On Impulse Noise and its Models

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***Abstract*—This article gives a discussion on impulse noise, its models and how it affects communications systems. We discuss the different impulse noise models in the literature, looking at their similarities and differences in communications systems. The impulse noise models discussed are memoryless (Middleton Class A and Bernoulli-Gaussian), and with memory (Markov-Middleton and Markov-Gaussian). We then go further to give performance comparisons in terms of bit error rates for some of the variants of impulse noise models. We also compare the bit error rate performance of single-carrier (SC) and multi-carrier (MC) communications systems operating under impulse noise. It can be seen that MC is not always better than SC under impulse noise. Lastly, the known impulse noise mitigation schemes (clipping/nulling using thresholds, iterative based and error control coding methods) are discussed.**

***Index Terms*—Impulse noise models, Multi-carrier modulation, Single-carrier modulation, Bernoulli-Gaussian, Middleton Class A.**

I. Middleton noise model

The phenomenon of impulse noise is first described by Middleton [1, Chapter 11], where he gave a model for impulse noise in communications systems. To come up with the model, Middleton [1, Chapter 11] described impulsive noise in a system as consisting of sequences of pulses (or impulses), of varying duration and intensity, and with the individual pulses occurring more or less random in time. He went further to divide the origin of impulse noise in two categories: (a) Man-made, which is induced by other devices connected in a communications network and (b) naturally occurring, due to atmospheric phenomena and solar static, due to thunder storms, sun spots etc.

In his later work, Middleton [1] developed statistical noise models which catered for noise due to both man-made and natural phenomena [2] and [3]. The most famous of these noise models is the so-called Middleton Class A noise model, which has been widely accepted to model the effects of impulse noise in communications systems. We will, in short, refer to the Middleton Class A model as Class A model. We dedicate space to describing the Class A noise model because it has become the cornerstone of impulse noise modelling and has been extensively studied and utilised in the literature (see [4]–[11].) The Class A noise model gives the probability density function (PDF) of a noise sample, say n_k as follows,

$$F_M(n_k) = \sum_{m=0}^{\infty} P_m \mathcal{N}(n_k; 0, \sigma_m^2), \qquad (1)$$

where

$\mathcal{N}(x_k; \mu, \sigma^2)$ represents a Gaussian PDF with mean μ and variance σ^2, from which the k^{th} sample x_k is taken.

$$P_m = \frac{A^m e^{-A}}{m!} \qquad (2)$$

and

$$\sigma_m^2 = \sigma_I^2 \frac{m}{A} + \sigma_g^2 = \sigma_g^2 \left(\frac{m}{A\Gamma} + 1 \right), \qquad (3)$$

where σ_I^2 is the variance of the impulse noise and σ_g^2 is the variance of the background noise (AWGN). The parameter $\Gamma = \sigma_g^2/\sigma_I^2$ gives the Gaussian to impulse noise power ratio. The parameter A here represents the density of impulses (of a certain width) in an observation period. Therefore, $A = \eta\tau/T_0$, where η is the average number of impulses per second and $T_0 = 1$, which is unit time. The parameter τ, is the average duration of each impulse, where all impulses are taken to have the same duration. We now talk of density of impulses instead of number of impulses. In (2) we therefore have the densities of impulse noise occurring according to a Poisson distribution.

The density is what has become accepted as "impulsive index", A. The impulsive index is a parameter that is not well explained in the literature. We therefore give some details about the impulsive index, to enhance its understanding. It is worth stating that $A \leq 1$, this follows from the definition of impulsive index being a fraction of impulses in a given observation period T_0. Therefore, for $\eta\tau > T_0$, the impulsive index is capped at 1 no matter how large $\eta\tau$ is, in the observation period T_0.

