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IMPLEMENT OF LLRNET TO 5G-NR ON LINK-LEVEL SIMULATION

Bircan Çalışır[*1]

[1]Firat University, Faculty of Engineering, Departmant of Electrical and Electronical Engineering, Elazig, Turkey

Abstract

Original scientific paper

Modern receivers apply smooth demodulation and demapping processes to received symbols, using bit log-likelihood ratios (LLRs). Known as “LLRnet" demodulator architecture is offered that is a global educatable neural network attributed in this paper. The calculation of the optimal LLR algorithm includes the calculation of each bit in the LLR value and requires the assessment of whole lattice points as high dimensional which is unpractical for the QAM modulation. Known the most in the literature the Maximum Likelihood (ML) detector shows very high computational complexity that is used in the QAM scheme. Besides LLRnet developed achievement importantly, all calculational complexity is also reduced. Via estimating exact log-likelihood, how to create symbols, and channel corruptions for training a neural network LLRNet is shown in this paper. New and contemporary radio communication systems, such as 5G- NR (New Radio) and DVB (Digital Video Broadcasting) for satellite, DVB (S.2 Second Generation) utilize the LLR approach that calculates soft bit values with FEC (Forward Error Correction) algorithms and utilizes demodulated smooth bit values. This article aims a link-level simulation study to implement of LLRnet to DVB S2 and 5G-NR. The motivation of this study is seen that performing machine learning techniques on physical layer scheme, makes LLRNet a powerful example for practicability. This paper offers to compare Max-Log Approximate LLR, Exact LLR, and LLRNet methods for 16, 32 and 128 QAM.

Keywords: *LLR, modulation, radio communication, OFDM.*

BAĞLANTI SEVİYESİ SİMÜLASYON ÜZERİNDE LLRNET'İN 5G-NR'YE UYGULANMASI

Özet

Orijinal bilimsel makale

Modern alıcılar, bit log-olasılık oranlarını (LLR'ler) kullanarak alınan sembollere yumuşak demodülasyon ve de-maping işlemleri uygular. Optimal LLR algoritmasının hesaplanması, LLR değerindeki her bir bitin hesaplanmasını içerir ve QAM modülasyonu için pratik olmayan, tüm kafes noktalarının yüksek boyutlu olarak değerlendirilmesini gerektirir. Literatürde en çok bilinen Maksimum Olabilirlik (ML) dedektörü, QAM şemasında kullanılan çok yüksek hesaplama karmaşıklığı gösterir. Bu makalede atfedilen, küresel bir eğitilebilir sinir ağı olan “LLRnet” demodülatör mimarisi sunulmaktadır. LLRnet başarıyı önemli ölçüde geliştirmesinin yanı sıra, tüm hesaplama karmaşıklığını da azaltır. Bu yazı, bir sinir ağının LLRNet'i eğitmek için tam log-olasılığını tahmin etmesini, sembollerin nasıl oluşturulacağını ve kanal bozulmalarının nasıl olacağını göstermektedir. Uydu için 5G-NR (Yeni Radyo) ve DVB (Dijital Video Yayını), DVB (S.2 İkinci Nesil) gibi yeni ve çağdaş radyo iletişim sistemleri, FEC (İleri Hata Düzeltme) ile yumuşak bit değerlerini hesaplayan algoritmalar ve demodüle edilmiş düzgün bit değerlerini kullanan LLR yaklaşımını kullanır. Bu makale, LLRnet'in DVB S2 ve 5G-NR'ye uygulanması için bağlantı düzeyinde bir simülasyon çalışması sunmaktadır. Bu çalışmada, makine öğrenmesi tekniklerinin fiziksel katman şeması üzerinde gerçekleştirilmesinin LLRnet'i uygulanabilirlik açısından güçlü bir örnek haline getirdiği görülmektedir. Yine bu makale, 16, 32 ve 128 QAM için Max-Log Approximate LLR, Tam LLR ve LLRNet yöntemlerini karşılaştırmayı önerir.

Anahtar Kelimeler: *LLR, modülasyon, radyo haberleşmesi, OFDM.*

1 Introduction

Demapping symbols on the receiver side back into their original bits is an important stage in any radio communication system. The log-likelihood ratio (LLR) is representatively stated the value of trust on demodulation process of the symbol. The log-MAP makes an exact assessment of the LLR [1], calculating the rate with the MAP (Maximum A Posteriori) possibilities of two hidden theories of bit. Even though statistically optimum, the dimension of the symbol constellation and the complexity of computation of the log-MAP algorithm scale, and applies directly to real systems. A popular approach to optimum log-MAP, a goal to design convenient systems, is the reputed max-log-MAP algorithm [2]. Generally, the approximated max log-MAP method eliminates the

*Corresponding author.

