Wireless FEC-less Frame Transmission for Model Aggregation of Distributed Learning Systems

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Introduction

Forward Error Correction (FEC): Reduces the throughput rate and increases the complexity by making redundancy the primary mode for transmitting information with error correction.

Semantic/Joint Communication: These communication strategies suggest that specifying a domain beforehand can increase throughput. Within certain contexts, FEC overburdens the systemic task.

Unequal Error Protection (UEP): Renewing this approach to uneven bit-wise integrity, the system is able to reduce information transmission redundancy. This ability is gained by reducing the communication domain and more evenly constraining the system task to model learning.

Federated Learning (FL): Distributes the model training task by sharing the individual model vectors or parameters. This specific task constraint reduces a system's need for absolute error protection.

Methodology

Floating Point (FP): The FP is the fundamental unit within most machine learning models. Being vectors with uneven bit significance, FP inherently provides unequal error protection.

Physical Layer (PHY) Modification: By omitting certain encoding and decoding steps in the standard 802.11a protocol and directly transmitting floating point data, the complexity is transferred from the physical layer to the application-specific domain. Removing the protection across the entire 802.11 data field also impacts the link or MAC layer. To mitigate link-layer errors, a carefully timed transmission can ensure proper link and model transport.

GNU Radio: These PHY modifications can be implemented using a Software-Defined Radio (SDR), and an FL model can be transmitted and received without FEC by modifying and recompiling the IEEE802_11 blocks. Python and Zero Messaging Queue (ZMQ) are then used to interface with both Pytorch and GNU Radio.

CNN and MNIST: By specifying the task of learning a Convolutional Neural Network (CNN) that can decode MNIST images, a model can be trained with no FEC.

IEEE 754 Floating Point Interchange

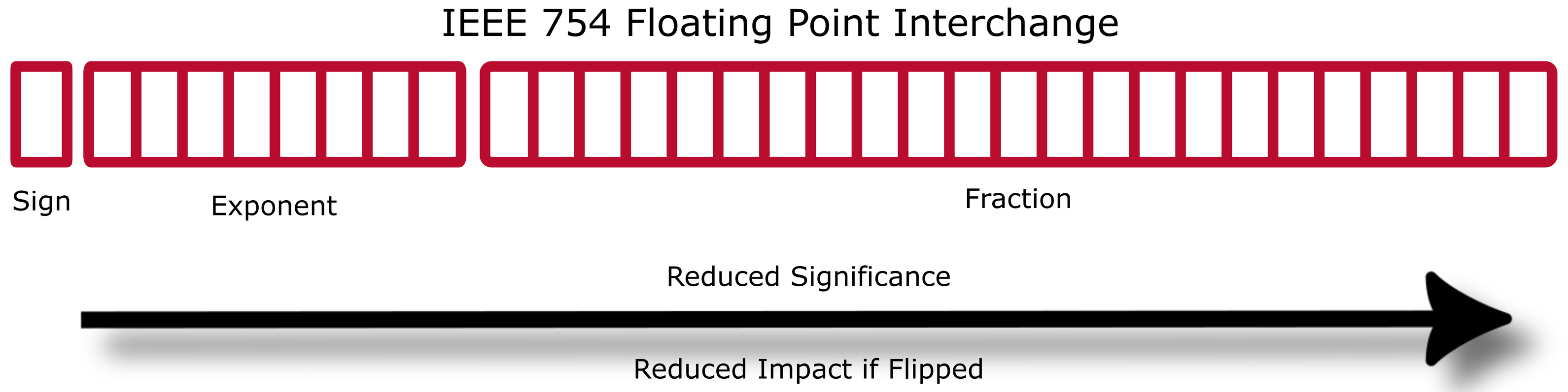

Figure 1.

This figure shows a 32-bit IEEE 754 floating point interchange format. It illustrates that since a majority of bits reside in fractions, a bit flip is more likely to flip a fraction bit. It also indicates that a bit flip error within the sign or exponent would have a much larger impact on the training task.