Fig. 1 shows a pictorial view of the impulsive index, A, and what it means. Fig. 1 (a) shows η impulses each of duration τ, where the impulses occur in bursts (next to each other). In Fig. 1 (b) we show $\eta = 3$ impulses each of duration τ, where the impulses do not necessarily occur in bursts. We also specify the period of observation as $T_0 = 1$ in Fig. 1 (b), which is usually the case in the calculation of the impulsive index. The conclusion drawn from Fig. 1 is that whether impulses occur

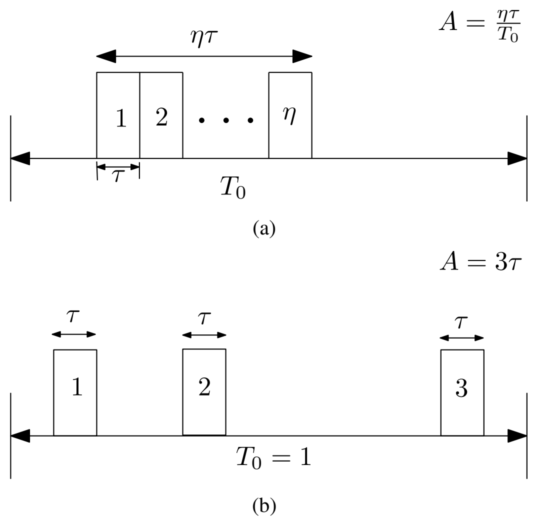


Fig. 1. Example of Impulsive index: (a) Impulsive index (density) of η impulses, each with width (duration) τ, occupying a given time period T_0 and (b) impulsive index (density) of 3 impulses, each with width (duration) τ, occupying a given time period $T_0 = 1$.

in bursts or not, the calculation of the impulsive index follows the same procedure.

II. Impulse noise Models

Following Middleton's noise models [1, Chapter 11], many authors studied impulse noise modelling. In this section, we discuss some impulse noise models found in the literature. To date, the following names come up in the literature for different impulse noise models:

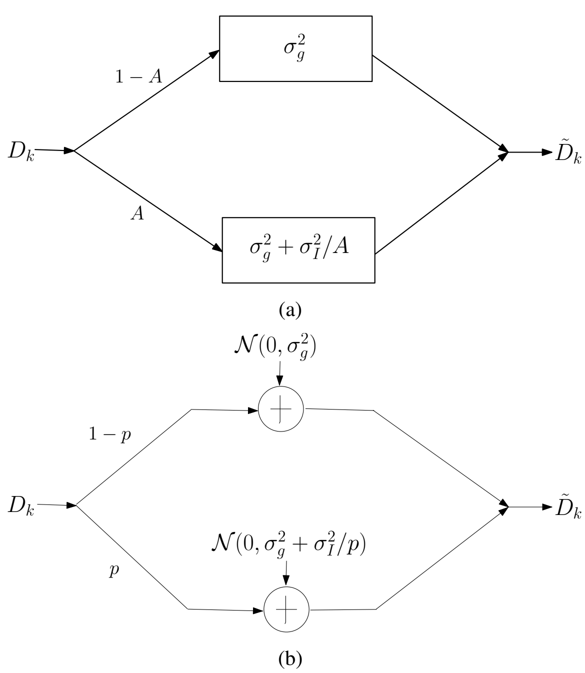


Fig. 2. (a) Two-state Class A noise model and (b) Bernoulli-Gaussian noise model.

1) Impulse noise models without memory
   - Middleton Class A
   - Bernoulli-Gaussian
2) Impulse noise models with memory
   - Markov-Middleton
   - Markov-Gaussian.

A. *Impulse noise models without memory*

The Middleton Class A noise model has already been explained in Section I. It can be seen that the PDF of the Class A noise model in (1) is a sum of different zero mean Gaussian PDFs with different variances σ_m^2, where the PDFs are weighted by the Poisson PDF P_m. Another popular impulse noise model, which is a sum of two Gaussian PDFs weighted according to the Bernoulli distribution, exists in the literature and is called the *Bernoulli-Gaussian* noise model (found in [12]–[15].) This noise model is described by the following PDF:

$$F_{BG}(n_k) = (1-p)\mathcal{N}(n_k; 0, \sigma_g^2) + p\mathcal{N}(n_k; 0, \sigma_g^2 + \sigma_I^2). \quad (4)$$

