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Channel Estimation in the Interplanetary Internet Using Deep Learning and Federated Learning †

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Abstract: Intelligent signal processing holds great importance for the future of resilient, adaptable communications networks. The unique qualities of deep space require an interplanetary Internet to be highly autonomous, efficient, and adaptable to varying Quality of Service (QoS). Deep learning has shown great promise in the field of signal processing for being computationally efficient, capable of handling errors from nonlinear effects (e.g., hardware impairments), and handling low signal-to-noise ratios. A recent survey by Pham et al. notes that none of the papers studied the improvements in classification in the high-order modulation regime. Additionally, these papers did not explore performance of their models in resource limited environments. A hierarchical interplanetary Internet that imposes a variety of constraints on its nodes offers a unique opportunity to explore realistic tradeoffs in model performance. This paper seeks to leverage the processing, storage, and data transmission capabilities of each level of the interplanetary Internet through federated learning. This will reduce data redundancy between nodes and minimize overhead transmission costs on the network. The goals of this project are the following: (i) detail possible insights into future channel estimation techniques applied to noisy, nonlinear models; (ii) explore application of deep learning models for high-order modulation schemes; (iii) quantify the resource-demand reduction resulting from the use of a deep neural network for intelligent signal processing; and (iv) analyze the adaptability of an interdependent system of deep neural networks in the context of a centralized/decentralized federated learning network.

Keywords: channel estimation; distributed machine learning; federated learning

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1. Introduction

A requirement for efficient utilization of available bandwidth in communications links is the estimation of the channel's distortion on transmitted signals. This is because the channel can distort the signals' amplitude, phase, and frequency spread, varying with distance, frequency, and in time. Variations in time-frequency phase space must nominally be characterized by known pilot waves sent at time intervals and on frequencies of interest.

The final result of detecting these channel distortions characterized is using signal filtration for appropriate detection of subsequent symbol transmission. The complete process is computationally expensive and creates expensive transmission time and processing overheads in communications links. Statistical inference of channel states for blind estimation has shown promise; a hybrid approach leveraging machine learning could reduce much of the typical system overheads.

Neural networks have recently been used for channel estimation, notably with deep neural networks [1,2], convolutional neural networks [3], and long short term memory neural networks [4]. These designs have been with the intention of reducing inefficiencies in typical channel estimation techniques including long Cyclic Prefix (CP) prefixes and redundancy in channel estimation by multiple nodes. Likewise, we can reduce the percentage of transmission blocks that is spent on pilot symbols by predicting the evolution of the channel noise. Additionally, the requirement for millisecond-scale channel estimation refresh for satellites strongly penalizes time-consuming algorithms. For this reason, this paper explores the possibility of using a decentralized architecture to share local models' learnings and speed up the processing of pilot symbols.

In most low-altitude satellite networks, connection topologies are variable and centralized processing is not viable. The lack of a global model state for optimization by the network will require the identification of parameters that do and do not benefit neighboring satellite nodes. Previous research into particle swarm optimization shows that it is possible to obtain quicker and more accurate results than with traditional synchronous computational methods [5]. Furthermore, it gives greater flexibility for individual nodes in a network to form more accurate estimations of channels and their evolution.

In Section 2, we introduce and discuss learning methods with potential to be used in this complex task of channel estimation for satellite links. We provide a brief insight on the features of interest and the learning characteristics. In Section 3, we introduce the conclusions with a brief view of the next steps on this problem of channel estimation.

2. Learning Methods for Channel Estimation

Channel estimation is a complex task where a system has to satisfy timeliness and accuracy criteria [6]. In satellite links, a channel's impulse response will change as time evolves, but this is accelerated by the movement of the satellites, which makes it difficult to satisfy an opportune estimation on time. We propose to use neural networks to estimate parameters and produce a learning experience that could be used for prediction of the channel. In order to have the whole picture, we also propose the use of federated learning to integrate all the information, produce a channel estimate, learn from that, and communicate back to the satellites the channel state information (CSI).

We propose conducting channel estimation with Convolutional Neural Networks (CNNs) which in previous studies has permitted quicker and more precise characterization of communication channels. Its architecture should be comprised of convolutional layers which are arranged in series and followed by one or more fully connected layers (FC) [7]. Convolutional neural networks have been used to determine and adjust for channel distortion in previous studies [3]. Convolutions will allow us to maintain some access to higher levels of abstraction in recognition of channel distortion. This is desirable given that the objective is to share limited amounts of parameters to great effect on the models of other communication nodes.

