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Machine Learning-Based Interference Mitigation in Wireless Networks

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Abstract:

The congestion of the electromagnetic spectrum and the diminishing size of cells in wireless networks have made crosstalk between base stations and consumers a significant issue. While hand-crafted functional blocks and coding schemes are established methods for ensuring reliable data transport, deep learning-based techniques have recently garnered significant interest in communication system modeling [1, 2]. This research presents a Neural Network (NN) based signal processing approach that integrates with conventional DSP techniques to address the interference issue in real-time. This approach does not need any feedback mechanism between the receiver and transmitter, making it very appropriate for low-latency and high data-rate applications such as autonomy and augmented reality. Recent research has focused on using Reinforcement Learning (RL) at the control layer to limit interference; however, our technique is innovative since it incorporates a neural network for signal processing at the baseband data rate and inside the physical layer. We illustrate the "Deep Interference Cancellation" method with a convolutional LSTM autoencoder. The use of QAM-OFDM modulation to the data results in a substantial enhancement of the symbol error rate (SER). We moreover examine the hardware implementation, encompassing latency, power consumption, memory needs, and chip space.

Introduction

The rapid advancement of modern wireless communication technologies is resulting in smaller cell areas, exacerbating the issue of crosstalk between cells (Figure 1). To mitigate this crosstalk, a prevalent technique involves the receiver providing feedback to the transmitter, which then adjusts the broadcast frequency. Nonetheless, these feedback loops add delay and disadvantage real-time applications that need low latency, such as autonomy and augmented reality (AR). To address this problem, blind methods are required, enabling the receiver to independently eliminate interference without necessitating communication with the transmitter. Figure 2 illustrates an instance of interference inside the LTE cellular communication system. As the user equipment (UE) nears the boundary of two adjacent cells, there exists a possibility that another user in the nearby cell is using the same frequency range for communication. This circumstance may disrupt both users operating inside the same frequency range and significantly diminish the data rate. To resolve this issue, the 3GPP collaboration determined that users situated at the same cell edge but affiliated with separate cells should use distinct frequency resources. Base stations equipped with this functionality may produce interference data for each frequency resource (RB) and communicate this information with adjacent base stations via messages. This solution may resolve the issue in sparsely populated regions; however, it is ineffective in densely populated cells

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because to the heightened demand for vacant frequency bands, necessitating the base station to utilize all available bands for transmission.

A viable method involves using phased array antennas at the receiver to execute spatial filtering for the rejection of interference. This approach may significantly reduce the strength of the interference signal, although it has limitations. The primary concern is that phased array antennas are very vulnerable to mismatches, and the construction process may readily introduce minor discrepancies, so limiting their spatial filtering capabilities. Moreover, the weights allocated to these antennas must be adaptively modified to monitor the orientation of the intended signal while continuously rejecting the interference signal. These modifications may elevate the system's latency when the connection requires probing and subsequent weight changes. Furthermore, beamwidth is directly proportional to the quantity of available phased array antennas. Consequently, a trade-off exists among the power, size, and beamwidth of the antenna.

Numerous conventional digital signal processing (DSP) methods exist to eliminate narrowband interference from the intended wideband stream. However, they are ineffective in scenarios involving wideband interference, where the interference might fill the same bandwidth as the intended signal. In OFDM/QAM modulation wireless systems, each resource element (RE) may assume a discrete value from the QAM symbol space. If this applies to both the user equipment (UE) and the interferer, their combination will provide a discrete sample space as well. Employing a Maximum Likelihood Estimation (MLE) method for classifying this novel sample space requires extensive computation and may be impractical. Traditional DSP methods restore distorted signals through a sequential cascade of custom physics models designed to address specific impairments. In contrast, emerging machine learning techniques utilizing neural networks are acknowledged for their potential to enhance communication signal processing by decreasing computational complexity and latency, while also offering novel capabilities in understanding the intricate behavior of signals.

