

AI model -Based Signal Restoration for X-Ray Communication

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***Keywords :** X-ray communication, deep learning, signal restoration, connectionist temporal classification, integrated sensing and communication

1. Introduction

X-ray communication (X-com) is an emerging wireless technology that utilizes modulated X-ray pulses as information carriers. It offers strong penetration capabilities through plasma sheaths and metallic barriers, making it uniquely suited for extreme environments such as spacecraft atmospheric re-entry and radiation-shielded facilities. Unlike conventional radio-frequency links, however, X-com lacks dedicated transceiver hardware or integrated circuits. Consequently, received waveforms must be reconstructed entirely in software from noisy analog detector traces.

Conventional deterministic decoders based on filtering and threshold binarization degrade rapidly in performance under timing jitter and distance-induced signal attenuation. In an X-com testbed operating under a Universal Asynchronous Receiver/Transmitter protocol at 28,800 bps, the cumulative restoration rate of a standard threshold decoder saturates near 77%.

To address the absence of a dedicated receiver hardware layer, we present a learned software receiver based on a Convolutional Recurrent Neural Network trained with Connectionist Temporal Classification. In addition, we demonstrate that the same received waveforms carry channel-state information, enabling simultaneous communication and channel sensing on a single X-ray link.

2. Methods and Results

In this section some of the techniques used to model the detector channel are described. The channel model includes a SiC detector, cable, preamplifier, amplifier, and discriminator models.

2.1 X-com testbed

The experimental setup consists of a carbon-nanotube X-ray tube transmitter and a scintillator-silicon photomultiplier sensor receiver mounted on a motorized linear stage (0–50 cm). A data-transfer PC outputs a 5 V UART logic pulse train (28,800 bps), which a gate driver converts into a ~4 kV gating voltage to modulate electron emission from the cathode.

The emitted X-ray pulses are detected by a scintillator optically coupled to a SiPM. The SiPM output is amplified by a low-noise preamplifier and digitized by an oscilloscope.

2.2 Timing-Error Characterization

Analysis of 21,689 measured edge transitions over 20,000 records reveals a strongly bimodal timing-error distribution: (1) Bit-level Jitter: Concentrated near 12 μ s during active tube operation; (2) Frame-start Propagation Delay: Concentrated near 55 μ s, originating from the finite turn-on time of the X-ray tube and high-voltage gating dynamics.

Because one bit period at 28,800 bps is 34.7 μ s, the 55 μ s delay systematically causes framing errors for decoders assuming a rigid bit grid.

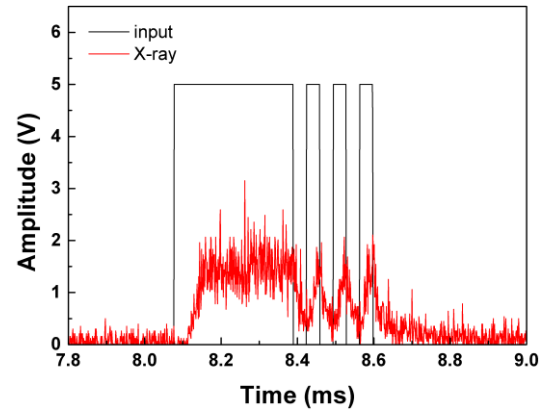


Fig. 1. Representative received waveform.

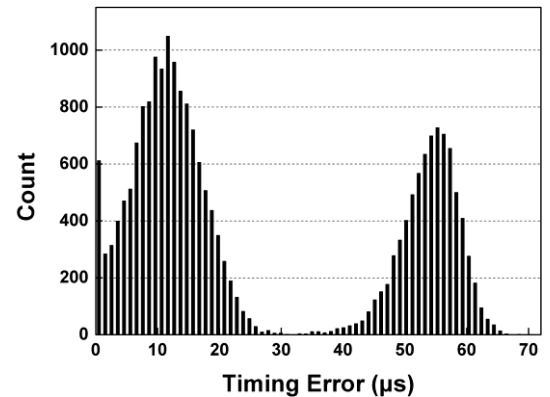


Fig. 2. Timing-error histogram over of measured edges

2.3 Ai Framework

The restoration network down samples a 30,000-point raw waveform using two 1D convolutional blocks, followed by a two-layer bidirectional Gated Recurrent Unit and a linear CTC projection layer over 257 classes. The network contains 2.0 million parameters. By marginalizing over all admissible temporal alignments, the CTC loss formulation eliminates the need for rigid bit-grid synchronization, directly overcoming high timing jitter.

2.4 Symbol Restoration Performance

Evaluating the CRNN on 10,000 held-out test waveforms shows a dramatic error reduction as the training set scales: 1,000 samples yield 100% error rate; 10,000 samples yield 0.28% error rate; 20,000 samples yield 0.00% error rate (error-free decoding). The learned receiver maintains near 0.00% error across all timing-jitter bins (including the dominant 50–60 μ s frame-delay region) and extends the usable communication range up to 40 cm separation without performance degradation.

3. Conclusions

We have demonstrated a learned software receiver that bridges the hardware gap in X-ray communication. The proposed CRNN-CTC network completely resolves severe bimodal timing jitter and frame delays, achieving 0.00% symbol restoration error. Furthermore, the concurrent channel-sensing network achieves 98.3% accuracy in estimating aluminum shield thickness. These results demonstrate that a single X-ray link can simultaneously perform high-reliability communication and channel sensing without requiring dedicated physical receiver hardware.

Acknowledgments

The authors would like to acknowledge the anonymous reviewers for their valuable comments and suggestions, which significantly strengthened the overall manuscript. This work was supported by the KAERI Institutional Program (Project no. 79756-25, 523160-26). Financial resources were granted by the Ministry of Trade, Industry & Energy, Republic of Korea.

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