E-mail address: bkamislioglu@firat.edu.tr (B. Çalışır)

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requirement of calculating complex exponential and logarithmic functions but expends a large number of processes that scale according to the modulation order.

In quadrature amplitude modulation (QAM) structure, the maxlog-MAP got below to a decreased complication of linear function and could be so applied using a lookup table (LUT). This means the natural constellation mapping symmetries of QAM and, the QAM can separate into two free PAM (Pulse Amplitude Modulations) in the imaginary and real components on the signal [3-6].

Deep learning has recently found its place in many applications and has achieved successful results. Deep learning (DL) is used for signal detection of OFDM-IM (orthogonal frequency division multiplexing with index modulation) systems [7]. A new deep learning (DL) aided receiver is developed for NOMA joint signal detection in [8]. DL is utilized here as receiver and used for channel estimation, equalization, and demodulation aims. In [9], a new deep learning based application is used for joint channel estimation and signal detection in OFDM systems. Channel Estimation Network (CENet) is specifically method designed to relay the conventional interpolation procedure in estimation layout.

In this work, we proposed a named "LLRnet" method that is an efficient machine-learning structure for universal smooth demodulation. While the demapping process is briefed as symbol to bit LLRs work, just, neural network is seen as an excellent method that approximates functions effectively. Obtained results from simulations show the LLRnet succeeds in achieving excellently the target demodulation performance. LLRnet is reduced seriously computational burden and reproduces the exact log-MAP algorithm for QAM constellations.

This paper is planned in this order. Section II describes The LLR estimation problem. The proposed LLRnet architecture is introduced in Section III. Results of simulation of the performance of LLRnet in the case of some work implementations such as the cellular 5G and the satellite DVBS.2 standards are given in Section IV, finally, a few deducing notes are contained in Section V.

1.1 Problem Modelling

In this section, link-level simulation study to implement of LLRnet to 5G-NR will realize for the remainder of this paper explored.

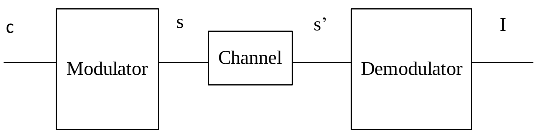


Figure 1. A communication system.

A basic radio communication technology as illustrated in Figure 1 comprises a modulator, composite channel and demodulator. Coded bits that are given in Figure 1 pointed out by $c \in \{0, 1\}$ and sequence of modulated symbols are shown by $s = s1, \ldots, sN\}T \in C, C \subset CN, N \in Z > 0$. As a result $c = \{c1, \ldots. cM\}T \in \{0, 1\}M$, is admitted to being some arbitrary M vector of successive bits in the stream is modulated to a complicated symbol s by N-dimensional [10, 11]. The symbol transmitting includes a composite channel, the physical channel additionally, and an abstraction of other crucial transceiver operation steps Pre-code process to transmit over MIMO (Multiple Input Multiple Output) techniques on the transmitter part, mapping for OFDM (Orthogonal Frequency- Division Multiplexing), and DAC (Digital Analog Conversion) for analog radio carriers are created by the composite channel. ADC (Analog Digital Conversion), mix down to base band, synchronization, filtering, demodulation of OFDM, MIMO demodulation, and estimation and equalization of the channel are realized on the receiver part, by the composite channel. The mentioned steps are standard for transceiver processing and are not related to the de-mapping, or smooth demodulation of the transceiver signal to bit LLRs particularly. On the receiver side, the demodulator traces the complex-valued symbol estimate of the compound channel, s^ ∈ CN, and the impact of the compound channel is defined by the correlation among the transmitting and tracing signals s, and $s\hat{}$ by turns. Though not certain, the compound channel is representatively shaped as an AWGN (Adding White Gauss Noises) given n for the intention of smooth demodulation to bit LLRs as seen Equation 1 [12].

$$s' = s + n \tag{1}$$

On the demodulator sides, we demap the traced signal, $s\hat{}$, in a vector of prediction of the M-bit LLRs, $l \in RM$, based on reliance on the conclusion of each of the inventive coded bits to facilitate advanced decoding in the following stage.