This research proposes a Neural Network (NN) architecture that integrates convolutional layers with LSTM (long short-term memory) layers to address the interference issue in the typical DSP baseband chain. This technology does not need any feedback mechanism between the receiver and transmitter, making it highly appropriate for low-latency and high data-rate applications.

Related Work

In a conventional receiver baseband system, the down-converted signal is processed by the OFDM demodulator to get the subcarrier values, which are then classified into corresponding QAM symbols using Maximum Likelihood Estimation (MLE). The subcarrier values are distorted due to the channel frequency response. The pilot subcarriers facilitate the estimation and equalization of the channel response by various digital signal processing techniques, including Minimum Mean Squared Error (MMSE), Zero Forcing (ZF), and Sphere Decoder (SD) algorithms.

Cell association and power control are two prevalent ways for managing interference and cooperation. Cell association refers to the correct linkage of mobile user equipment to the designated base stations. Notable systems include the Reference Signal Received Power (RSRP)-Based Scheme , Bias-Based Cell Range Expansion (CRE) , and the Almost Blank Sub-frame (ABS) Ratio-Based Scheme . Power control refers to the reduction of power to minimize interference with other connections while maintaining the requisite link quality. Prominent systems include Target-SIR-tracking Power Control (TPC), TPC with Gradual Removal (TPC-GR) , and Opportunistic

Power Control (OPC) .

Efforts have been made to use Reinforcement Learning (RL) in interference management via the optimization of power transmission techniques. A decentralized power control technique based on reinforcement learning is described in , whereby small cells collaboratively evaluate time-average performance and optimize the probability distribution for interference management in closed-access small cell networks. Recently, introduced a reinforcement learning-based downlink interference management approach for ultra-dense small cell systems, whereby a base station optimizes transmit power without knowledge of nearby cell channel states, therefore mitigating inter-cell interference.

To our knowledge, all current solutions concentrate on identifying an optimum strategy for associating multi-tier cells and managing transmission power to mitigate interference. Consequently, prior research has used AI at the control layer; we are the first to leverage AI for real-time data transformation.

A Blind Approach Of Interference Cancellation Using Neural Networks

We contend that the issue of interference in wideband cellular communication may be mitigated by the use of neural networks. During the training phase, the network acquires knowledge of the intricate dynamics of wideband interference using training data. The learned model functions as a real-time signal processing module during data transmission. To mitigate computational load and latency challenges, we will enhance the neural network for real-time functionality using model compression methods, including network pruning and coarse quantization [14].

Neural Network-Enhanced Receiver

Figure 3 illustrates our notion for a deep learning-based receiver designed for next-generation wireless communication. Rather than substituting the traditional DSP, we enhance it using neural networks inside the DSP pipeline to execute jobs inadequately addressed by conventional DSP. This encompasses wideband error correction for the analog-to-digital converter (ADC) and the mitigation of inter-cell interference. This study will primarily concentrate on the interference cancellation component.

Convolutional LSTM Autoencoder

Interference from an unidentified channel manifests as stochastic noise. In contrast to physical noise, such as thermal or shot noise, the interference signal is not entirely random, since it is associated with a distinct QAM constellation. The nuanced understanding is the essential element that enables us to acquire knowledge and eliminate distractions unconsciously. Among several network topologies, autoencoders have proven effective for image and voice denoising and provide a solid foundation. In the context of wireless communication, we use an autoencoder including convolutional layers and LSTM (long short-term memory) layers, as seen in Figure 4. The network acquires a block of symbols compromised by interference and simultaneously reconstructs the accurate symbols. Convolutional layers execute feature extraction, whereas LSTM layers operate as an autoencoder to eliminate noise-like interference. The Mean Squared Error (MSE) between the recovered symbol block and the ideal symbol block serves as the loss function.

