A blind LLR estimation for impulsive noise

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***Abstract*—Many decoding schemes rely on the log-likelihood ratio (LLR). Its derivation rely on the knowledge of the noise distribution. In dense and hetrogeneous network settings, this knowledge can be difficult. Besides, when interference exhibits an impulsive behaviour, the LLR becomes highly non-linear and, consequently, computationally prohibitive. In this paper, we propose to directly estimate the LLR, without relying on the interference plus noise knowledge. We propose to select the LLR in a parametric family of functions, flexible enough to be able to represent many different communication contexts. It also allows to limit the number of parameters to be estimated. Furthermore, we propose an unsupervised estimation approach which do not necessitate a training sequence. Our estimation method is shown to be efficient and, if the set of parametric function is well chosen, the receiver exhibits a near-optimal performance.**

***Index Terms*—LLR estimation, impulsive noise, unsupervised learning.**

I. Introduction

5G will have to deal with dense and heterogeneous networks. In such situations, interference may exhibit a dynamic behaviour [1], [2], [3] where the Gaussian assumption is no longer suited. In order to establish reliable and efficient communications, one needs to take into account the impulsive nature of the interference while designing the receivers. Indeed, traditional linear receivers under impulsive noise were shown not to be robust enough leading to a dramatic performance degradation [4]. Several papers proposed ways to overcome the presence of non-Gaussian interference by using different metrics to make the decision, e.g. a robust metric mixing euclidean distance and erasure [5], p-norm [6], Hubber metric [7]... Nevertheless, the approaches are designed for a specific noise model and their robustness against a model mismatch is not ensured. The choice of a more universal solution that can be used for various impulsive noise is thus salutary.

Many receivers rely on the Likelihood. In the binary case, this can be captured through the log-likelihood ratio (LLR). This is very attractive when noise is Gaussian because it leads to a linear receiver, straightforward to implement. However, when rare events with large amplitudes (impulsive noise) arise, the LLR becomes a non-linear function. Its implementation is complex and highly depends on the noise distribution. Consequently, to obtain the optimal receiver, the noise distribution has to be known and if it falls in a parametric family, the parameters have to be estimated. In addition to the complex implementation of a non-linear function, we can identify two sources of performance degradation: a noise model mismatch and errors in parameters estimation.

In this paper we propose to address these questions. Our solutions resides in three steps:

1) First, we propose to approximate the LLR by a function which will be chosen in a family of parametric functions. If the family is large enough, this allows to adapt to many different types of noises but it does not rely on a noise assumption. Besides, if we consider a family defined by a limited number of parameters and easy to implement, it reduced both the estimation and implementation complexities.
2) Second, we propose a robust way to estimate the parameters of the LLR approximation. The solution is based on a mutual information maximization.
3) Finally, we propose a blind estimation solution. It avoids the need of training data that reduce the useful information rate. It also allows to take benefit from the whole data sequence to improve the accuracy of the estimation.

Our work can be seen as a generalization of some previous works that dealt with an approximation of the LLR function. If the soft limiter and the hole puncher are probably the best-known solutions, we previously proposed the approximation function: $f(x) = \text{sign}(x)\text{min}(a|x|, b/|x|)$ [8]. The family $f(x) = x/(ax^2 + b)$ was proposed in [9] and linear by parts functions in [10]. We will not focus in this paper on the best family choice but on a generic way to estimate the approximation parameters in an unsupervised manner.

The remaining of the paper is organized as follow. Once the system model and some background material are given in section **??**, section **??** undertakes the parameters' optimization in supervised and unsupervised ways. Section **??** presents numerical simulations under alpha-stable noise. Thereafter section **??** investigates the robustness and adaptability of our receiver in various noise models and, finally, section IV concludes the paper.

II. LLR approximation and estimation

A. System model and LLR

Let us consider the transmission of a binary message $X \in \{+1; -1\}$ with equal probability. The received signal Y can be written as $Y = X + N$, the addition of the source signal X and an interference term (interference limited regime) N, where N is assumed to be independent of X. Throughout this paper, we focus on a transmission over a memory-less binary input symmetric-output (MBISO) channel. Such a channel can be described by its conditional pdf $f_{Y|X}(y|x)$ with $f_{Y|X}(y|x = +1) = f_{Y|X}(-y|x = -1)$.

By considering an additive noise MBISO channel, the LLR of the binary channel input X associated with the channel output Y is given by:

$$\Lambda(y) = \log \frac{\Pr(Y = y|X = +1)}{\Pr(Y = y|X = -1)} = \log \frac{f_N(y - 1)}{f_N(y + 1)} \quad (1)$$

where $f_N(\cdot)$ is the pdf of the noise N.

