, Limerick, Ireland, Apr. 2000, pp. 9–14.
- [7] 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, Jan. 2008.
- [8] D. Middleton, "Canonical and quasi-canonical probability models of class A interference," *IEEE Trans. Electromagn. Compat.*, vol. EMC-25, no. 2, pp. 76–106, May 1983.
- [9] E. Biglieri, "Coding and modulation for a horrible channel," *IEEE Commun. Mag.*, vol. 41, no. 5, pp. 92–98, May 2003.



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