Results

We produce a total of 1000 radio frames via simulation. Each frame has 11 subframes, with each subframe containing 140 OFDM symbols, and each OFDM symbol encompassing 180 subcarriers. Five hundred frames are allocated for training, one hundred frames for validation, and the remaining four hundred frames for testing. The bandwidth is 3 MHz, with a subcarrier spacing of 15 kHz, using 256QAM as the modulation technique. The results of interference cancellation are shown in Figure 5. The constellation map of the interfering symbols in Figure 5(a) and the recovered symbols for the same frame in Figure 5(b) indicate that the symbols experience significant interference, while the neural network effectively performs interference cancellation. We show and compare the symbol error rate (SER) distribution of all testing frames before and after interference cancellation in Figure 5(c), revealing a substantial improvement in the SER. The mean SER of the 400 test frames decreases from 0.37618 to 0.0003.

Towards Hardware Implementation

The neural network built in FPGA or ASIC should adhere to fixed-point calculation principles rather than using floating-point computation in the software simulation. Efforts have been made to quantize neural networks during both the training and testing phases to achieve efficient and precise integer-arithmetic-only inference [18] [19], alongside the deployment of widely-used neural network architectures, such as convolutional neural networks (CNN) and recurrent neural networks (RNN), on FPGA [20] [21], demonstrating the viability of hardware implementation for our proposed architecture.

The majority of previous research has focused on classification tasks, which exhibit more tolerance for quantization mistakes. The issue under discussion is fundamentally a regression problem that exhibits heightened sensitivity to quantization issues. Nonetheless, a QAM length of up to 1024 should be attainable with meticulously crafted fixed-point arithmetic.

Moreover, latency and power consumption are essential for wireless communication applications. Our first findings indicate that NN is proficient at mitigating interference and crosstalk. This inquiry addresses the feasibility of implementing our neural network in hardware with sufficiently low latency and power consumption. A Xilinx FPGA RFSoC is used to realize our suggested system. This FPGA comprises eight instances of 12-bit, 4 GS/s ADCs. Consequently, this FPGA may be used by only connecting the output of the anti-aliasing filter to its analog port, with all further processing conducted on the FPGA. The whole DSP baseband processing may be executed inside the FPGA. Power consumption is directly contingent upon the clock frequency used for baseband processing. Neural network computation may introduce an extra 200 clock cycles to the overall delay of the system. At a clock frequency of 200 MHz for the FPGA, the neural network's power consumption yields an estimated increase of 1 Watt. Power consumption will be much lower with an ASIC compared to an FPGA and may be further reduced by model compression. The delay will be 1 microsecond, which is insignificant relative to the desired latency of 1 millisecond for 6G networks.

System Design

The suggested approach in this study consists of four primary modules: interference estimates, feature extraction, machine learning classification, and a look-up table. Figure 1 illustrates the whole design of the system, including various components. The system acquires sampled RSSI traces from the PHY layer and retains them for analysis. The first procedure is interference estimate conducted by the interference estimation module. Upon detecting any interference, this module does feature extraction on the trace with a lightweight feature extraction module. If no interference is identified, the message is sent immediately to the look-up table. The recovered feature vector of the RSSI trace serves as the input to the machine learning classification model [24], which categorizes the interfering signal into one of the classes: Bluetooth, WiFi, or microwave oven. The classification result, indicating the kind of interference, is sent to the look-up database to determine the appropriate countermeasure for the observed interference [25]. The mitigation countermeasure data is sent to the MAC layer for implementation. The following sections elucidate the design process by providing an in-depth analysis of each module's design.