In various situations, obtaining the LLR can be computationally very costly; for instance over additive symmetric α-stable (SαS) noise (AISαSN) channel for which no closed form of the LLR can be obtained [4]; or with Middleton type noises which involve infinite series [11]. However, many decoding solutions rely on the soft information given by the LLR, like the Belief Propagation algorithm used to decode LDPC codes. In such cases, obtaining an easy to implement approximation of the LLR can be crucial. This can be done through the use of simple approximations. It has been shown in several papers [8], [9], [10] and it allows good performance in terms of BER with a drastic reduction in the computation complexity. In order to narrow the search space of the best approximation, the functions that we look for belong to a parametric family L_θ. Our goal is to find a generic way to estimate θ. For this we first choose a criteria design. Because there is not an easy analytic link between the LLR and the BER or PER (that is what we aim at minimizing), we propose to use the capacity of the MBISO channel that can be expressed as a function of the LLR.

B. Capacity, LLR and optimization problem

The capacity of a MBISO channel is given by the mutual information (MI) between the input X and the output Y as $C(X,Y) = I(X,Y)$, such that $\Pr(X=1) = \Pr(X=-1) = 1/2$. In this case, the capacity [12] can be given as:

$$C_L(X,Y) = 1 - \mathbb{E}\left[\log_2\left(1 + e^{-X.\Lambda(Y)}\right)\right]. \tag{2}$$

If now we modify the LLR calculation by using the approximation function L_θ, the mutual information is modified. We can calculate the capacity of a MBISO channel that includes the approximated LLR by:

$$C_{L_\theta}(X,Y) = 1 - \mathbb{E}\left[\log_2(1 + e^{-X.L_\theta(Y)})\right] \tag{3}$$

$$\approx 1 - \lim_{N\to\infty} \frac{1}{N}\sum_{n=1}^{N} \log_2\left(1 + e^{-x_n L_\theta(y_n)}\right), \tag{4}$$

where in (4) we estimate the expectation based on samples x_n and y_n that represent the input and the output of the channel respectively. Authors in [13] proved that (3) is maximized if $L_\theta = \Lambda$, leading to $C_{L_\theta} = C_L$.

Maximizing C_{L_θ} in (4) over the possible choices of θ will allow us to find the approximation in the considered family that maximizing the mutual information and, consequently, should be a good choice for our decoding algorithm. PAS TRÈS SUR DE COMMENT ARGUMENTER ÇÀ... FAUT-IL LE FAIRE?. Our optimization problem is therefore given as:

$$\begin{aligned}\theta^* &= \arg\max_\theta C_{L_\theta}(X,Y). \\ &= \arg\min_\theta \underbrace{\frac{1}{N}\sum_{n=1}^{N}\log_2\left(1+e^{-x_n L_\theta(y_n)}\right)}_{f_{opt}(\theta)}.\end{aligned} \tag{5}$$

Equivalently, the maximization of the capacity is achieved by minimizing $f_{opt}(\cdot)$.

Our next question is then to know if our problem has a solution and if that solution will be easy to find

C. Convexity

In the following we consider linear piece-wise functions.

Proposition 1 *If the estimate LLR L_θ is a linear piece-wise function of θ, then the optimization problem is convex and there exists a unique optimal value θ^* that minimizes f_{opt}, hence that maximizes C_{L_θ}.*

Proof: For clarity reasons, we present the proof based on $L_\theta = L_{a,b}$ defined in (10), but the result can be easily extended to any linear piece-wise function.

$$L_{a,b}(y) = \begin{cases} ay & \text{if } y^2 \le b/a \\ b/y & \text{else}\end{cases} \tag{6}$$

Let us consider the function $f(a,b) = \log_2(1 + e^{-x.L_{ab}(y)})$. Note that f_{opt} is given as a weighted sum of such functions thus if one can prove that f is a convex function then $f_{opt}(a,b)$ is also convex.

The Hessian of the function f is given as

$$\bigtriangledown^2 f = \begin{cases} \begin{bmatrix} \frac{y^2x^2e^{axy}}{(1+e^{axy})^2} & 0 \\ 0 & 0\end{bmatrix} & \text{if } y^2 \le b/a \\ \begin{bmatrix} 0 & 0 \\ 0 & \frac{x^2e^{bx/y}}{y^2(1+e^{bx/y})^2}\end{bmatrix} & \text{else}\end{cases} \tag{7}$$

To show that our problem is convex, one need to show that $\forall z \in \mathbb{R}^2$, $z^T \bigtriangledown^2 f z \ge 0$. Let $z = [z_1, z_2]^T \in \mathbb{R}^2$.

$$z^T \bigtriangledown^2 f z = \begin{cases} z_1^2 \frac{y^2x^2e^{axy}}{(1+e^{axy})^2} & \text{if } y^2 \le b/a \\ z_2^2 \frac{x^2e^{bx/y}}{y^2(1+e^{bx/y})^2} & \text{else}\end{cases} \tag{8}$$

$$\ge 0 \,\forall z \in \mathbb{R}^2 \tag{9}$$

Thus, the function f_{opt} is convex leading to the existence of a unique optimal point $\theta^* = [a^*, b^*]$ that maximizes the capacity under the approximated LLR L_θ.