The Bernoulli-Gaussian noise model has similarities to the Class A noise model. To show the similarities, we use the channel models in Fig. 2. Fig. 2 (a) is a two-state representation of the Class A noise model, and Fig. 2 (b) is a representation the Bernoulli-Gaussian noise model. The models in Fig. 2 look very similar, with the only difference that in Fig. 2 (b) it is explicitly stated that the noise sample added to the data symbol D_k, in either of the two states, is Gaussian distributed. Whereas in Fig. 2 (a), only the state with variance σ_g^2 can have a Gaussian distribution. However, the state with impulse noise may not necessarily have a Gaussian distribution. For the two models in Fig. 2 to be more similar, the probabilities of being in the impulse noise sates should be the same, $A = p$.

The Bernoulli-Gaussian noise model has been widely adopted in the literature, and some researchers prefer to employ it over the Class A noise model because it is more tractable than the Class A noise model. The Class A model has the advantage of having its parameters directly related to the physical channel. If so desired the Class A model can be adjusted to approximate the Bernoulli-Gaussian, hence giving the Bernoulli-Gaussian model the advantages of the Class A model as well.

The Class A model can also be simplified, and be made more manageable. It was shown in [5] that the PDF of the Class A noise model in (1) can be approximated by the first few terms of the summation and still be sufficiently accurate. Truncating (1) to the first K terms results in the approximation PDF (normalised), which is

$$F_{M,K}(n_k) = \sum_{m=0}^{K-1} P'_m \mathcal{N}(n_k; 0, \sigma_m^2), \quad (5)$$

where

$$P'_m = \frac{P_m}{\sum_{m=0}^{K-1} P_m}.$$

The model in (5) allowed Vastola [5] to design a threshold detector with a simpler structure than he would with the model in (1) which has infinite terms. It was also shown in [5] that the first two or three terms are good enough in (5) to approximate the PDF in (1). In [11], the first four terms were used to approximate the PDF of the Class A model. In our simulations, we shall use up to the first five terms of (5), and such a model is shown in Fig. 3.

We now give some results showing the bit error rate (BER) versus SNR, when using the model in (5) for different K values. Such results are shown in Figs. 4 and 5, where BPSK modulation is used and $K = 2$, 3 and 5. In each figure, we use a theoretical BER curve for BPSK (given by (6) for $M = 2$, where M is the order of the PSK modulation and E_b is the signal's bit energy) as a reference curve against which all curves are compared. Figs. 4 and 5 show the effect of different values of A and Γ on the model.

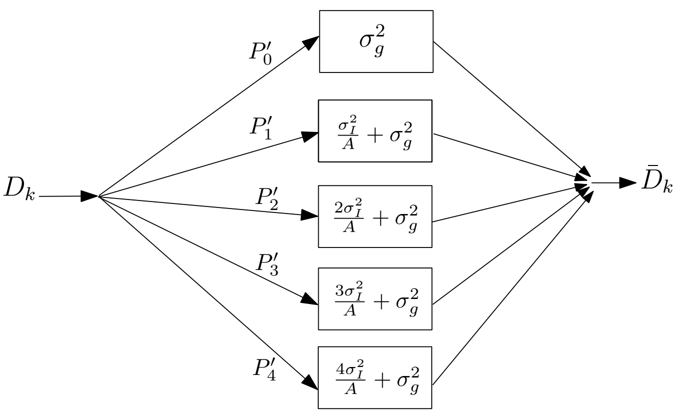
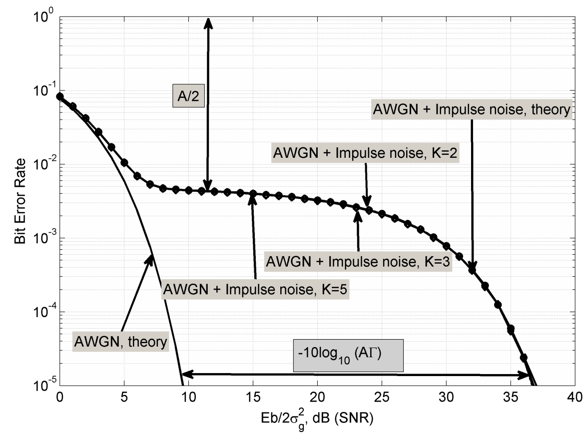
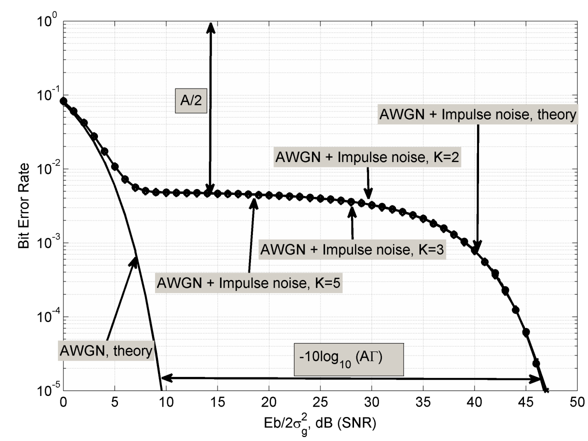