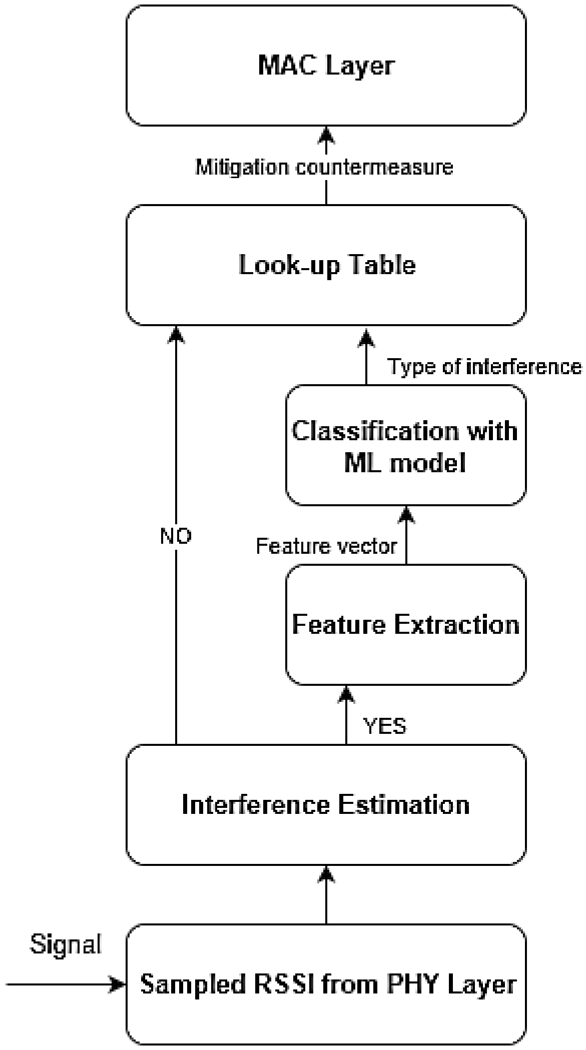

Figure 1. Overall architecture of the scheme

Signal sampling

The devised technique use the ED approach to extract characteristics and ascertain the sort of interference. The ED value, usually referred to as the RSSI value, approximately indicates the power of the received signal at the receiver's radio. The suggested approach utilizes RSSI values obtained from tests conducted in [13]. The readings consist of sampling RSSI values for several interfering technologies in the ISM band, namely WiFi, Bluetooth, and microwave ovens, collected every 16 µs during a controlled experiment. Figure 2 illustrates the regulated experimental configuration used in [13] to assess the RSSI for various interfering technologies.

Interference estimation

The interference estimation module focuses on identifying any interference in the sampled RSSI trace obtained from the PHY layer. The interference estimate module sequentially analyzes the '1s' of the RSSI trace and conducts interference estimation based on a threshold. The RSSI data are transformed to dBm by applying an offset of -45

to each sequentially read RSSI value. The last step is determining the interference threshold. This is accomplished by determining the power level of the received signal in the absence of interference. When the signal encounters interference, the power level rises due to the additive nature of the interference. The analysis of the RSSI trace for various interference sources indicates that the power level of the received signal in the absence of interference is the most often occurring RSSI value. Consequently, this number is regarded as the threshold. The trace graphs indicate that some values exhibit change of less than 1 dBm from the threshold. The values are unaffected by the interfering source; rather, the fluctuation arises from ambient circumstances like as multipath propagation. Subsequently, the series are transformed into a binary trace using this information. Any value exhibiting a deviation of less than 1 dBm from the threshold, or any value falling below the threshold, is shown as 0. The remainder are transformed into 1. Consequently, in the resultant binary trace, 1 denotes samples affected by interference, while 0 signifies samples devoid of interference. In the last phase of the module, the active ratio of the binary trace is computed using (1). When the active ratio exceeds 0, the module assesses that the received signal is subject to interference. If the active ratio equals 0, it determines that the signal is free from interference.
Active ratio = number of samples converted as 1 to total number of samples (1)

Feature extraction

This module seeks to identify the temporal characteristics of the binary signal produced by the interference estimation module. The characteristics retrieved in this study are listed below. – Maximum time of channel utilization – Maximum duration of channel clearance Channel utilization ratio Periodicity that delineates a distinctive transmission pattern of a wireless signal Two models are developed to extract these properties, and the one with lower memory usage is chosen for the final scheme. Both models use identical ways to identify the first three properties, although they utilize distinct methods to ascertain the last element, periodicity. Model 1 employs Fast Fourier Transform (FFT) to assess the periodicity of the binary signal, while the suggested lightweight approach is used for periodicity estimation in Model 2. The techniques for feature extraction are further upon below:

Maximum channel use duration: This denotes the longest period during which the signal is susceptible to external interference. The maximum period for which the binary signal remains at the value 1 is determined by calculation.
Maximum channel clear duration: This denotes the longest period during which the signal remains free from external interference. The greatest period for which the binary signal remains at the value 0 is determined by calculation.