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A consequence is that we can implement the optimization problem via a simplex method based algorithm [14].

Proposition 2 *If the estimate LLR L_θ is a non-linear function of θ, then we cannot guarantee the convexity of the optimization problem, thus, a global search method is used to find a unique optimal value θ^* that minimizes f_{opt}, hence maximizes C_{L_θ}.*

Proof: For clarity reasons, we present the proof based on non linear approximation $L_\theta = L_{a,b}$ defined in (10).

$$L_{a,b}(y) = \frac{y}{ay^2 + b} \tag{10}$$

Let us consider the function $f(a,b) = \log_2(1 + e^{-x.\frac{y}{ay^2+b}})$. Note that f_{opt} is given as a weighted sum of such functions thus if one can prove that f is a convex function then $f_{opt}(a,b)$ is also convex.

The Hessian of the function f is given as

$$\bigtriangledown^2 f = xy\mathbf{K}\begin{bmatrix} y^4 & y^2 \\ y^2 & 1\end{bmatrix} \tag{11}$$

where

$$xy\mathbf{K} = \frac{\varphi y^2 x^2 - 2xy\left(\varphi + 1\right)\left(ay^2 + b\right)}{\ln\left(2\right)\left(\varphi + 1\right)^2\left(ay^2 + b\right)^4} \tag{12}$$

$$\varphi = \mathrm{e}^{\frac{y}{ay^2+b}} \tag{13}$$

To show that our problem is convex, one need to show that $\forall z \in \mathbb{R}^2$, $z^T \bigtriangledown^2 fz \geq 0$. Let $z = [z_1, z_2]^T \in \mathbb{R}^2$.

$$z^T \bigtriangledown^2 fz = xy\mathbf{K}(z_1 y^2 + z_2)^2 \qquad \geq 0 \, \forall z \in \mathbb{R}^2 \tag{14}$$

Thus, the function f_{opt} cannot be guaranteed to be positive leading to the existence of a several local solutions.

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D. Unsupervised optimization.

To solve (5), we need a received sequence y_n as well as the corresponding transmitted one x_n. This is usually obtained thanks to the use of a training sequence [15]. However, the consequence is an increase in the signaling and a decrease in the useful data rate.

Unsupervised optimization is thus attractive since it does not imply any overload. Besides, a good aspect of having such an unsupervised approach is that we optimize the approximation function directly from the sequence that we are going to decode. In other words, the noise impacting the training phase and the decoding phase will be the same ensuring the best knowledge of the actual channel state.

The idea behind our approach is to obtain a noise sequence N from the received sequence Y. To do this, we use a sign-detector ($\text{sign}(x) = x/|x|$)

$$\widetilde{N} = Y - \text{sign}(Y). \tag{15}$$

where $\widetilde{N}$ is the generated noise sequence. Using $\widetilde{N}$, a new channel can be simulated with a known input $\widetilde{X}$ as shown in Fig. 1. More precisely, $\widetilde{X}$ is an i.i.d. BPSK random variable that is independent of $\widetilde{N}$. The channel output $\widetilde{Y}$ is obtained by adding $\widetilde{X}$ and $\widetilde{N}$ and the optimization parameter θ can be estimated based on (5) but with the newly generated input and output:

$$\theta^* = \arg\max_{\theta} C_{L_\theta}(\widetilde{X}, \widetilde{Y}). \tag{16}$$

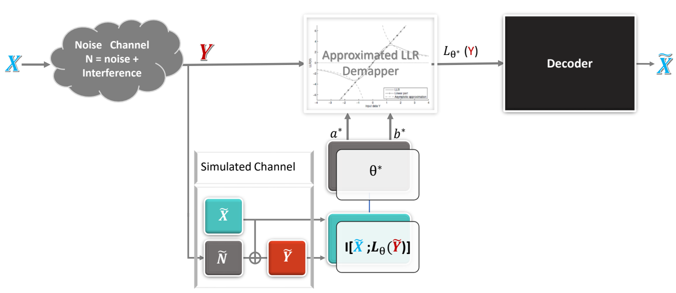

Fig. 1: Unsupervised LLR demapper.

Once the optimal parameters θ^* are obtained, the LLR will be approximated by $L_{\theta^*}(Y)$.

III. Application to LDPC coding used over additive impulsive noise

A. Simulation setup

1) Source: To validate our approach we use a Low-Density Parity Check (LDPC) code and a belief propagation (BP) decoding algorithm. This case is well-suited to our proposal because the LLR have to be estimated and fed to the BP algorithm.