LLRs vector for the i'th entry, li, based on the logarithm of the MAP relation given in Equation 2 [12] On the receiver side, $C_i^{\delta} \in C$ i'th bit is equal to δ ∈ {0, 1} and corresponds to the subseries of constellation dots.

$$l_i = \log\left(\frac{P_r(c_i=0, s')}{P_r(c_i=1, s')}\right) \qquad \mathrm{i} = 1, \ldots.., \mathrm{M} \tag{2}$$

A certain calculation of the log-MAP statement, in the investigated model output is given in Equation 3 [12]. In Equation 3, σ^2 is defined as noise variance.

$$l_i = \log \frac{\sum s \in c_i^0 \exp(-\frac{\|s'-s\|_2^2}{\sigma^2})}{\sum s \in c_i^1 \exp(-\frac{\|s'-s\|_2^2}{\sigma^2})} \qquad \mathrm{i} = 1, \ldots.., \mathrm{M} \tag{3}$$

Approximated LLR estimates remove from a facilitated formula, known to all as the max-log-MAP on the exact log-MAP process as seen in Equation 4 [12].

$$l_i = \frac{1}{\sigma^2}(min_{s \in c_i^1}\|s' - s\|_2^2 - min_{s \in c_i^0}\|s' - s\|_2^2) \tag{4}$$

The advantageous feature of the approximated max-log-MAP de-mapping law is that eliminates the requirement for calculating functions of complex exponential and logarithmic. For QAM constellations, while to be violently sub optimal the max-log-MAP is a characteristically the widespread de-mapper because of degraded to a sole LUT application of part-wise linear functions, which is measured SNR linearly [9-12].

2 OFDM Modulation

Quadrature amplitude modulation (QAM) is a developed modulation layout broadly utilized in radio communication technologies that consubstantiate amplitude modulation and phase modulation. In digital signal modulation, QAM obtains a higher rate than widespread amplitude and phase modulation, which promote just two kinds of symbols to separate 0 and 1. In amplitude modulation, 0 and 1 are separated by replacing the amplitude of carrier and in phase modulation, 0 and 1 are separated by replacing the phase of carrier. For example in QPSK, 2 bits per symbol (00, 01, 10, or 11) can be encoded through the following four phases: 0°, 90°, 180°, and 270°. In other hand QPSK is admitted as a particular sort of QAM, that is 4-QAM. In QAM, signals are loaded to two orthogonal carriers (representatively sin and cos), the carriers' amplitudes are adjusted, and added their amplitudes to create the signals modulated by both the phase and amplitude. The carriers are generally defined as I and Q signals. So, the mentioned modulation method is also described as I-Q modulation.

OFDM is described as a multi carrier digital modulation plan that broadens single subcarrier modulation by utilizing multiple subcarriers within the identical channel. OFDM uses a big number of orthogonal subcarriers which transmitted in parallel rather than provide a high rate sequence of data using one subcarrier. Traditional digital modulation schemes (such as QPSK, 16QAM, etc.) modulate each subcarrier with a at low symbol rate. However, the compound of many subcarriers lets resemblance data rates to traditional one carrier modulation layouts within equal bandwidths [3].

OFDM produces Q (Quadrature) and I (In-phase) elements of cn(m) in complex domain utilizing data bits. M length an IFFT (Inverse Fast Fourier Transform) applies and M complex data block is created in the time area. In the IFFT input, zero adds to unused sub-carriers. Relation of input and output of OFDM base band modulation scheme is noted in the discrete time area as given in Equation 5 [12].

$$s_n(k) = \sum_{m=0}^{(M-1)} c_n(m) e^{(j2\pi mk/M)} \qquad (5)$$

In Equation 5, M expresses the number of subcarriers, and the data symbols with complex values ensured from a QAM constellation are indicated by cn(m). Taking into account that m is the subcarrier index and n is block index, s(k) shows the complex valued output of data symbols of OFDM modulation process.

3 Smooth Demodulation With LLRNET

A neural network named as LLRnet in order to learn a desired smooth demodulation layout is purposed to de-map a symbol by valued complexity to this reel valuable LLRs of transmitted bits.