Fig. 3. Five-term, $K = 5$, approximation of the Class A model.



(a) $A = 0.01$, $\Gamma = 0.1$.



(b) $A = 0.01$, $\Gamma = 0.01$.

Fig. 4. Bit error rate results using the impulse noise model shown in Fig. 3, with $K = 2$, 3 and 5. BPSK was used for the modulation.

$$P_{e,MPSK} = (1-A)\frac{M-1}{M}Q\left(\sqrt{\frac{E_b}{\sigma_g^2}}\right) + A\frac{M-1}{M}Q\left(\sqrt{\frac{E_b}{\sigma_g^2(1+1/A\Gamma)}}\right). \quad (6)$$

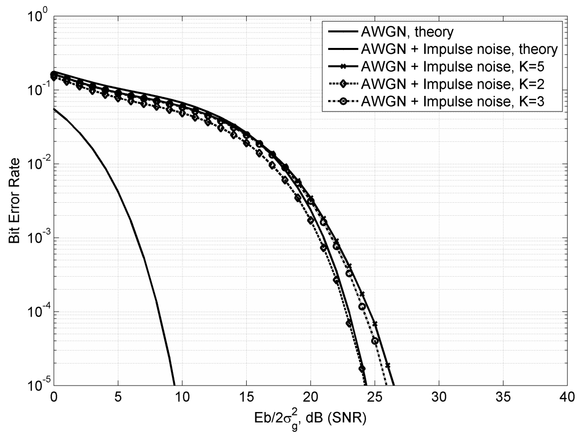
Note that the expression in (6) is normally written without the term $(M-1)/M$. However, for accuracy, the $(M-1)/M$ term needs to be included in the expression to indicate that a symbol affected by noise only gets to be in error with probability $(M-1)/M$. This is important for low order modulation, but can be neglected for higher order modulation because the term approaches one as M gets larger.

It can be observed in Figs. 4 and 5 that the model in (5) approximates the Class A model in (1) better for low values of A (see Fig. 4), such that even for two terms, $K = 2$, we get a very good approximation of the theoretical BER curve. For high values of A (see Fig. 5), however, we require more terms in (5) to approximate the results of the model in (1), at least for the part of the curve influenced by A (the error floor).

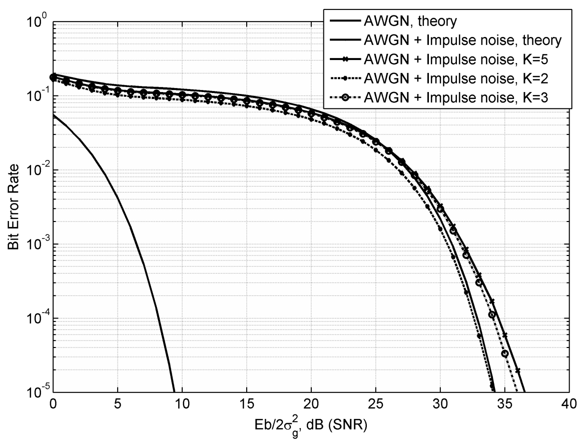
Fig. 5 shows that the results of the $K = 5$ channel model closely approximate the effect of A on the BER curve better than when $K = 2$. This is obviously due to the fact that the more terms (higher K values), the better the approximation of the Class A PDF. However, the $K = 2$ channel model results show a better approximation of the impulse noise power ($1/(A\Gamma)$, which is observed around a BER of 10^{-5}) compared to when $K = 5$. This is because of the m parameter in the term $\sigma_I^2 m/A$ in (3), which influences the impulse noise power. Using more terms in (5) to approximate the results of the model in (1) is more effective in estimating the effect of A in the BERs, but not the impulse noise power.