The binary message X is encoded using a regular (3,6) LDPC code of length 20000. LDPC codes introduced by Gallager [16] and rediscovered by Mackay [17] are powerful block codes due to their near capacity performance under Gaussian noise. They are widely used in various standards such as DVB-S2 and WiMAX. Thanks to the sparseness of the parity check matrix of the LDPC codes, the BP algorithm exhibits a quasi-linear complexity as the code length growth.

2) Noise: Non Gaussian noises can arise in networks like it has been shown many times. In the following we assume that the additive noise impacting the transmission exhibits an impulsive nature. In a first step, we will use Symmetric α-stable ($S\alpha S$) distributions to model this impulsive interference, since the heavy tail property of their pdf has been shown to coincide with the impulsive nature of network interference in various environment types [18], [19], [20], [21] . Unfortunately, in general, no closed-form expression of its pdf exists, which prevents the extraction of a simple metric based on the noise pdf in the decoding algorithm. This is precisely a case that can be solved by our proposal.

We also want to be model agnostic. Consequently we will study the behavior of our approach with other classical noise models: a simple Gaussian noise, a Middleton class A and an ϵ-contaminated.

3) LLR approximation: If the noise is Gaussian, the decoder's inputs (LLR) are given as a linear function of the received signal Y. The family of function should then simply be:

$$L_a(y) = ay \tag{17}$$

and θ is a single parameter, the slope a of the linear function. The optimal a in additive white Gaussian noise channel only depends on the noise variance as $L_a(y) = \frac{2}{\sigma_N^2} y$.

Nevertheless, using only a linear scaling whose slope depends on the additive noise variance leads to severe performance loss as soon as noise is impulsive. This performance loss occurs because with this linear scaling, large values in Y result into large LLR. However, under impulsive noise, large values in Y are more likely due to an impulsive event so that the LLR should be small, meaning a poorly reliable sample due to the presence of a large noise sample.

Fig. 2 lightens the non-linearity of the LLR function for the channel output Y when the noise is α-stable. Even if Fig. 2 delineates a specific noise model, the overall appearance of the LLR exhibits a similar behavior when noise is impulsive. At a first look, two different parts in the LLR can be observed: a first one when y is close to zero and another one when y becomes large enough. When y is close to zero, the LLR is almost linear, whereas when y is large enough, the LLR presents a power-law decrease. The linear region spreads with

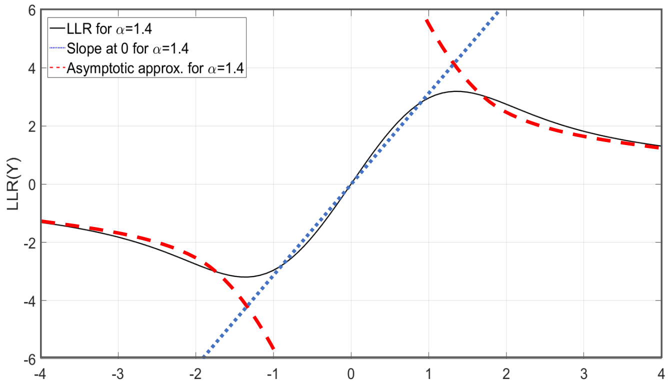

Fig. 2: LLR demapper for $\alpha = 1.4$, $\gamma = 0.5$, and its approximation.

the decrease of the noise impulsiveness until reaching the limit (only the linear part exists), when the noise is Gaussian. Several approximations taking into account these two parts have been proposed [8], [22], [23], [24]. For illustration purposes, we choose the LLR approximation family $L_{a,b}$ given in (10).

B. Estimation in Additive $S\alpha S$ Noise

1) Analysis: In a first step, we investigate the shape of the function $f_{\text{opt}}(a, b)$ in (5). In this paper we present the obtained results for a highly impulsive noise when $\alpha = 1.4$, but the same observations and conclusions can be made for higher α. In Fig. 3, we draw a 3D and contour plot that delineates the different f_{opt} level values for different combinations of a and b. We verify the convexity of the function. We also notice that the function is rather flat, the convergence should be easy but the estimation steps could be quite sensitive to noise. The optimization procedure could then have a significant impact and the system could be sensitive to the length of the training sequence. Using the whole data set in an unsupervised approach can then be a source of robustness.

In Fig. 4 we illustrate the link between the function $f_{\text{opt}}(a, b)$ and the BER obtained after decoding. We show the contour plot of $f_{\text{opt}}(a, b)$, meaning all values inside the circle corresponds to a smal value of the function. We also show the BER contour plots. The region matches and all the values minimizing $f_{\text{opt}}(a, b)$ give a BER under 10^{-4}. These pictures conforts us in the choice of the criteria to find θ.

The enclosed minimal level of f_{opt} value matches the low BER levels as shown in Fig. 4, thus, obtaining the optimal value of f_{opt} ideally, will result with the optimal BER.