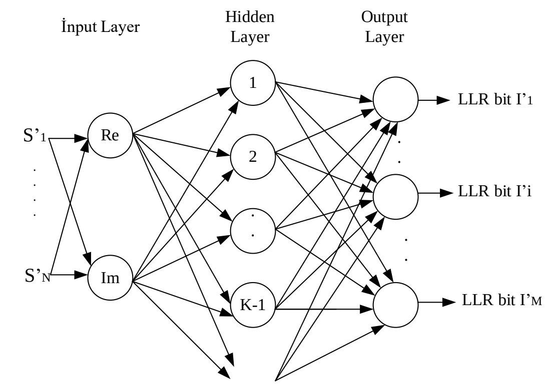


Figure 2. LLRnet structure [8].

The structure of LLRnet is depicted in Figure 2 and from figure, the received symbol prediction vector, sˆ, feeds the entrance of the LLRnet. LLRnet injects the output vectors of the two input loops into a secret sheet of K neurons.

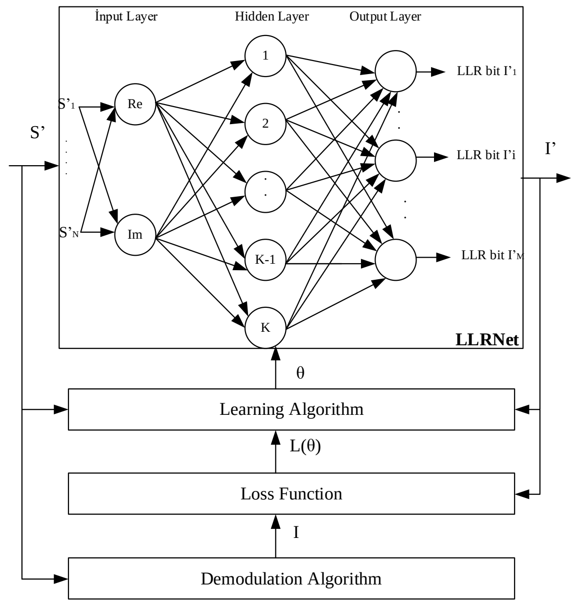


Figure 3. Training diagram of LLRnet structure [8].

The training diagram of the neural network demodulator is shown in Figure 3 schematically. Because the input-to-output function of the LLRnet fully consists of the setting of overall training coefficients, θ, as a training process, a gradient-based approximation could accept. The identical bit LLRs are calculated using a desired demapping algorithm for a specific batch of receipt signals B, sˆ(b), b = 1, . . . , B. Then both the traditionally calculated LLRs, l(b), and the LLRs calculated via LLRnet, lˆ(b) feed a lost of function that is clearly described as a trained coefficients sequence function of the θ. Loss function can be defined as Equation 6 [12].

$$L^{MSE}(\theta) = \frac{1}{B}\sum_{b=1}^{B} \left\| I'^{(b)} - I^{(b)} \right\|_2^2 \qquad (6)$$

An arrest criterion is defined which can be either a constant count of repetitions, a sill value for the loss, or a count of repetitions with no reduced loss. The parameter set, θ is updated up to the stop criterion is satisfied. As the arrest criterion is satisfied and training is finished, the

LLRnet is admitted as the only demodulator, productively copying the functionality of the demanded smooth demodulator [13, 15].

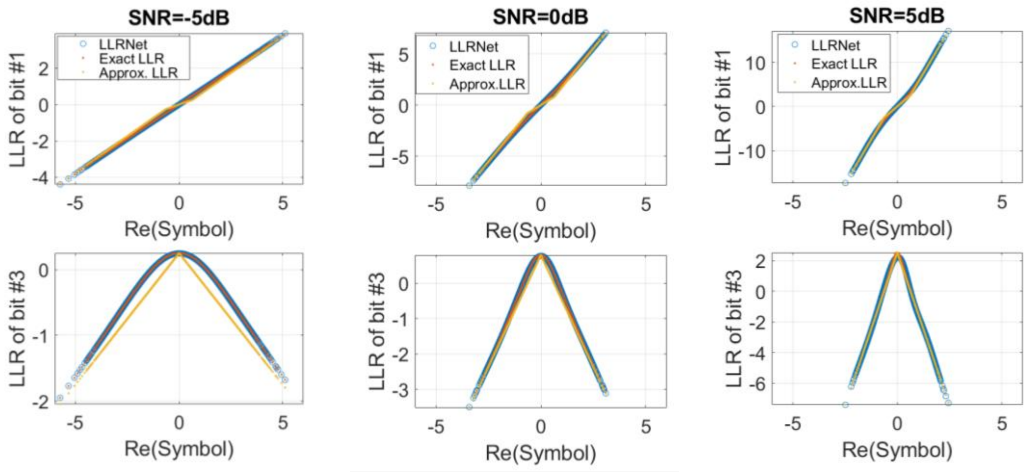
The performance criteria of the defined network are mean square error (MSE). The performance criteria of the defined network are mean square error (MSE). The obtained last MSE worths from simulations explain the used neural network converging to an MSE worth that is at least 40 dB less than the mean square exact LLR worths given in Table 1.