B. Impulse noise models with memory

Through measurements in a practical communications channel, Zimmermann and Dostert [16] showed that impulse noise samples sometimes occur in bursts, hence presenting a channel with memory. They further proposed an impulse noise model that takes into account the memory nature of impulse noise. Following the work [16], other authors studied impulse noise with memory as seen in [17], [18], [11] and [19]. To model impulse noise with memory, Markov chains are invariably used



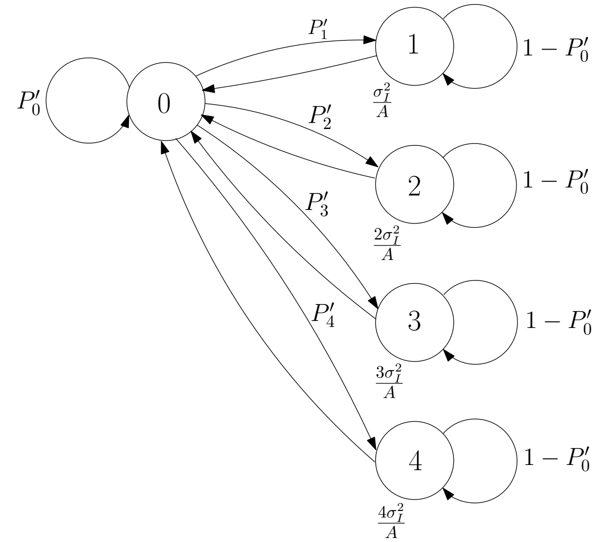
(a) $A = 0.3$, $\Gamma = 0.1$.



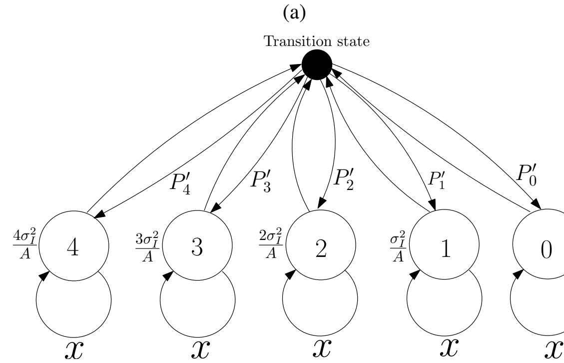
(b) $A = 0.3$, $\Gamma = 0.01$.

Fig. 5. Bit error rate results using the impulse noise model shown in Fig. 3, with $K = 2$, 3 and 5. BPSK was used for the modulation.

by most authors in the literature. The two models, *Markov-Middleton* [11] and *Markov-Gaussian* [18] are modifications of the Class A and Bernoulli-Gaussian models, respectively, by including Markov chains. Having discussed the impulse noise models without memory, there is no need for a lengthy discussion about the impulse noise models with memory. This is because the impulse noise models with memory are founded on those models without memory. In Fig. 6 we show Markov-Middleton models, which means Class A model with memory. These models in Fig. 6 are an adaptation of the model shown in Fig. 3. The model in Fig. 6 (a) is a "direct" adaptation of the one in Fig. 3, with all the parameters unchanged except for the introduction of memory. However, the model in Fig. 6 (b) [11] allows for all states to be connected such that it is possible to move from one bad state (state with impulse noise) to another bad state, which was not possible with the models in Fig. 3 and Fig. 6 (a). With this modification, in Fig. 6 (b), comes a new parameter x, which is independent of the Class A model parameters A, Γ and σ_I^2. The parameter x describes the time correlation between noise samples. The transition state in Fig. 6 (b) has no time duration, it facilitates the connection of the other states. It was shown in [11] that the PDF of their model in Fig. 6 (b) is equivalent to that of Class A model shown in (5).