2) Estimation performance: Fig. 5, respectively Fig. 6, compares the evolution of the mean and variance of the estimated parameter a, respectively b, as a function of the dispersion γ of a $S\alpha S$ noise with $\alpha = 1.4$ under supervised and unsupervised optimization. For each noise dispersion, we ran 100 experiments. For the supervised case, we use a learning sequence of 20000 samples to estimate a and b. This allows to have a good idea of the results with a very small estimation error but, in a practical setting, such a long training sequence is not reasonable and additional errors can be expected.

In Fig. 5, the gap between the obtained values for parameter a under supervised and unsupervised optimization is small. In Fig. 6, the one obtained for b is significantly larger. This difference can be explained because b mainly depends on large noise samples which are rare events. Consequently, its estimation is less accurate. Nevertheless, the unsupervised approach generates a bias.

We can however expect that the error on b will have a limmited impact in terms of BER performance. Indeed, as shown in Fig. 4 when $\gamma = 0.45$, both a and b estimated mean values under the supervised and unsupervised approach fall in the small BER region. Besides, the small variance of the estimation ensures that most of the estimated values will fall in the same reagion.

To complete the study we present in Table I the influence of the training sequence length. The variance in a and b gets large when the training sequence gets short. This will probably influence the performance of the system and degrade the BER.

C. BER performance

1) $S\alpha S$ additive noise channel: Once our demapper is tuned with the estimated value θ, it is used as a front-end to the 20000 bits long regular (3,6) LDPC decoder using the BP algorithm over an additive impulsive $S\alpha S$ noise. We study a highly impulsive situation with $\alpha = 1.4$ and a more moderate case with $\alpha = 1.8$.

Fig. 7 and Fig. 8 present the obtained BER for $\alpha = 1.4$ and $\alpha = 1.8$ respectively, as a function of the dispersion γ of the α-stable noise[1]. In both cases, we compare the BER obtained via demapping function, either in a blind or supervised manner, to the BER obtained with the true LLR computed via numerical integration. For each channel set, we use a learning sequence of length (1200 or 20000) to optimize θ in the supervised case; the long training sequence (20000) allows to assess the optimal performance of the supervised estimation, the shorter one (1200) allows to evaluate the loss due to estimation with more realistic training sequences.

First, we note that the estimation with a long training sequence gives performance close to the optimal LLR which shows the good behavior of our demapping function. Moreover, the unsupervised approach does not perform as well as the supervised one with long training sequence but the gap is not so large and the gain in comparison to a linear receiver is enormous. However, when the training sequence is shortened, the supervised estimation degrades and the performance of the blind approach is then much better.

[1]In case of an impulsive environment with $\alpha < 2$, the second-order moment of a stable variable is infinite [18, Theorem 3], making the conventional noise power measurement infinite. Accordingly, we present our simulation results as a function of the dispersion parameter γ, which is used as a measurement of the strength of the α-stable noise.