Machine Learning Model-Decision Tree

The suggested approach in this research requires the classification of the kind of interfering signal based on an extracted feature set. Consequently, a supervised learning model is requisite. The first prerequisite for developing a supervised machine learning model is the possession of a suitable dataset. To obtain the necessary dataset, feature extraction is performed using the established approach on 70 distinct traces. Upon generation of the dataset, the method for developing the ML model is executed. The dataset is first divided into training data and testing data at random. Seventy percent of the dataset is allocated for training, whereas thirty percent is designated for testing. The training data is used for model development and training, whilst the test data is employed for verifying the established model. Two models, namely a decision tree model and a logistic regression model, are created independently. The final approach employs the model that exhibits minimal memory use while maintaining excellent accuracy. In all models, the four numerical properties of the dataset (periodicity, busy time, channel usage, and idle time) will serve as inputs. The decision tree is constructed via the CART method, employing the Gini index as the attribute selection measure. Figure 3 displays the constructed trained decision tree. Simulation results indicate that the decision tree outperforms the logistic regression model in terms of accuracy and efficiency. Consequently, the decision tree is regarded as the machine learning model in the final framework.

Lookup table

The look-up table utilizes the result of the ML classification model as input and selects the best suitable countermeasure for the specific kind of input interference. The table is derived from findings presented in [7, 8] on various countermeasures for interference in WSN. These data indicate that each interfering technology uniquely influences the affected channel. Various responses will be effective against distinct forms of interference. For example, the microwave oven use the channel extensively with a gradual but consistent and punctual transmission. The transmission exhibits consistent on-off cycles. Transmission or interference intervals may be circumvented by using a regularly scheduled packet transmission method [7]. Therefore, if the input to the look-up table includes microwave oven interference, it will choose packet scheduling as the mitigation strategy. Conversely, WiFi extensively occupies the channel for prolonged durations under substantial data traffic conditions. In contrast to microwave oven transmission, it lacks a consistent on-off transmission pattern. The optimal approach to mitigate WiFi interference is to alter the existing transmission channel [8]. Consequently, the look-up table determines that channel switching is the best suitable countermeasure when the input interference type is WiFi. In contrast to WiFi and microwave ovens, Bluetooth exerts the minimal interference on Wireless Sensor Network signals. Moreover, Bluetooth interference occurs sporadically due to its use of an adaptive frequency hopping method for data transmission between channels. The optimal method to mitigate Bluetooth interference is to stay inside the channel and retransmit in the event of a packet collision [7]. Packet collisions may be identified by the use of acknowledgments (ACKs). Consequently, if the identified interference is Bluetooth, the look-up table will choose retransmission with ACK as the mitigation strategy. Table 1 depicts the lookup table used in the devised strategy.

Conclusion

This research presents a deep learning-based blind method for mitigating inter-cell interference in the physical layer of wireless communication. Our encouraging findings indicate that the autoencoder design, including both convolutional and LSTM layers, is very successful. The assessment of delay and power consumption indicates the viability of hardware implementation in next-generation communication systems. Our research suggests the use of neural networks inside the DSP pipeline to improve the communication system.

References

1. P. Du and G. Roussos, “Adaptive time slotted channel hopping for wireless sensor networks,” *2012 4th Computer Science and Electronic Engineering Conference (CEEC),* pp. 29-34, 2012.
2. N. Azmi, L. M. Kamarudin, “Interference Issues and Mitigation Method in WSN 2.4GHz ISM Band: A Survey,” *2014 2nd International Conference on Electronic Design (ICED),* 2014.
3. Anwar Hithnawi, “Low-power Wireless Systems Coexistence,” Thesis, Doctor of Science, ETH Zurich, 2016.

