NELoRa: Neural-enhanced Demodulation for Low-Power WANs

Low-Power Wide-Area Networks (LPWANs) has emerged as a promising mechanism to connect billions of low-cost Internet of Things (IoT) devices for wide-area data collection. Long Range (LoRa) [1] is a LPWAN that breaks the SNR threshold of short chirp segments form a linearly increasing energy peak distribution in its amplitude spectrum. The initial frequency of the energy peak distribution is determined by the initial frequency of the chirp symbol, which corresponds to the data bits it represents. As shown at the top of Figure 2, although the encoded initial frequencies among the four chirps are close, we can clearly observe the energy peak distributions of the four chirps are different. The results are shown in Figure 2. The spectrograms of chirp symbols are a useful feature dimension. Additionally, as shown in Figure 2c, we can see peaks (e.g., bright areas) and valleys (e.g., dark areas) appear alternatively in both amplitude (e.g., circle) and phase (e.g., dashed rectangle) spectrograms. Specifically, the patterns observed by amplitude and phase can be correlated, but different chirp symbols exhibit diverse patterns. Hence, the staggered pattern is another feature dimension of the dual-channel spectrum to distinguish different chirp symbols. When SNR is getting low, however, the dual-channel spectrum will be polluted by noise. To illustrate this, we collect a chirp symbol to calculate its amplitude spectrogram under different SNR levels. As shown in Figure 3, when SNR is 35 dB, we can see the spectrum energy peaks of all short chirp segments. When SNR drops to -10 dB, Figure 3 shows only several short chirp segments’ energy peaks (e.g., white circles) that can be explicitly observed compared to surrounding noise energy. Facing the seriously polluted dual-channel spectrogram, a DNN can succeed in recognizing chirp symbols due to the noise-resistant patterns obtained from...
both amplitude and phase spectrums. Specifically, the energy peak distribution exhibits a linear pattern, which can still be observed with several explicit energy peaks in Figure 3. Moreover, the staggered pattern exists in both amplitude and phase spectrums. Since the amplitude and phase of a short chirp segment’s spectrum are affected by the noise independently, the staggered pattern has the potential to tolerate specific noise. A well-designed DNN is good at learning these patterns. Although random noises may be much stronger than chirp symbols, it is hard to simultaneously form similar patterns in multi-dimensional feature space to mislead the DNN. Hence, we feed the dual-channel spectrogram of a chirp symbol to our DNN.

**NELoRa OVERVIEW**

Figure 5 illustrates the overall architecture of NELoRa. NELoRa consists of three stages to achieve reliable symbol generation and neural-enhanced demodulation. In the Packet Identification stage, a LoRa packet is first detected from raw signal samples via the Chirp Enhance and Preamble Detection modules. The detected packet is then imported into the DNN Input Generation stage. The Offset Recovery module exploits the redundant chirp symbols in packet preamble to compensate offsets in frequency and time domains to generate the time-aligned and offset-free chirp symbols in packet payload. Each extracted chirp symbol is then transformed by the Symbol Transform module into a dual-channel spectrogram. The final stage is DNN-based Demodulation. Given the dual-channel spectrogram, the Mask-enabled Filter module alleviates the channel noise to obtain a masked spectrogram, which is then decoded by the Spectrogram-based Decoder module to generate the packet.

**Packet Identification.** The default packet detection method utilizes the preamble of a LoRa packet, which consists of multiple continuous base up-chirps. To tolerate a lower SNR threshold than the one used in chirp detection, instead of using the energy peak of a window chirp, we sum up multiple continuous window chirps to form an enhanced window chirp. Since the energy of window chirps are added up coherently, but the random noise is not. We apply dichirp on the enhanced window chirp to obtain an accumulated energy peak, surpassing the randomly increased noise energy. In theory, when we sum up eight window chirps coherently, the resulting SNR gains will be 9 dB. If the energy peak of the enhanced window chirp is higher than the average noise energy, a LoRa packet is detected. Due to the existence of carrier frequency offset (CFO) and sampling frequency offsets (SFO), which introduce phase shifts onto the window chirps that accumulate over time, different window chirps may have different initial phases. To take advantage of coherently overlapping, we use a greedy search method to find the clock drift, which can approximately estimate the phase offset.