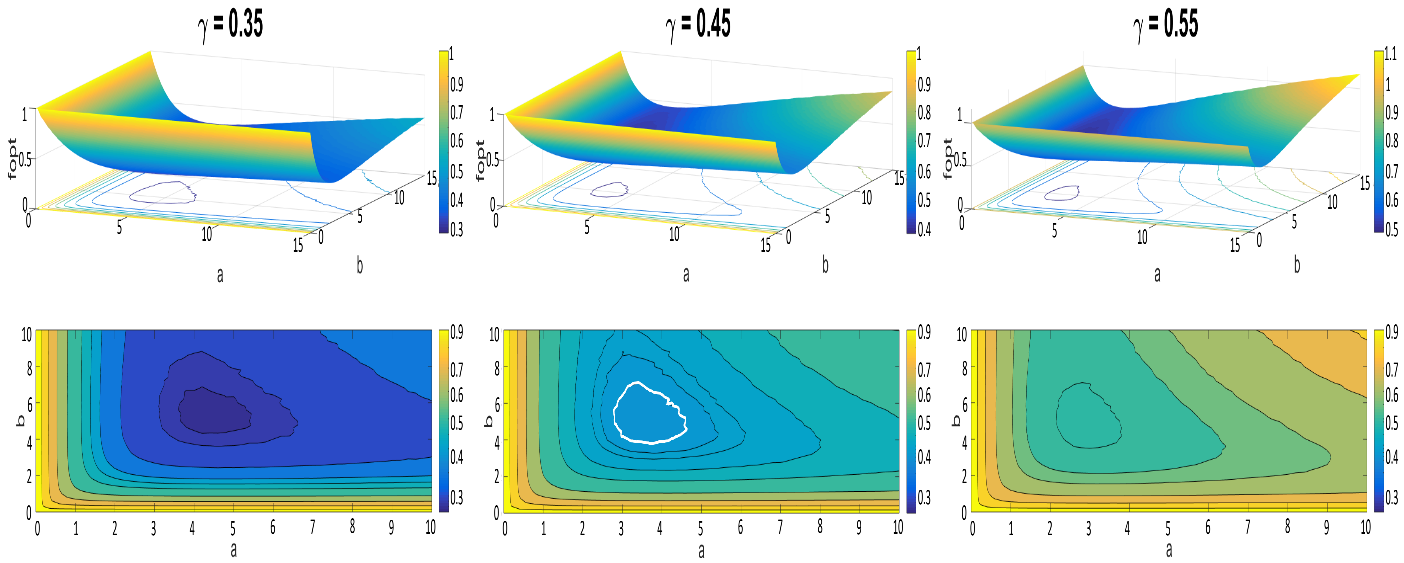

Fig. 3: Behaviour study of the f_{opt} function, as a function of parameters a and b for different values of γ, under highly impulsive $S\alpha S$ noise with $\alpha = 1.4$.

			μ_a	σ_a	μ_b	σ_b
$\alpha = 1.8$	$\gamma = 0.53$	Unsupervised	3.43	0.06	5.73	0.15
		$\text{Sup}_{\text{LS}=20000}$	3.25	0.05	7.59	0.28
		$\text{Sup}_{\text{LS}=1200}$	3.27	0.24	8.50	14.48
		$\text{Sup}_{\text{LS}=900}$	3.27	0.27	11.72	46.15
	$\gamma = 0.55$	Unsupervised	3.23	0.05	5.61	0.14
		$\text{Sup}_{\text{LS}=20000}$	3.05	0.05	7.62	0.28
		$\text{Sup}_{\text{LS}=1200}$	3.07	0.22	7.97	1.54
		$\text{Sup}_{\text{LS}=900}$	3.07	0.26	10.73	30.41

TABLE I: Comparison of the mean and standard deviation evolution for the parameters (a, b) as a function of the dispersion γ of a SαS noise with $\alpha = 1.8$ for the supervised with different learning sequences and unsupervised optimization.

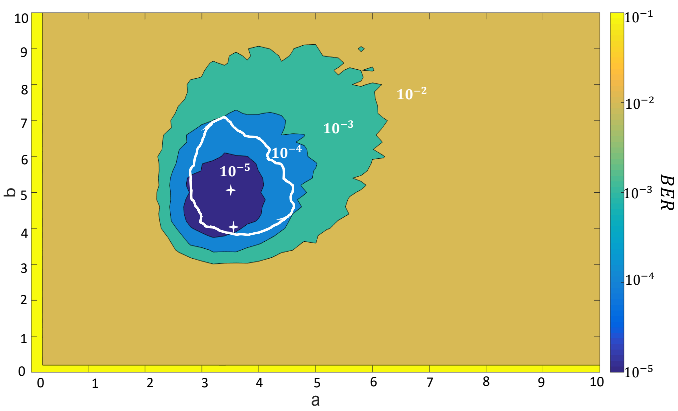

Fig. 4: BER comparison as a function of a and b parameters with $\gamma = 0.45$ and $\alpha = 1.4$ under the supervised approximation.

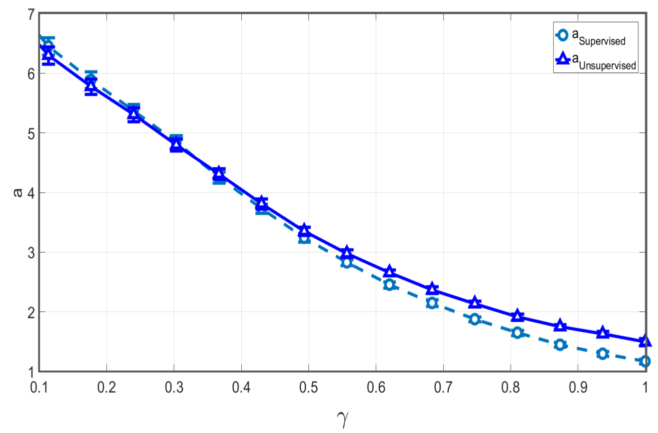

Fig. 5: Comparison of the mean and standard deviation evolution for parameter a as a function of the dispersion γ of a SαS noise with $\alpha = 1.4$ for the supervised and unsupervised optimization.

