ORIGINAL RESEARCH PAPER

Parameter estimation of impulsive noise for channel coded communication systems

Chun-Yin Chen | Mao-Ching Chiu

1 INTRODUCTION

In some wireless communication networks and power line communications (PLC), the receivers suffer from interference from other users and even non-communication interference sources which are mostly caused by the man-made sources including the electrical appliances [1]. In practice, this interference occurring in such communication systems is recognised to be non-Gaussian and exhibits a significant impulsive nature [2]. Several statistical models for the impulsive noise have been proposed, and the most widely used of them are the Bernoulli-Gaussian (B-G) model [3] and the Middleton class-A (M-CA) model [4–6].

Channel coding has been used to overcome the channel noise. Some powerful codes, such as low-density parity-check (LDPC) codes [7] and turbo codes [8, 9], are well investigated and can achieve the channel capacity under AWGN channels. However, for impulsive noise channels, the performance of a channel coded system is significantly degraded if the impulsive noise behavior is not considered in the design of the receiver. There are two approaches to designing the detection algorithms for channel coded systems in impulsive noise environments: the first is to design detection algorithms that do not require knowledge of the impulsive noise statistics and the second is to design the detector in the maximum-likelihood (ML) sense, which requires the parameters of an assumed impulsive noise model.

For the first approach, the joint erasure marking Viterbi algorithm (JEVA) proposed in [10] has been shown to provide excellent performance. Its performance is achieved by using a Viterbi algorithm over an erasure-expanded trellis that is the product of an erasure trellis and the trellis of the convolutional code. The complexity of the JEVA is therefore several times greater than that of the VA. In [11–16], it has been shown that a simple metric clipping method can overcome the impact of strong impulsive noise. The clipping level depends on a design parameter that should be a fixed value regardless of the impulse noise statistics, and a proper selection of the design parameter is obtained through simulations. The major problem of the metric clipping method is that it generates zero (log-likelihood ratio) LLR if the received signal is larger than a certain threshold. This is equivalent to puncturing those coded bits whose received signals are larger than a certain threshold. However, under low-to-medium impulsive noise power, puncturing of coded bits whose received signals are larger than a certain threshold suffers from performance degradation, as observed in [15, 16].

For the second approach, a parameter estimator is required to estimate the parameters of the impulsive noise. A related work that combines the decoding algorithm with the parameter estimation for convolutional coded system was presented in...
However, the algorithm proposed in [17] is channel-code dependent, that is, different types of channel codes may require different parameter estimation and decoding algorithms, which may not be a good feature for modularity.

In this paper, we propose a low-complexity estimation algorithm for the B–G impulsive noise model based on the expectation-maximisation (EM) algorithm [18–20]. The B–G noise model is composed of background AWGN and impulse noise. The impulse noise is the most dominant factor that degrades communication signals [21–25]. The accuracies of the estimated parameters are very important. Without the estimation of the impulsive noise or with bad accuracies of the estimated parameters, the system performance will be seriously degraded. Our proposed parameter estimation algorithm operates without the assistance of the channel decoder. Therefore, the proposed structure has the advantage that any channel codes can be used provided that the channel codes have soft-input decoders. Moreover, the complexity of our separated parameter estimation and decoding is less than the joint decoding and parameter estimation algorithm which required more decoding iterations to achieve optimal performance for convolutional coded systems [16].

This paper is organised as follows. Section 2 describes the system and channel model. The estimator of the impulsive noise is given in Section 3. The LLR generator for the decoder is given in Section 4. Simulation results are given in Section 5. Conclusions are drawn in Section 6.