System of Federated Learning

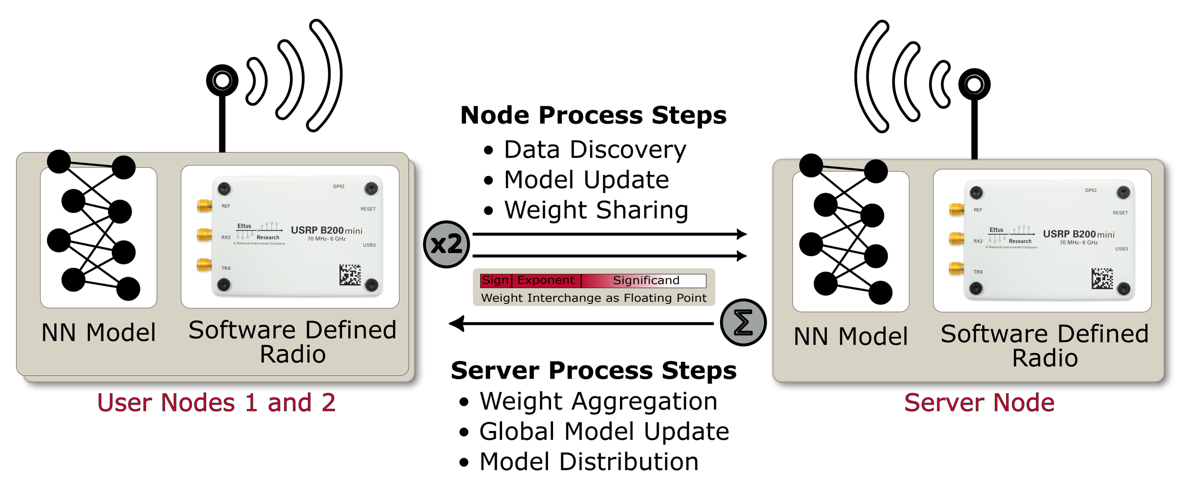

Figure 2.

A picture of the lab testbed setup. The black square highlights the receiver testbed moving platform, and the red indicates the fixed transmitter position. On the lower right is a picture of the Software-Defined Radio (SDR).

IEEE 802.11a Frame Structure

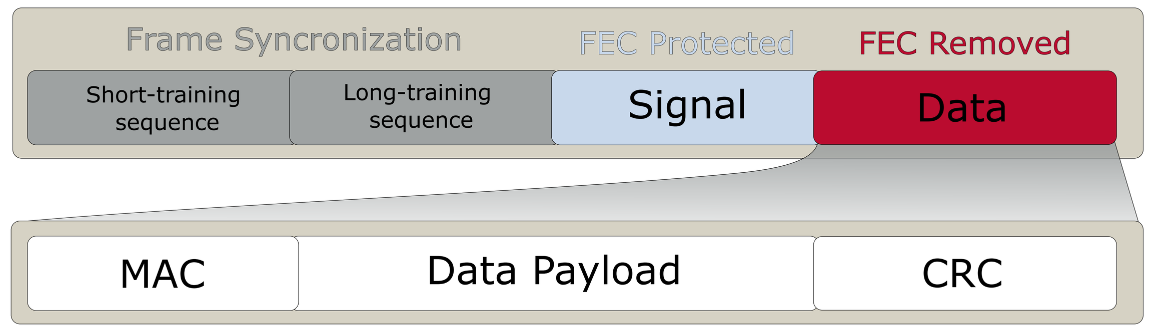

Figure 3.

This figure shows the frame structure modified from the 802.11g/a/p standard. The Forward Error Correction (FEC) is removed from the data packet.