D. Robustness study of the proposed LLR approximation over impulsive channels

1) Other additive impulsive noise channels: We now consider other models of impulsive noise: the Middleton Class A [25] and ε-contaminated noises [26] We keep the proposed LLR approximation $L_{a,b}$ and test it under three configurations:

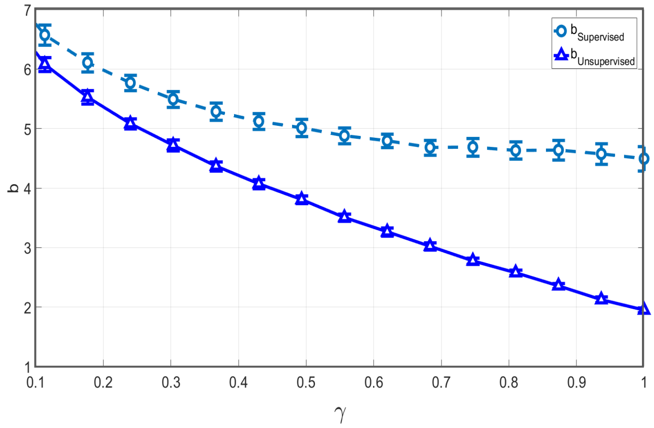

Fig. 6: Comparison of the mean and standard deviation evolution for the parameter b as a function of the dispersion γ of a SαS noise with $\alpha = 1.4$ for the supervised and unsupervised optimization.

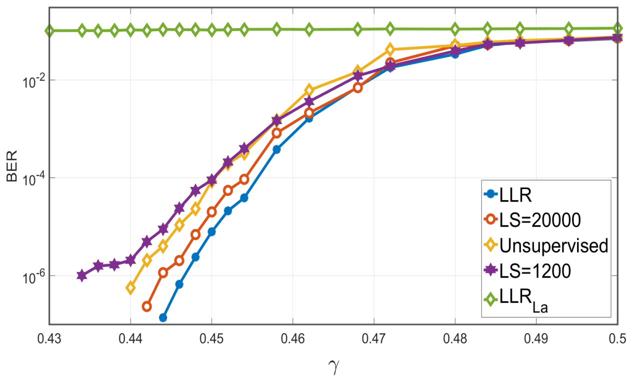

Fig. 8: Evolution comparison of the BER as a function of the dispersion γ of a SαS noise in highly impulsive environment with $\alpha = 1.4$, between the supervised with different learning sequence sizes, unsupervised, Gaussian designed LLR approximations and the LLR obtained by numerical integration.

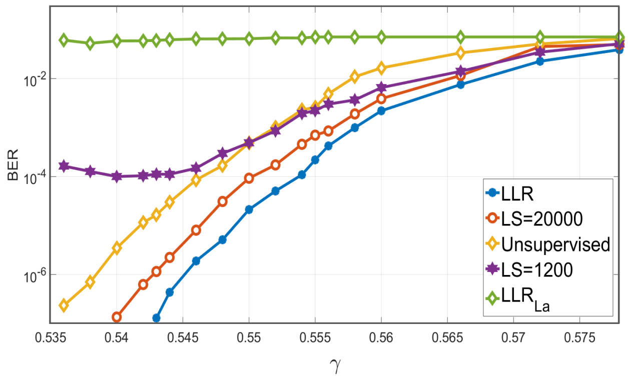

Fig. 7: Evolution comparison of the BER as a function of the dispersion γ of a SαS noise in poorly impulsive environment with $\alpha = 1.8$, between the supervised with different learning sequence sizes, unsupervised, Gaussian designed LLR approximations and the LLR obtained by numerical integration.

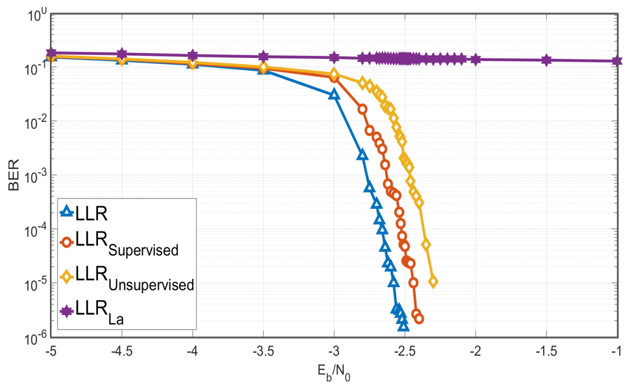

Fig. 9: BER comparison as a function of E_b/N_0 between the supervised, unsupervised, Gaussian designed LLR approximations and the LLR obtained by numerical integration, in highly impulsive ε-Contaminated noise with $\varepsilon = 0.1$ and $K = 10$.

- Highly impulsive ε-contaminated with ε = 10% and $K = 10$, Fig. 9,
- Poorly impulsive Middleton class A with $A = 0.01$ and $\Gamma = 0.01$ taken from [27], Fig. 10,
- Highly impulsive Middleton class A with $A = 0.1$ and $\Gamma = 0.1$ taken from [28], Fig. 11,

In that cases, one can compute the noise variance. We thus present all numerical simulations as a function of the signal-to-noise ratio E_b/N_0. For all cases, we compare the true LLR, obtained via numerical integration to the LLR approximations under supervised, unsupervised parameter estimation and Gaussian designed demapper L_a. For each channel set, in the supervised way, a learning sequence of length 20000 is used to optimize θ.

The high robustness of our demapper can be seen through the close performance obtained between the blind and supervised case from one side, and between both approximations to the true LLR from the other side in spite of the change of the type of noise.