**Neural-enhanced Demodulation.** As shown in Figure 5, our dual-DNN model includes two modules, the noise filter and the spectrogram-based decoder for noise reduction and chirp symbol decoding, respectively. The first module aims to preserve the primary spectrogram features of a chirp symbol by masking the raw dual-channel spectrogram. In a conceptual sense, the noise filter is more like an end-to-end shortcut connection in the ResNet block [8] by transforming the shortcut from layers into ends. It contains multiple blocks of CNN and one LSTM to fully exploit the spatial and temporal features of the input, followed by two dense layers to output a well-matched mask. Moreover, a four-layer CNN-based decoder is designed to fully capture the spatial energy peak distribution and temporal staggered pattern in the masked spectrogram.

**Data Augmentation.** We improve the generalization of our DNN model by training it with millions of synthesizes LoRa chirp symbols, which cover different SNR levels with diverse random noise patterns. Specifically, we collect each type of chirp symbol at high SNR using an indoor testbed. To achieve fine-grained SNR control, we add various Gaussian white noises with controlled amplitude on the collected I and Q traces [9–11] to generate new chirp symbols.

**DNN Model Compression.** We adopt the structured pruning [12] to compress the original model for efficient inference. Specifically, we calculated the L1-norm of weights in each filter of CNN and dense layer and preserved those with the largest L1-norm. Besides, we also replace the LSTM layer with the GRU layer, which is a more computation-efficient version of RNN, while achieving similar performance when the input sequence is not too long.

**SYSTEM IMPLEMENTATION**

We have implemented NELoRa and evaluated its performance with commercial LoRa nodes. Figure 6 illustrates the system prototype of NELoRa. Specifically, we use the USRP N210 software-defined radio (SDR) platform for capturing over-the-air LoRa signals, operating on a USR daughter board at the 470MHz bands. The captured signal samples are then delivered to a back-end host for pre-processing and demodulation. Note that demodulation methods of NELoRa are hardware-independent, so they can be implemented on any other commercial LoRa gateways as long as the signal samples can be obtained. On the transmitter side, we use SX1278 chipset radio-based commodity LoRa nodes for transmitting LoRa packets.

**PERFORMANCE EVALUATION**

To examine the performance in the outdoor environment, we deployed our testbed on a university campus covering various land cover types (e.g., trees, buildings, roads, and pond) as illustrated in Figure 7(a). Specifically, we deployed the LoRa nodes at six different locations. Each LoRa node transmits 25 packets, each of which contains 188 chirp symbols. Besides the pre-trained DNN decoder, we use the newly collected...
symbols in the campus environment to fine-tune our DNN model to achieve higher performance. We use the standard chirp as the baseline. As shown in Figure 7(b), in general, SER is increased as the distance between the gateway and the LoRa node increases. Although location 2 is near the gateway, it has a high SER due to low SNR caused by the building blockage. Compared with the baseline, the original NELoRa decreases SER by 5.1% to 31.9%, and the re-trained NELoRa further reduces the SER by 7.72% to 46.9%. We estimate the battery lifetime of the operating LoRa node at each location. Figure 7(c) shows the battery life can be extended by 1.32 to 5.73 years with the original NELoRa. The maximum battery life gain can reach 8.06 years by using the re-trained NELoRa at location 2. SER of location 2.5, and 6 reach 100% using the chirp. The gateway cannot demodulate any data from these locations even if the LoRa node drains out their battery. With NELoRa, the SER is lowered, and the battery lifetime is increased significantly.

CONCLUSION AND FUTURE DIRECTIONS
Neural-enhanced LoRa demodulation is a promising way to break the SNR threshold of the standard chirp approach. In this work, we propose NELoRa based on such neural-enhanced demodulation design, and demonstrate that the obtained SNR gains enable longer communication distance and battery lifetime in LoRa. For a detailed evaluation of NELoRa, please refer to the original paper [13]. To improve the performance of NELoRa, a DNN model optimization is needed when the length and types of chirp symbols are getting larger. Moreover, an online DNN model adaption scheme is needed to cope with the environment dynamics in real-world deployment. We leave these as our future works.

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