Forward Error Correction Process Flow

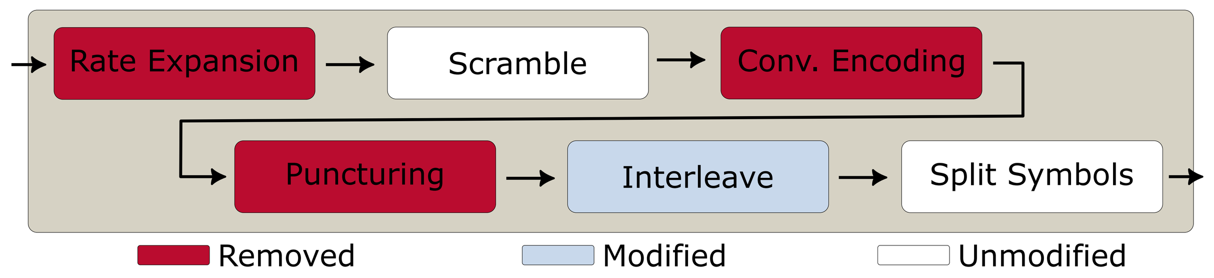

Figure 4.

This figure shows the modification made to disable FEC as a functional flow graph. The blocks in red indicate where FEC was disabled. The blue blocks were investigated for future modifications. The Split Symbols block was left unmodified.