## 2 SYSTEM AND CHANNEL MODEL

A binary coded point-to-point communication system is considered in this paper as shown in Figure 1 which employs a binary \((N,K)\) linear code. The channel encoder accepts \(K\) message bits \(a = [a_1, \ldots, a_K]\) as input and produces an \(N\)-tuple binary codeword \(c = [c_1, \ldots, c_N]\) as output. The codeword \(c\) is then mapped to an antipodal transmission vector \(x = [x_1, \ldots, x_N]\) with \(x_i = 1 - 2c_i\) for \(i = 1, \ldots, N\). At the receiver side, the received signal can be represented by

\[
r_i = x_i + w_i, \text{ for } i = 1, \ldots, N
\]

where \(w_i\) is the additive noise. Conventionally, the noise \(w_i\) is assumed to be an i.i.d. Gaussian random process. However, in certain communication systems, for example, power line communication (PLC) systems, the noise is typically non-Gaussian and has impulsive characteristic. There are several impulsive noise models proposed in the literature. In this paper, we consider two widely known impulsive noise models. The first is the Bernoulli–Gaussian (B–G) model [3] and the second is the Middleton Class-A (M-CA) model [4–6]. These two models are briefly reviewed as follows.

### 2.1 Bernoulli–Gaussian model

The noise of the B–G model can be represented by \(w_i = g_i + b_i z_i\), where \(g_i\) represents the background AWGN and is a zero-mean i.i.d. Gaussian random process with variance \(\sigma^2_G = N_0/2\), \(b_i \in \{0, 1\}\) is the Bernoulli process with probability of impulse occurrence \(\text{Pr}[b_i = 1] = p_b\), and \(z_i\) is a zero-mean i.i.d. Gaussian random process with variance \(\Gamma N_0/2\). Parameter \(\Gamma\) is the mean power ratio between the impulse noise \(z_i\) and the AWGN \(g_i\). The p.d.f. of \(w_i\) can be represented as a Gaussian mixture model given by

\[
f_W(w_i) = f_{BG}(p_b, \sigma^2_G, \Gamma)(w_i) = (1 - p_b)\mathcal{N}(w_i|0, \sigma^2_G) + p_b\mathcal{N}(w_i|0, (1 + \Gamma)\sigma^2_G),
\]

where \(\mathcal{N}(w_i|\mu, \sigma^2) = \frac{1}{\sqrt{2\pi\sigma^2}} \exp(-\frac{(w_i - \mu)^2}{2\sigma^2})\) represents the Gaussian p.d.f. with mean \(\mu\) and variance \(\sigma^2\). The average noise power can be represented by

\[
E[w_i^2] = (1 + p_b\Gamma)\sigma^2_G.
\]

The B–G model is characterised by three parameters \(\Omega = (p_b, \sigma^2_G, \Gamma)\).

### 2.2 Middleton class-A model

The M-CA model is also a Gaussian mixture model that can be considered as an extension of the 2-state B–G model. Let \(S\) be a Poisson random variable with probability mass function \(\text{Pr}[S = k] = \frac{e^{-A} A^k}{k!}\), where \(A\) is referred as impulsive index. If \(S_i = k_i\), the noise \(w_i\) is obtained by

\[
w_i = \sqrt{1 + \frac{k_i}{A\Lambda}} g_i,
\]

where \(g_i\) is a zero-mean i.i.d. Gaussian random process with variance \(\sigma^2_G = N_0/2\) and the \(A\) is the mean power ratio between the AWGN and the impulsive noise. If \(S_i = k_i\) from (4), the variance of \(w_i\) is given by

\[
\sigma^2_{k_i} = \left(1 + \frac{k_i}{A\Lambda}\right)\sigma^2_G.
\]

The p.d.f. of the impulsive noise can be represented by

\[
f_{MCA}(A|\sigma^2_G, A) = \sum_{k=0}^{\infty} \left(\frac{e^{-A} A^k}{k!}\right) \mathcal{N}(w_i|0, \sigma^2_{k_i}).
\]
The noise intensity increases linearly with \( k \). When \( k = 0 \), the noise contains only AWGN with variance \( \sigma_0^2 \). The average noise power can be computed as

\[
E[w^2] = \sum_{k=0}^{\infty} \frac{e^{-A} A^k}{k^2} \sigma_k^2 = \left(1 + \frac{1}{\Lambda}\right) \sigma_G^2.
\]

The M-CA model is characterised by three parameters \( \Omega = (\mathcal{A}, \sigma_G^2, \Lambda) \).

