Poster: Online Learning for Reliable Packet-level Cross-Technology Communication

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Abstract

Cross-Technology Communication (CTC) is an emerging technology to enable direct communication between devices that follow different wireless standards. However, channel dynamics may affect the performance of the existing CTC approaches. This work proposes an online learning framework for existing CTCs. In the framework, the decoders could update its parameters and adapt to dynamics environments. the evaluation shows that the framework can effectively reduce the SER.

1 Introduction

The tremendous advance of Internet of Things (IoT) brings the widespread deployments as well as the rich diversity of wireless technologies (e.g. WiFi, Bluetooth and ZigBee). Recently, Cross-Technology Communication (CTC) has been proposed to enable the direct communication between heterogeneous devices that follow different wireless technologies.

Existing packet-level CTCs tend to design recognizable patterns of the mutually accessible carrier. For example, ESense [1] modulates packet lengths. GSense [7] customized packet preambles by embedding symbols into gaps . FreeBee [6] shifts the transmission timings of beacons. B2W2 [2] mimics the DAFSK for communication from BLE to WiFi For CTC receivers, decoding CTC symbols means distinguishing these patterns. Existing approaches typically leverage threshold [4, 6] or machine learning model [3] to recognize different CTC symbols. However, the intrinsic dynamics and diversities of wireless channels cause feature distortions and decoding errors. Enabling reliable performance in dynamic channels is therefore a fundamental problem for CTC in dynamic environment.

In order to tackle the above problem, we propose a general and lightweight online learning framework for existing packet-level CTC. In this framework, the CTC receiver adjusts its decoding model according to predefined training sequences acquired from the CTC sender. Because training sequences incorporate instant channel dynamics, by periodically training decoding model from these sequences, the decoder has opportunity to adapt itself to channel dynamics, thus achieving reliable performance.

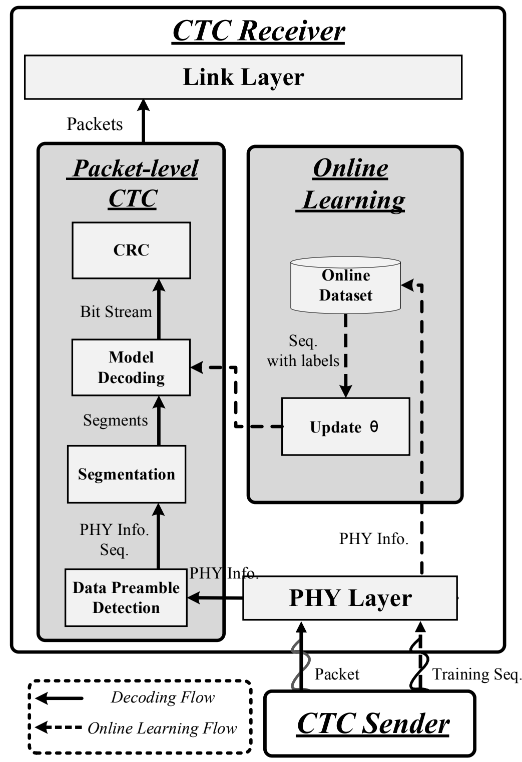

Figure 1. Online Learning framework.

2 Design

Architecture Fig. 1 shows the architecture of the framework. The framework consists of two major parts: CTC decoding and online learning. In CTC decoding component, the data preamble detection module first detects the exis-

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tence of modulated CTC symbols and passes the modulated channel state sequences to the segmentation module. The segments are then decoded by decoding model. The demodulated bits will be checked by Cyclic Redundancy Check (CRC) for correctness checking. The packets that pass CRC check will be delivered to CTC link layer. We propose an online learning mechanism to update the parameters θ of decoding model using the online dataset, thus adjusting the decoding model to dynamic environments.

Wireless channels can change significantly and cause serious performance degradation. We propose full training mechanism to quickly recover from the failed model. Once the mechanism is triggered, the CTC receiver will require the bursty training sequences from the CTC sender. Then the sender broadcasts the training sequences. Note that when channel state significantly changes, the data preamble detection method may also fail detecting CTC preambles due to the invalid decoding model. Hence, we propose a dedicated preamble for training sequences, based on barker code.

Decoding Model: Channel dynamics can result in features distortions. Extracting manually pre-defined features may lose the information embedded in raw data. A popular technique, neural network, is promising to tackle this problem, because it has the ability of automatically learning the features from raw data without any prior domain knowledge. Hence, we try to leverage the neural networks to automatically learn the features that reveal the channel dynamic information.

Online Dataset: We construct training sequences with a dedicated pattern to help the receiver extract labeled data. The training sequence consists of continuous symbol 1s followed by continuous symbol 0s. The periods for continuous symbol 1 and 0 typically larger than symbol length for robustness. Then we use the sliding window to segment the sequence to obtain labeled symbol frames. We can infer the label based on the fixed structure of the dedicated training sequence. Then we build the online dataset by accumulating pairs of the symbol and the label.

3 Performance Evaluation

Setup: To evaluate the framework we proposed, we implement the framework based on ZigFi [3] on commercial off-the-shelf devices. We use commercial computers with Intel 5300 NICs as WiFi sender and receiver to create a WiFi link. CSITool [5] is installed on the WiFi Rx to collect CSI samples. The CSI sample interval is 0.2ms. We use TelosB, a commercial ZigBee platform, to implement the ZigBee sender as CTC sender. The ZigBee symbol length $T_s = 4$ms. The communication channel of WiFi and ZigBee is set to channel 11 and channel 23 respectively, so that they overlap in frequency domain.

Symbol Error Rate: Obviously, the transmission power of ZigBee affects the signal strength at WiFi receiver. We evaluate the performance of ZigFi with and without online learning under different transmission level. The transmission power of TelosB(CC2420) has 31 levels from -24 to 0 dBm.

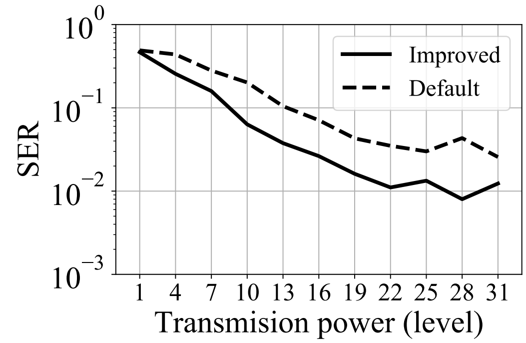

Figure 2. Online Learning framework.

The distance between the ZigBee sender and the WiFi receiver is 3m, and the distance between the WiFi sender and the WiFi receiver is 3m. Fig. 2 show that, not surprisingly, the SER decreases when the transmission power increases. When transmission level is 1, ZigBee signal hardly reach the WiFi receiver. The situation is getting better when the transmission level increases. The SER of ZigFi with online learning is lower than 0.01 when the transmission level increases to 28.

4 Conclusions

In this work, we propose a general online learning CTC framework that maintains reliable performance in dynamic channel environments. The framework utilizes online learning to adapt to channel dynamics. The framework keeps updating the receivers decoding model by requiring instant training sequences to quickly recover from the decoding failure. We implement the framework on commercial devices and evaluate its performance. The experiment results show that the framework could reduce SER effectively.

5 Acknowledgments

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6 References

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