We can use Long Short Term Memory (LSTM) for recognition of channel evolution patterns. This deep learning architecture is based on an artificial recurrent neural network (RNN). It consists of a set of recurrently connected sub-networks, known as memory blocks, that fulfill the function of maintaining their state over time and regulate the information flow thought nonlinear gating units for several cycles. This permits the comparison of sequential signals in the context of previously received data; typical applications include speech recognition and language analysis. It has previously been used for successfully predicting channel evolution over some time [4].

2.1. Decentralized Federated Learning

The main objective of our research is to identify the parameters to be shared between nodes in a satellite network to eliminate redundant optimization of deep learning models used in channel estimation and prediction.

In Federated Learning (FL), not all data can be processed in the central server, so our model predicts and transmits the channel coefficients between satellite 1 and satellite 2, where the data sent by 1 to 2 are used to train channel estimation and prediction encoders on the latter [8,9]. Satellite 2 communicates learned parameters with satellite 3, reducing the computational load on one element in the network. As a whole, this should produce marked improvements in a wider network, see Figure 1.

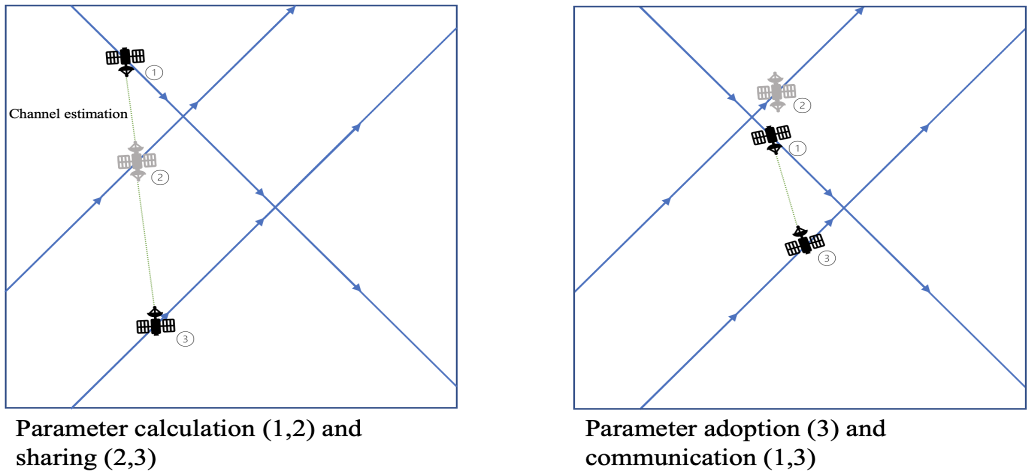

Figure 1. Sharing of learned parameters in a satellite network.

Particle sharing, as conducted in PSO-PS:Parameter Synchronization with Particle Swarm Optimization for Distributed Training of Deep Neural Networks, can quickly inform the proximal nodes in the network of the parameters 'found' to be optimal in channel denoising/classification encoders.

2.2. Benchmark Measurements

We propose the following benchmarks for the appropriate evaluation of the functioning of the channel estimation and channel evolution models, see [10]:

- Bit error rate as a function of given signal-to-noise ratio (BER vs. SNR);
- Number of pilot symbols required for conventional channel estimation vs. channel estimation with deep learning.

For evaluation of the impact of distributed learning and parameter sharing on computational demand on elements in the network and speed of optimization, we propose the following metrics:

- Improved time of channel coherence for given signal-to-noise ratio (SNR) with prediction of channel evolution;
- Parameters of greatest impact for sharing in federated learning framework;
- Predicted improvements in channel estimation and prediction metrics with learnings from a network of satellites.

3. Conclusions

Once the basic architecture is verified, the next steps include estimating the effects of network density on learning-sharing transmission overhead and a possibly greater impact of learnings shared between more proximal nodes. If learnings from Single Input, Single Output systems prove valuable for sharing between communications nodes, it opens up the possibility of sharing those learnings between communications links on a MIMO system. This would allow for greater scalability of the system without a linear increase in computational complexity. This would in turn generate more data for optimization within a single satellite and reduce demand for learnings from other nodes.

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