### 2.3 Receiver structure

The receiver structure is also shown in Figure 1. In this paper, it is assumed that the receiver has no prior information regarding the impulsive noise statistics but assumed a specific impulsive noise model for the receiver design. Therefore, a parameter estimator is used to estimate the noise statistics with its output denoted as \( \hat{\Omega} \). Based on the estimated parameter \( \hat{\Omega} \) and the received signal \( r \), the LLR generator calculates bit LLRs of each coded bits, denoted as \( L \).

The receiver has no prior information regarding which impulsive noise model better fits to the actual noise realisation. Although the M-CA model is also a Gaussian mixture model, it is not merely involved in estimating the Poisson random variable but also rendering significant computational complexity [1]. Consequently, we only apply the B–G model in the receiver design to simplify the problem. The receiver tries to estimate \( \hat{\Omega} \) based on the received signal \( r \) without assistance from the decoder. Simulation results show that the receiver designed based on the B–G model can achieve almost optimal performance even though the actual channel is M-CA model.

### 3 Parameter estimation of impulsive noise

The optimal parameter estimation is based on the maximum-likelihood (ML) criterion given by

\[
\hat{\Omega}_{\text{ML}} = \arg \max_{\Omega} \sum_{x \in \mathcal{L}} f_r(r|x, \Omega),
\]

where \( f_r(r|x, \Omega) \) is the conditional p.d.f. of \( r \) given the transmitted codeword \( x \) and the channel parameter \( \Omega \). The optimal estimation becomes

\[
\hat{\Omega}_{\text{ML}} = \arg \max_{\Omega} \sum_{x \in \mathcal{L}} \prod_{i=1}^{N} f_{w_i}(r_i - x_i),
\]

where \( f_{w_i}(w) \) is the p.d.f. of the noise which is given by (2) for the B–G model. The complexity of the estimator is very high since the summation is over all the possible codewords. To reduce the complexity, we perform parameter estimation and decoding separately. The proposed estimation algorithm utilises the EM algorithm to estimate the parameters of the impulsive noise. The EM algorithm and its variants are utilised to solve a broad range of estimation problems, from the motif finding in DNA sequences, to the disambiguating targets from clutters in radar systems [26].

#### 3.1 The expectation-maximisation (EM) algorithm

In general, the EM algorithm consists of two iterative processes [27, 28]. The first step is the expectation step which computes the expectation of the joint log-likelihood of the observations and the hidden data, conditional upon the observations and the current estimates. The second step is the maximisation step which computes parameters by maximising the expected log-likelihood evaluated in the expectation step.

The p.d.f. of the received signal (1) can be represented as

\[
f_r(r_i) = \frac{1}{2} f_{w_i}(r_i - 1) + \frac{1}{2} f_{w_i}(r_i + 1),
\]

where we assume that \( \Pr\{x_i = 1\} = \Pr\{x_i = -1\} = 1/2 \). In this paper, we only apply the B–G impulsive noise model in the receiver design because estimating parameters in M-CA model is involved [29]. The notation \( k \) is adopted to represent the noise category occurrence, which is either the impulsive noise \( (k=1) \) or only the AWGN \( (k=0) \). As an iterative algorithm, the EM algorithm computes a new estimated set based on the current estimate in each iteration. The EM algorithm may be summarised as follows.

- **Initialisation**: Denote the initial parameters \( \hat{\theta}^{(0)}_{x,k} \) and \( \sigma^{(0)}_{x,k} \) which are associated with the transmitted code bit \( x \) and the noise category \( k \) as the noise occurrence probability and variance of the received signal, respectively. Define the parameter set \( \Theta^{(0)} = \{\theta^{(0)}_{x,k}, \sigma^{(0)}_{x,k}\} \) and the overall parameter set \( \Theta^{(0)} = \{\theta^{(0)}_{x,k} : \forall x \in \{+1, -1\} \text{ and } k \in \{0, 1\}\} \). Therefore, the p.d.f. of the received signal \( r_i \) given the initial overall parameter set \( \Theta^{(0)} \), denoted as \( f_r(r_i|\Theta^{(0)}) \) which can be represented as

\[
\begin{align*}
f_r(r_i|\Theta^{(0)}) &= \sum_{x_k} f_r(r_i|\theta^{(0)}_{x,k}) \sigma^{(0)}_{x,k} = \sum_{x_k} \theta^{(0)}_{x,k} N(r_i|x_i, \sigma^{(0)}_{x,k}).
\end{align*}
\]