Table 1. SNR and MSE relation.

SNR	MS $_{LLR}$	MSE $_{last}$
-5	4.43	6.80e-5
0	15.74	9.05e-5
5	60.01	8.50e-3

4 Simulation Examples

The proposed in this work LLRnet demodulation method is used in both PDSCH (Physically Down link Share Channel) with utilizing 5G-NR link and the 3GPP standard. QAM modulation is one of the modulation methods utilized for 5G NR. In this section correctness guess of LLRNet on the LLR worths for 16, 32, and 128 QAM modulation is explored. Considering an M-QAM modulation method that has AWGN channel circumstance, this approximation fits both the channel has frequency selective property and symbols are equalized. The consequent figures show computed LLR worths for the mentioned three algorithms.



a) b) c)

Figure 4. LLR comparison for 16-QAM (a for -5dB SNR, b for 0dB SNR, c for 5dB SNR).

LLR comparison of LLRNet, exact LLR and approximation LLR for 16-QAM (a for -5dB SNR, b for 0dB SNR, c for 5dB SNR) is illustrated in Figure 4. Simulations are realized for 1 bit and 3 bit for each SNR values. In Figure 5, LLR comparison of LLRNet, exact LLR and approximation LLR for 32-QAM (a for 0 dB SNR, b for 5 dB SNR, c for 10 dB SNR) is shown and simulations are applied for 1 bit, 3 bit and 5 bit for each SNR values. As seen in Figure 6, LLR comparison of LLRNet, exact LLR and approximation LLR for 128-QAM (a for 0 dB SNR, b for 10 dB SNR, c for 20 dB SNR) is obtained and applications are simulated for 1 bit, 3 bit and 5 bit for each SNR values

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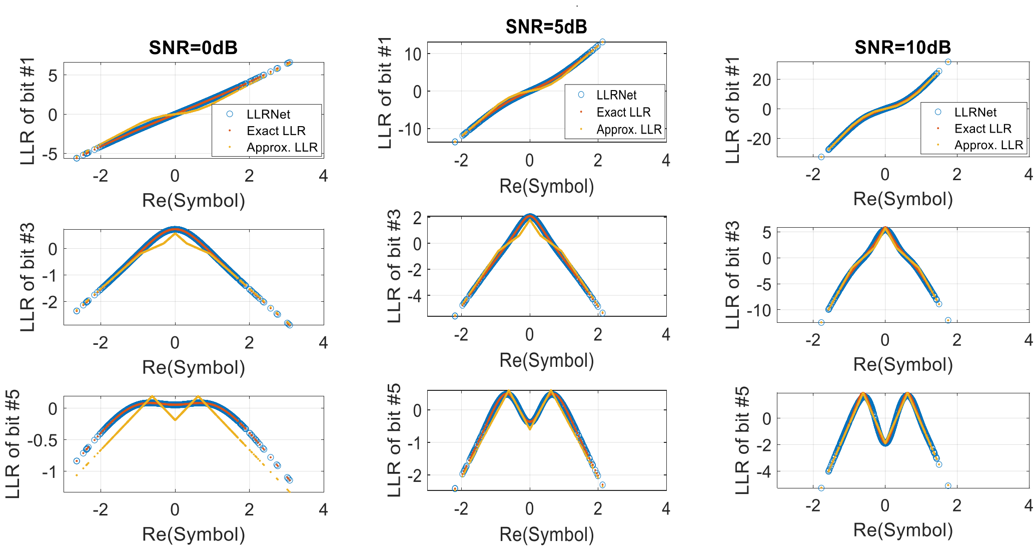
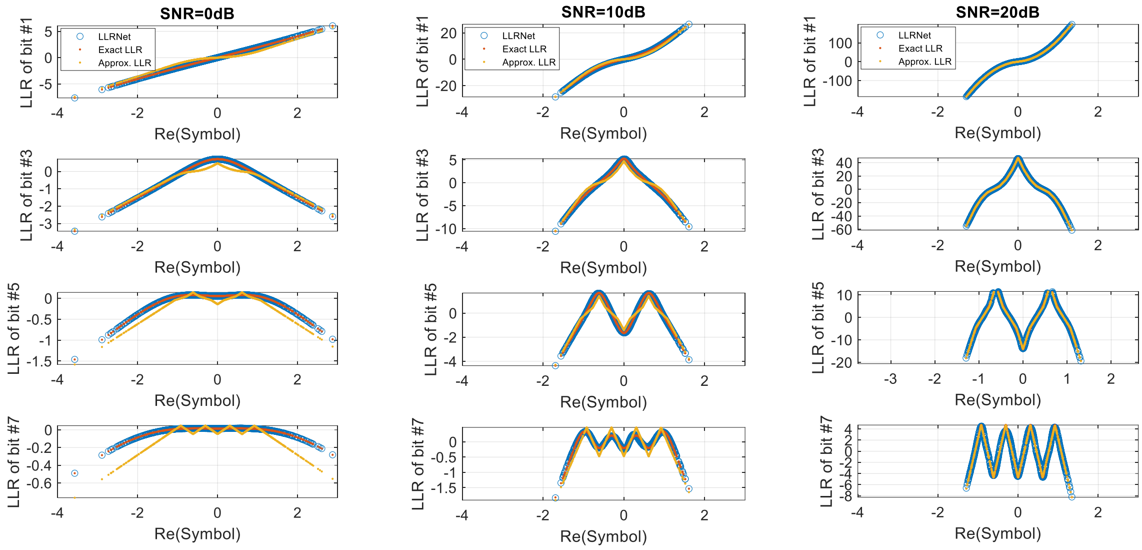