(a)



(b)

Fig. 6. Markov-Middleton impulse noise models with five terms: (a) is adapted from [20] and (b) is adapted from [11]

C. Multi-carrier and Single-carrier modulation with Impulse noise

Many authors may correctly argue that the short fall of the Class A and Bernoulli-Gaussian noise models is that they do not take into account the bursty nature of impulse noise. However, for MC modulation it does not matter whether the noise model employed has memory or is memoryless. This is because in MC modulation like OFDM, the transform spreads the time domain impulse noise on all the subcarriers in the frequency such that it becomes irrelevant how the noise occurred (in bursts or randomly). When it comes to SC modulation, however, it is important to distinguish impulse noise with and without memory.

Here we employ the two-state Class A memoryless model in Fig. 2 (a), with the PDF of the state with impulse noise and AWGN being Gaussian. This makes the model more similar to the Bernoulli-Gaussian in Fig. 2 (b). In this two-state Class A model, ignoring the effect of the background noise for a moment, we know that the average impulse noise power is

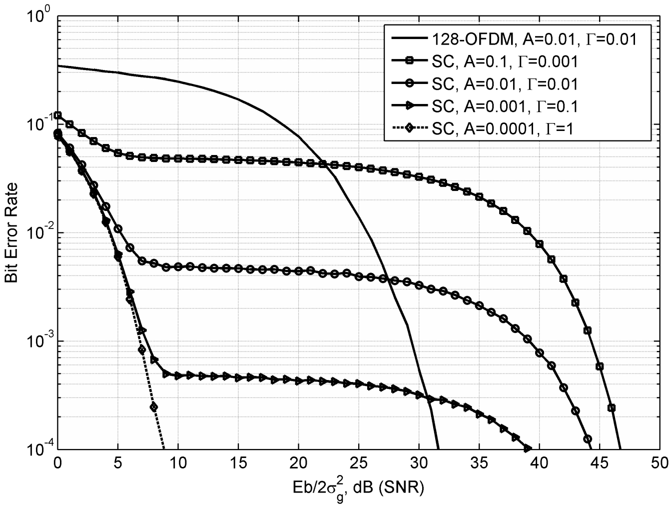


Fig. 7. Comparison of MC and SC modulation in a channel with AWGN and impulse noise of variance $\bar{\sigma}_I^2 = \sigma_g^2/A\Gamma = 1/(0.01 \times 0.01) = 10^4$. $\bar{\sigma}_I^2$ is fixed at 10^4 while different values of A (10^{-1}, 10^{-2}, 10^{-3} and 10^{-4}) are seen to influence the performance of SC modulation.

$\sigma_I^2 = \sigma_g^2/\Gamma$. The impulse noise power affecting a symbol is $\bar{\sigma}_I^2 = \sigma_I^2/A = \sigma_g^2/A\Gamma$. For discussions and analysis, we will be using the impulse noise power $\bar{\sigma}_I^2 = \sigma_g^2/A\Gamma$.

Given a fixed impulse noise power $\bar{\sigma}_I^2 = \sigma_g^2/A\Gamma$, we vary impulse noise probability A and the impulse noise strength Γ such that $\bar{\sigma}_I^2$ remains the same. This means that if we lower A by a certain amount, we have to increase Γ by the same amount such that the product $A\Gamma$ is unchanged. This we do in order to keep $\bar{\sigma}_I^2$ the same, while observing the effect of changing the probability of impulse noise A on the performance of Single-Carrier and Multi-Carrier Modulation. It is interesting to note that for very low A, SC modulation performs better in the low SNR region compared to MC modulation. However, SC modulation gives an error floor, while MC modulation does not. This behaviour is seen in Fig. 7.