- **Expectation step**: Compute the responsibility

\[
\gamma^{(a)}_{x,k} = \Pr\{f_r(r_i|\theta_{x,k}^{(a)}) | f_r(r_i|\theta_{x,k}^{(a)})\}
\]

which is the expectation of the received signal \( r_i \) given the parameter set \( \theta_{x,k}^{(a)} \) that are calculated in the \( m \)-th iteration maximisation step of the received signal \( r_i \) given the received
signal $f_r(r_i|\Theta^{(s)})$.

$$
\gamma_{\omega,i,k}^{(s)} = \frac{f_r(r_i|\Theta^{(s)}_{\omega,i,k})}{\sum_{\omega,i,k} f_r(r_i|\Theta^{(s)}_{\omega,i,k})} = \frac{p_{\omega,i,k}^{(s)}N'(r_i;x_i\omega_{\omega,i,k})}{\sum_{\omega,i,k} p_{\omega,i,k}^{(s)}N'(r_i;x_i\omega_{\omega,i,k})},
$$

for $i = 1, \ldots, N$.

- Maximisation step: The new estimated parameters can be derived by maximising the expected value of log-likelihood using the current responsibilities (10) which is given by

$$
p_{\omega,i,k}^{(s+1)} = \frac{\sum_{i=1}^{N} \gamma_{\omega,i,k}^{(s)}}{N},
\sigma_{\omega,i,k}^{2(s+1)} = \frac{\sum_{i=1}^{N} \gamma_{\omega,i,k}^{(s)} (r_i - x_i)^2}{\sum_{i=1}^{N} \gamma_{\omega,i,k}^{(s)}}.
$$

- If the convergence criterion

$$
\frac{1}{N} \sum_{i=1}^{N} \log f_r(r_i|\Theta^{(s+1)}) - \frac{1}{N} \sum_{i=1}^{N} \log f_r(r_i|\Theta^{(s)}) < \delta
$$

is satisfied or the maximum number of iterations $i_{\text{max}}$ is reached, stop the algorithm; else return to the expectation step and perform the iteration again. The lower $\delta$ is set, the more accurate the approximation would be [30]. A proper value of $\delta$ should be selected such that a good balance between the accuracy and the number of iterations can be obtained.

Finally, the estimate $\hat{\Theta} = (\hat{p}_b, \hat{\sigma}_G^2, \hat{\Gamma})$ is given by

$$
\hat{p}_b = \sum_x p_{\omega,i,k}^{(s+1)},
\hat{\sigma}_G^2 = \frac{1}{2} \sum_x \sigma_{\omega,i,k}^{2(s+1)},
\hat{\Gamma} = \frac{1}{2} (\hat{\sigma}_Z^2 - \hat{\sigma}_G^2),
$$

where

$$
\hat{\sigma}_Z^2 = \frac{1}{2} \sum_x \sigma_{\omega,i,k}^{2(s+1)}.
$$

The EM algorithm is an iterative algorithm, in which the model depends on some unobserved variables [31]. Each iteration includes an expectation step that finds the distribution for the unobserved variables, given the known observed variables and the current estimated parameters. The maximisation step re-estimates the parameters which maximise the expected value of the log-likelihood function.

### 3.2 Complexity analysis

Since the summation in the likelihood function is over all possible codewords as given in (7), the complexity of the ML scheme is at least $O(2^K)$. In addition, there is no closed-form solution for the ML scheme, which makes the ML scheme hard to implement even for simulations. For the EM algorithm, the complexity of a single EM iteration is $O(4(N + 1))$ [32]. Therefore, the complexity of the EM algorithm is $O(4I(N + 1))$, where $I$ is the number of iterations.

### 4 BIT LOG-likelihood ratios generator

After estimating the parameters of the impulsive noise, the bit LLRs are generated according to the estimated parameters. To simplify the notations, we still use the parameters $(\hat{p}_b, \hat{\sigma}_G^2, \hat{\Gamma})$ for B–G models, to generate the bit LLRs with the understanding that they should be replaced by the estimates $(\hat{p}_b, \hat{\sigma}_G^2, \hat{\Gamma})$.