https://github.com/SunLab-UGA/NO_FEC

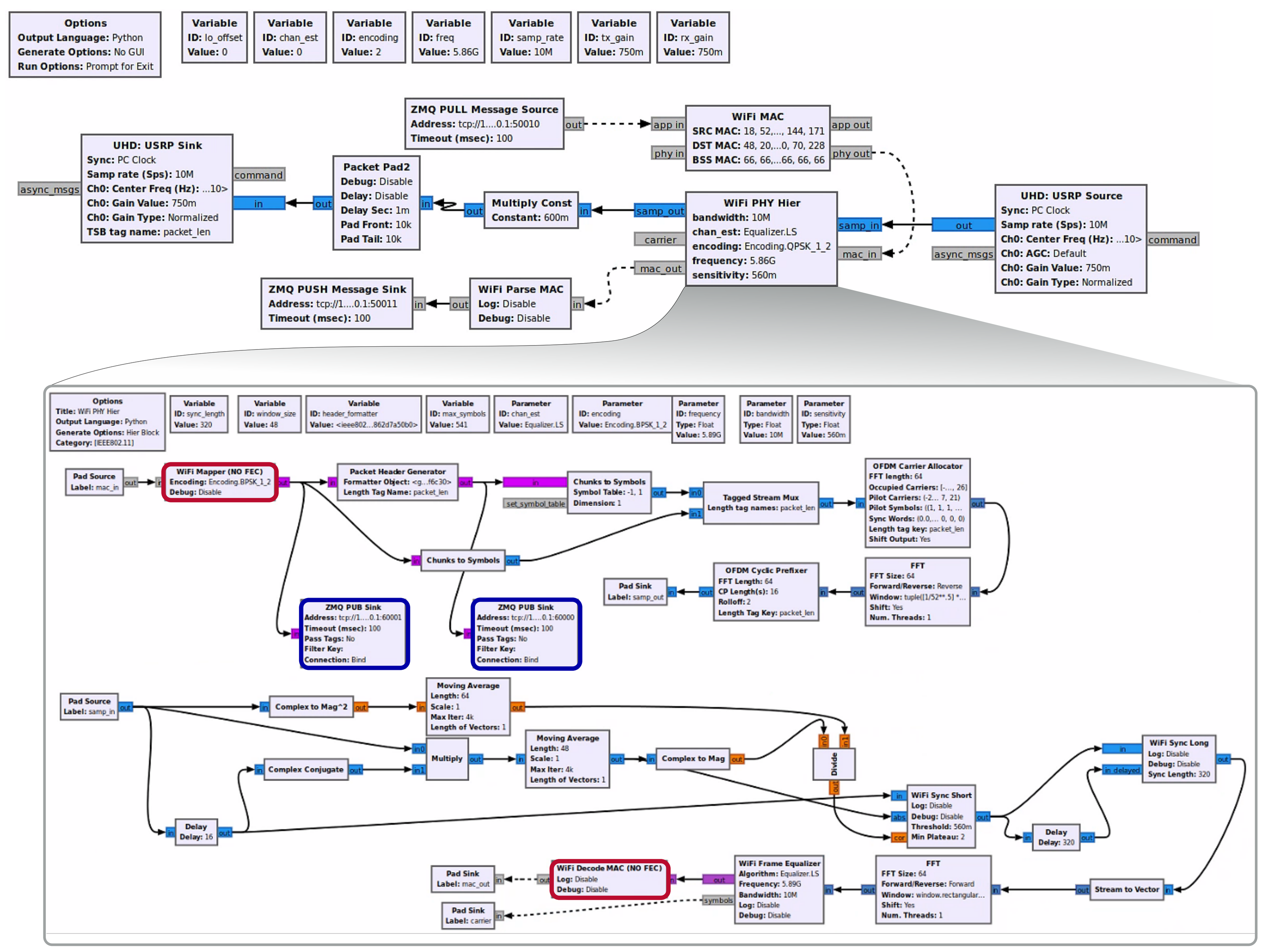

Figure 5.

This figure shows the two GNU Radio flowgraphs used to transmit and receive. The red outlines indicate the blocks which were modified to disable the FEC functionality. The blue blocks indicate the blocks added to interface with the GNU Radio process and pass packet data and debugging information. This shows the modificatons to the gr_ieee802-11 library.

Results and Conclusions

Enhanced Communication Rates: The lowest FEC rate is ½. Removing all FEC can double the per-packet throughput data rate.

Packet Retransmission: The receiver currently has no packet retransmit functionality. To ensure a model's complete transmission, the model needs to be sent repeatedly to ensure a complete set of packets is received.

Noise and Model Convergence: By specifying the task of training a large Convolutional Neural Network (CNN), the effect of any errors can be quickly overcome by a standard federated averaging.

Model Weights: Many of the model weights tend to converge between zero and one. This observation can help heuristically identify vector outliers due to high-priority bit errors, even without redundancy.

Resilience to Errors: The simulated results in Figure 6 show that introducing a 50% chance to flip a bit within the fraction has little impact on the model's ability to train over time.

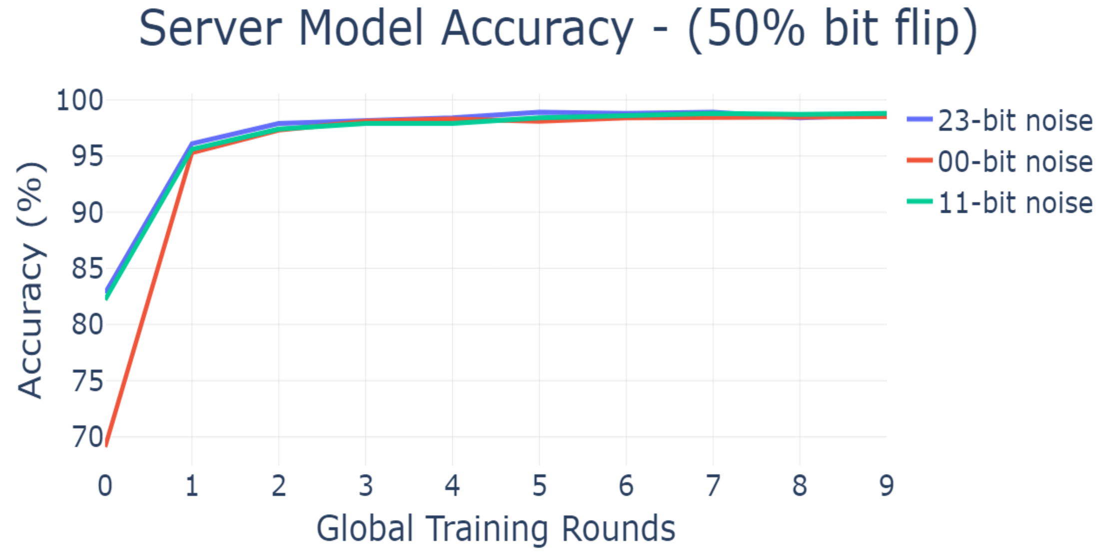

Figure 6.

This figure shows three runs of simulated transmission on CNN training. Noise is added between each trip between server and client. The added noise is a 50% chance to flip a bit part of the fraction. The blue line indicates that all bits of the fraction are susceptible to flipping. The red line has no noise, and the green line has the lowest eleven bits impacted. One global training round is one epoch per client.