Two important conclusions can be drawn from the behaviour observed in Fig. 7:

- For very low A, very few symbols are affected in SC modulation, hence the low probability of error in SC no matter the strength (or average variance) of the impulse noise. However, with MC modulation, what matters is the average impulse noise variance in the system because the noise power is spread on all subcarriers causing every symbol to be affected by the impulse noise.
- MC modulation has the benefit of eventually outperforming SC modulation as the SNR increases. This is because with MC modulation, the factor $1/A$ does not show up in the SNR requirement like in SC modulation.

From the two points above, we can say that one has to carefully choose between MC and SC modulation depending on the probability of impulse noise that can be tolerated in the communication. By this we mean that if, for example in Fig. 7, $A = 10^{-4}$ and communication is acceptable at probability of error of 10^{-4}, then SC modulation will be the best choice over MC modulation because it will only give an error floor just below A, at $A(M-1)/M$. Ghosh [12] also mentioned that there are conditions where SC modulation performs better than MC modulation. It was also shown in [13], using the Bernoulli-Gaussian noise model, that the impact of impulse noise on the information rate of SC schemes is negligible as long as the occurrence of an impulse noise event is sufficiently small (i.e. very low p in (4).)

III. Combating Impulse noise

Several techniques for combating impulse noise have been presented in the literature. These techniques fall into the following three broad categories:

1) *Clipping and Nulling (or Blanking)*:
With clipping or nulling, a threshold T_h is used to detect impulse noise in the received signal vector $\mathbf{r}$ before demodulation. Clipping and nulling differ in the action taken when impulse noise is detected in $\mathbf{r}$. If a sample of $\mathbf{r}$, r_k is detected to be corrupted with impulse noise, its magnitude is clipped/limited according to T_h (Clipping), or set to zero (Nulling). Given the received sample r_k, then the resulting sample $\tilde{r}_k$, from the clipping technique, is given by

$$\tilde{r}_k = \begin{cases} r_k, & \text{for } |r_k| \le T_h \\ T_h e^{j\arg(r_k)}, & \text{for } |r_k| > T_h \end{cases},$$

and the resulting sample $\tilde{r}_k$, from the nulling technique, is given by

$$\tilde{r}_k = \begin{cases} r_k, & \text{for } |r_k| \le T_h \\ 0, & \text{for } |r_k| > T_h \end{cases}.$$

Zhidkov [21] gave performance analysis and optimization of blanking for OFDM receivers in the presence of impulse noise, as well as a comparison of clipping, blanking, and combined clipping and blanking in [22]. In [23], the authors advocated for the clipping technique to combat impulse noise in digital television systems. The clipping technique is also seen in [24].

2) *Iterative*:
With the iterative technique, the idea is to estimate the impulse noise as accurately as possible and then subtract the noise from the received vector $\mathbf{r}$. The noise estimation can be done in the time and/or frequency domains. For good iterative methods, the more iterations the better the estimate of the impulse noise. There is of course a limit to the number of iterations, above which there is little or no improvement in the technique. One of the earliest works on the iterative technique to suppress impulse noise is by Haering and Vinck [7]. Another application of the iterative technique against impulse noise is found in [25].

3) *Error correcting coding*:
Error correcting coding has become a necessary part of any communications system in order to correct errors caused by channel noise. In impulse noise environments, error correcting codes are employed to correct errors

cause by impulse noise. Most research on using error correcting codes to combat impulse noise effects tend to lean towards convolutional coding [26] [27], Turbo coding [28] [29] and low density parity-check coding [30] [31] or codes that are iteratively decoded [9].

IV. Conclusion

We have discussed some important impulse noise models found in the literature. The noise models are divided into those without memory (Middleton Class A and Bernoulli-Gaussian) and those with memory (Markov-Middleton and Markov-Gaussian). We went further to look at the approximation of the PDF of the Middleton Class A model with five terms. We also showed that the Bernoulli-Gaussian model has similarities with the Middleton Class A, and it can be approximated with the Middleton Class A model. We then showed Bit error rate simulation results of the approximation of the Middleton Class A with five terms. Using the Middleton Class A model with five terms we showed equivalent Markov-Middleton models. We also showed that single-carrier modulation performs better than multi-carrier modulation under low probability of impulse noise occurrence. Lastly, we discussed impulse noise mitigation schemes: clipping, nulling, iterative and error correcting coding.

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