For the M–CA model, if the parameters $(\Lambda, \sigma_G^2, \Gamma)$ are perfectly known, the bit LLR of the $j$th code bit is given by

$$
L_j^{(MCA)} = \log \frac{\sum_{k=0}^{\infty} \left( - \frac{\Lambda^k}{2(1 + \frac{\Gamma}{\Lambda})^2 \sigma_G^2} \right)}{\sum_{k=0}^{\infty} \left( - \frac{\Lambda^k}{2(1 + \frac{\Gamma}{\Lambda})^2 \sigma_G^2} \right)}.
$$

The bit LLR for M–CA model with perfect parameters is used as a benchmark of the decoding performance which can be used to justify if the receiver design can really approach the ideal performance. For the B–G model, the bit LLR of the $j$th code bit is given by

$$
L_j^{(BG)} = \log \frac{f_{BG}(p_b, \sigma_G^2, \Gamma)(r_i - 1)}{f_{BG}(p_b, \sigma_G^2, \Gamma)(r_i + 1)} = \log \frac{(1 - p_b)N'(r_i) - 1, \sigma_G^2 + p_bN'(r_i) - 1, (1 + \Gamma)\sigma_G^2}{(1 - p_b)N'(r_i) + 1, \sigma_G^2 + p_bN'(r_i) + 1, (1 + \Gamma)\sigma_G^2}.
$$

Another approximation is made by assuming that $\Gamma$ is very large (strong impulsive noise power). This results in a clipping approximation given by

$$
L_j^{(BG-CLIP)} = \min \left( (r_i + 1)^2, \frac{2 \sigma_G^2}{b} \right) - \min \left( (r_i - 1)^2, \frac{2 \sigma_G^2}{b} \right),
$$

(15)
where $h$ is the threshold. Metric clipping methods have been adapted in several works [15, 16] and perform well when $\Gamma >> 0$, that is, under strong impulsive noise power. The clipping approximation results in a zero LLR if $|r| > \sqrt{h} + 1$ which is equivalent to puncturing those code bits whose received signals are larger than a certain threshold. However, under the weak-to-medium impulsive noise power, the zero LLR region is still very important and should not be set to zero.

Several metric clipping algorithms which do not require knowledge of the impulsive noise statistics were proposed in [15, 16]. However, the algorithms proposed in [15, 16] still require knowledge of the background AWGN variance $\sigma^2_G$ which is assumed to be perfectly known by the receiver. For example, the algorithm proposed in [15] uses a fixed design parameter $\Delta$. The method is equivalent to (15) by setting $h = 2\sigma^2_G \ln(1/\Delta)$. It was suggested that $\Delta = 10^{-3}$ is effective irrespectively of the actual impulsive noise statistics. The simulation results shown in [15] indicate that the performance of the metric clipping algorithm approaches optimal performance under strong impulsive noise power. However, some performance loss was observed under the weak-to-medium impulsive noise power [15].

### 5 SIMULATION RESULTS

We consider a (3,6)-regular LDPC code of rate $1/2$ with block size $N = 3990$ based on Gallager’s random construction [7]. For the convergence criterion in the EM algorithm, we set $\delta = 4 \times 10^{-3}$ and the maximum number of iterations $I_{\text{max}} = 100$. The reason to select $\delta = 4 \times 10^{-3}$ is to have a good balance between the accuracy and the number of iterations. The distribution of the number of iterations will be studied in Section 5.1.

At the receiver, the belief propagation (BP) algorithm with 50 iterations is employed to decode the LDPC code. In the following, to unify the parameters under different models, both M-CA and B–G models are specified using the same parameters $p_b$ and $\Gamma$. The relation to the parameters of the B–G model is given by

\begin{align}
    p_b &= 1 - \exp(-A), \\
    \Gamma &= \frac{1}{(1 - \exp(-A))\Lambda}.
\end{align}

The relations (16) and (17) ensure that the probabilities of the impulse occurrence of both models are the same and the total noise powers of both models are equal, that is, (3) equals to (5). According to previous studies [2, 25, 33, 34], the value of $p_b$ is from $10^{-4}$ to $10^{-2}$ and $\Gamma$ is from $10^{-1}$ to $10^2$ for PLC systems. Nevertheless, we apply wider range of $p_b$ and $\Gamma$ to test the robustness of the parameter estimation.