a) b) c)

Figure 5. LLR comparison for 32-QAM (a for 0 dB SNR, b for 5 dB SNR, c for 10 dB SNR).



a) b) c)

Figure 6. LLR comparison for 128-QAM (a for 0 dB SNR, b for 10dB SNR, c for 20dB SNR).

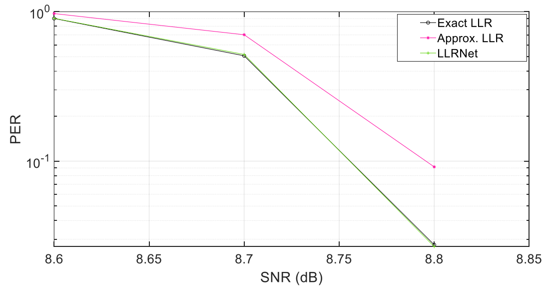


Figure 7. PER to Es/N0 for exact LLR, approximation LLR and LLRNet.

This paper presents an application of exact LLR, approximation LLR and LLRNet neural network methods that are applicable and work well fairly to apply QAM modulation for different orders. Considering Figure 4, Figure 5 and Figure 6, in the higher SNR values (c), the exact LLR shows a fine prediction of the optimal approximation LLR rule for the analyzed three different orders of QAM modulations. However, (b) the exact LLR only works as a rough for low SNR, and fair for mid SNR to the full demapper in the low and mid SNR values. As the last, the smooth bits obtained by the LLRnet practically trace the optimum bits for all three QAM modulation cases in all SNR values [10]. In Figure 7, PER to Es/N_0 for exact LLR, approximation LLR and LLRNet are obtained for 100 number of frames. Exact LLR and LLRNet shows similar behavior but approximation LLR shows different behavior considering PER-SNR.

5 Conclusion

This paper presents a machine learning approximation which an easy neural network structure. This structure is trained to smooth demodulated symbols productively to bit LLRs. So, an AI (Artificial Intelligence) algorithm converts into the most general construction units of the operation of the physical case. LLRnet, which suggested opinion of this work, can be both expanded to deep learning structures with multi layers and be combined with a trainable receiver model. In addition, the comparison of exact LLR, approximation LLR and LLRNet is presented about LLR bits correspond to real symbols and PER to Es/N_0. This application is illustrated effective performance of LLRNet cases in all SNR values.

Declaration

Ethics committee approval document is not required for this study.

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