4. S. Zacharias, “Effects, classification and mitigation of external interference in IEEE 802.15.4 based sensor networks,” Thesis, Doctor oF Science, University of Limerick, 2014.
5. W. Yuan, J. P. M. G. Linnartz, and I. G. M. M. Niemegeers, “Adaptive CCA for IEEE802.15. 4 wireless sensor networks to mitigate interference,” *Proceedings of the 2010 IEEE Wireless Communications and Networking Conference (WCNC)*, Sydney, New South Wales, pp. 1-5, 18-21 April 2010.
6. A. King and U. Roedig, “Differentiating clear channel assessment using transmit power variation,” *ACM Transaction on Sensor Network*, vol. 14, no. 2, pp. 1-15, May 2018.
7. J. Huang, G. Xing, G. Zhou, R. Zhou, “Beyond co-existence: Exploiting WiFi white space for Zigbee performance assurance,” *18th IEEE Int. Conf. Network Protocol*, pp. 305-314, Oct 2010.
8. Liang, C. J, Priyantha, “Surviving wifi interference in low powered zigbee network,” *Proceeding of the 18th ACM conference on Embedded Networked Sensor Systems*, pp 309-322, Nov 2015. https://doi.org/10.1145/ 1869983.1870014.
9. F. Yao, S. H. Yang, W. Zheng, “Mitigating interference caused by IEEE 802.11 b in the IEEE 802.15. 4 WSN within the environment of smart house,” *2010 IEEE International Conference on Systems, Man and Cybernetics*, pp. 2800-2807, 2010.
10. N. H. Mahalin, H. S. Sharifah, S. K. S. Yusof, N. Fisal, and R. A. Rashid, “RSSI measurements for enabling IEEE802.15.4 coexistence with IEEE802.11b/g.,” *TENCON 2009-2009 IEEE Region 10 Conference*, 2009.
11. M. A. Sarijari, Anthony Lo, M. S. Abdullah, S. H. De Groot, I. G. M. M. Niemegeers, Rozeha A. Rashid, “Coexistence of Heterogeneous and Homogeneous Technologies in Smart Grid Home Area Network,” *2013 International Conference on Parallel and Distributed Systems*, Seoul, South Korea, 15-18 Dec 2013.
12. Rozeha A. Rashid, M. Rezan Resat, M. A. Sarijari, N. Mahalin, M. S. Abdullah, A. H. F. A. Hamid, “Performance Investigations on Frequency Agile Enabled TelosB Testbed in Home Area Network,” 2014 *IEEE 2nd International Symposium on Telecommunication Technologies (ISTT)*, Langkawi, Malaysia, 24-26 November, 2014.
13. A. H. F. A. Hamid, Rozeha A. Rashid, Lye Kong Weng, N. Fisal, “IEEE802.11 Interference Management for Wirelss Sensor Node,” *International Conference on Power, Energy, and Communication Systems (IPECS)*, Perlis, Malaysia, 24-25 August, 2015.
14. K. R. Chowdhury and I. F. Akyildiz, “Interferer classification, channel selection and transmission adaptation for wireless sensor networks,” *2009 IEEE International Conference on Communications*, pp. 1-5, Jun 2009.
15. S. Zacharias, T. Newe, S. O’Keeffe, and E. Lewis, “A lightweight classification algorithm for external sources of interference in IEEE 802.15.4-based wireless sesor networks,” *International Journal of Distributed Sensor Network*, vol. 10, no. 9, pp. 265-286, 2014.
16. Meng Hou, Fengyuang Ren, Chuang Lin, Mao Miao, “HEIR: Heterogeneous Interference Recognition for Wireless Sensor Network,” *Proceedings of IEEE International Symposium on a World of Wireless, Mobile and Multimedia Networks*, Sydney, NSW, Australia, 09 October 2014.
17. Iyer V., Hermans F., Voigt T., “Detecting and Avoiding Multiple Sources of Interference in the 2.4 GHz Spectrum,” *European Conference on Wireless Sensor Networks*, vol. 8965, pp. 35-51, Springer, 2015.