#### 5.1 Performance of EM algorithm

The normalised squared error (NSE) of an estimate $\hat{F}$ of a parameter $F$ is defined by $D = (\hat{F} - F)^2 / F^2$. The normalised mean squared error (NMSE) is defined as $E[D]$. In this simulation, the parameters of the B–G model are set as $p_b = 0.09$, $\Gamma = 100$ and $\sigma^2_G = 0.4751$. Figures 2, 3, and 4 show the distributions of the NMSE’s of the estimated parameters. The estimated parameters are accurate as all distributions concentrate to zero. The NMSE for $p_b$, $\Gamma$, and $\sigma^2_G$ are 0.0401, 0.0237, and 0.0013, respectively. The estimated parameters are accurate enough as will be verified by the bit error rate (BER) simulations. Figure 5 shows the distribution of the number of iterations for the EM algorithm by setting $\delta = 4 \times 10^{-3}$. The average number of iterations is 9.30 which is acceptable for a practical implementation.

#### 5.2 Regular performance simulation

Figure 6 shows the BER curves of various algorithms for the receiver under the B–G model. The performance of the
5.3 Performance simulation over a wide range of impulsive noise power and probability of impulse occurrence

To test the robustness of the receiver over a wide range of impulsive noise power, the values of parameters $p_b$ are set to 0.09, and 0.18, respectively, and $\Gamma$ is swept from $10^{-1}$ to $10^4$. The setting $\Gamma = 10^4$ represents a very strong impulsive noise power; while $\Gamma = 10^{-1}$ represents a weak impulsive noise power. Figure 7 shows the required $E_b/N_0$ at BER of $10^{-5}$ for the receiver under the B–G channel model. Simulation results show that the proposed estimation algorithm has almost the same performance as that of the ideal LLR. This means that the parameters estimated by the EM algorithm are accurate enough for the LLR generation. Also the metric clipping algorithm proposed in [15] with $\Delta = 10^{-3}$ has a very significant performance loss under low-to-medium impulse noise power.

Figure 8 depicts the required SNR for the BER of $10^{-5}$ with $\Gamma = 10$ and $\Gamma = 100$ under various values of the parameter $p_b$. The results show that the proposed parameter estimation can achieve the optimal performance. The metric clipping algorithm proposed in [15], in the worst case, gives about 4.35 dB loss when the probability of impulse occurrence $p_b$ is high. When the value of $p_b$ is low, the required SNR for $\Gamma = 10$ is close to...
FIGURE 8 The required $E_b/N_0$ for BER of $10^{-5}$ over the B–G channel with $\Gamma = 10$ and $\Gamma = 100$ under various values of the parameter $p_b$. The receiver assumes the B–G model for parameter estimation and LLR generation.

FIGURE 9 The Required $E_b/N_0$ for BER of $10^{-5}$ over the M-CA channel with $p_b = 0.09$ and $p_b = 0.18$ and $\Gamma$ is swept from $10^{-1}$ to $10^4$. The receiver assumes the B–G model for parameter estimation with and LLR generation.

the performance levels of the proposed parameter estimator and LLR generation schemes approach to those of ideal LLR. Especially, the proposed low-complexity receiver with LLR generator has almost no performance loss.

6 | CONCLUSION

This paper proposed a parameter estimation algorithm for the design of receivers in impulsive noise environments. This low-complexity estimation algorithm is based on EM algorithm which operates without the assistance of the channel decoder. Therefore, the proposed structure has the advantage that any channel codes can be used provided that the channel codes have soft-input decoders. And, with the channel coding techniques, we do not require the exact values of estimated parameters, that is, the accuracies of the parameters can be relaxed. The estimated parameters are employed by the LLR generator to generate the bit LLRs for channel decoding. Simulation results show that the proposed receivers achieve almost the optimal performance over a wide range of the impulsive noise occurrence probability and impulsive noise power even under model mismatch.

ORCID
Mao-Ching Chiu https://orcid.org/0000-0002-5662-4301

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