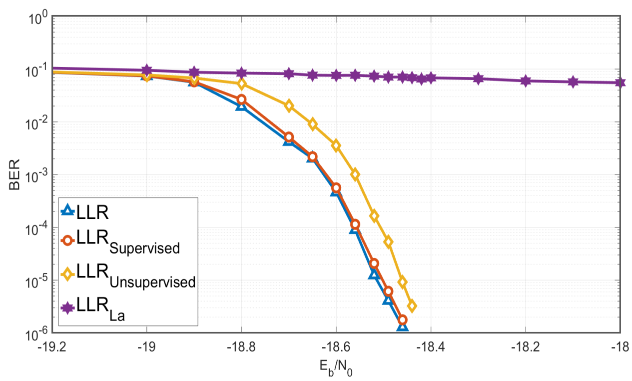

Fig. 10: BER comparison as a function of E_b/N_0 between the supervised, unsupervised, Gaussian designed LLR approximations and the LLR obtained by numerical integration, in poorly impulsive Middleton Class A noise with $A = 0.01$ and $\Gamma = 0.01$.

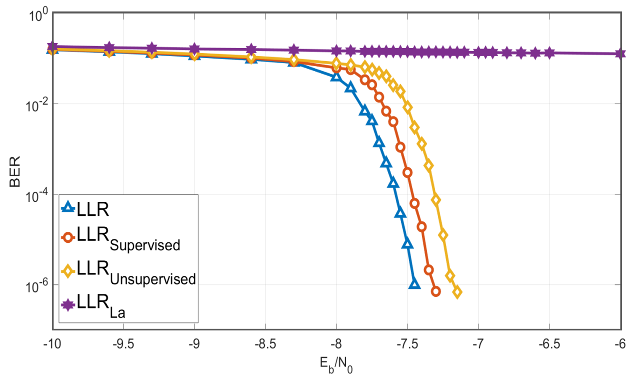

Fig. 11: BER comparison as a function of E_b/N_0 between the supervised, unsupervised, Gaussian designed LLR approximations and the LLR obtained by numerical integration, in highly impulsive Middleton Class A noise with $A = 0.1$ and $\Gamma = 0.1$.

2) Additive Gaussian noise channel: We also want to check if the performance of our decoding scheme is not degraded in a purely Gaussian noise. The approximated LLR $L_{a,b}$ is tested in the presence of a Gaussian noise and results are shon in Fig. 12.

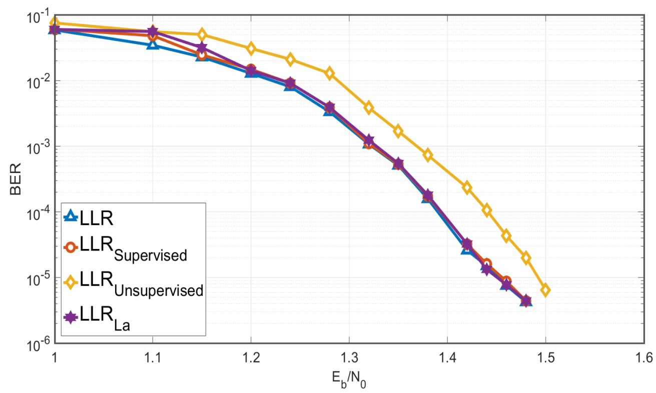

Fig. 12: BER comparison as a function of E_b/N_0 between the supervised, unsupervised LLR approximations and the optimal LLR.

The results show that the proposed approach is still efficient in a Gaussian environment.

3) Analysis: These numerical simulations illustrate the universality of the approach. The LLR family has to be wide enough to be able to represent the linear behavior of exponential-tail noises like the Gaussian and the non-linear behavior of sub-exponential distributions of the impulsive noises. The estimation of the LLR approximation parameter rely on an information theory criteria which does not depend on any noise assumption nor function to be estimated. As long as the approximation family ensures the convexity of the optimization problem, a solution will exist and will be efficient in the communication context.

The gap between the blind optimization and the true LLR is of the order of 0.3 dB in the worst case, showing the strength of the blind optimized demapper. Moreover, one can achieve an enormous gap within the range [9.5-15] dB between L_{ab} and L_a, showing the influence of handling correctly the impulses that arise due to the presence of interference. Moreover, our demapper function does not impact the performance if you do not have impulsive noise so that we do not need a detection step to distinguish between Gaussian or impulsive noise.

IV. Conclusion

We propose in this paper a Universal receiver design. We use an LLR approximation function f_θ in a parametric family. The parameters θ are estimated through the maximization of the mutual information. A blind solution is propose in order to benefit form the whole received sequence but also to increase the useful data rate. Our results show that the receiver design is efficient in a large variety of noises and that the blind estimation allows to reach performance close to the optimal and better than the supervised approach if a reasonable training sequence length is considered.

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