

Wireless Channels as Fingerprints: Towards Collision-Free LoRa Networks

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Abstract—LoRa enables long-range Internet of Things (IoT) connectivity but suffers from collision issues in dense deployments, where concurrent transmissions overlap at gateways, leading to decoding errors. Existing solutions rely on time/frequency separation or protocol modifications, requiring either hardware changes or dedicated codings, and failing to resolve collisions that are completely aligned in time or frequency. We present CD-LoRa, a Channel-Division based LoRa parallel transmission scheme for LoRa collisions. CD-LoRa exploits distinct channel signatures as inherent orthogonal fingerprints, enabling parallel decoding even when collisions are completely aligned. We present a phase calibration model that decouples genuine channel features from hardware imperfections and payload modulation distortions. We enhance low-SNR LoRa signals through energy-concentration processing. We address channel variations in mobile scenarios with a dynamic temporal sequence based clustering design. We implement CD-LoRa on commodity LoRa devices and evaluate its performance in real-world deployments. Experimental results show that CD-LoRa effectively decodes up to 8 time-frequency-aligned packets, and improves network throughput by 1.72 $\times$ compared to state-of-the-art methods.

I. INTRODUCTION

LoRa, as a widely used Low-Power Wide-Area Network (LPWAN) technology, enables long-range communication with ultra-low power consumption [1]–[3]. It uses chirp-modulated signals at the physical layer, which resist noise interference, multipath fading, and Doppler effects. Typical LoRa links cover 5~10 kilometers, and end-node batteries can last up to 10 years. These strengths make LoRa ideal for various Internet of Things (IoT) applications, such as smart cities [4], [5], smart agriculture [6], [7], smart health [8], [9], industrial automation [10], [11], and environmental monitoring [12], [13]. To date, over 20 billion devices use LoRa for Internet connection with an increasing rate of 17% [14].

LoRa adopts a star network topology, where each end node communicates directly with a central gateway in a single hop [15]. As the number of node grows, concurrent uplink transmissions increasingly overlap at the gateway, resulting in signal collisions [16], [17]. Such collisions manifest as decoding failures and consequent packet loss [18], [19]. Even worse, LoRa uses narrow-band channels and inherently a low physical-layer data rate, widening the time window in which overlaps can occur. LoRa protocol lacks native mechanisms

for collision detection or avoidance, maintaining reliable performance in dense deployments poses a significant challenge.

Existing Approaches. Recent research proposes parallel decoding mechanisms to mitigate LoRa collisions. By exploring multi-dimensional features of overlapping transmissions, these receivers can disentangle colliding signals and decode in parallel. Existing approaches fall into three categories based on features they used: (1) *Frequency based methods* [20], [21], [27]: They leverage the frequency domain features, like frequency shifts, FFT peaks, or frequency continuity, to identify collisions. For example, Choir [20] identifies concurrent FFT peaks by exploiting their distinct frequency offsets, and CIC [21] uses frequency component cancellation to separate overlapping packets. (2) *Time based methods* [22]–[24], [28]–[31]: They focus on the temporal distribution of chirps, either by tracking their arrival times or detecting changes in their peak heights across time windows. For example, FTrack [22] identifies overlapping signals by analyzing the spectrum time distribution of chirps, while NScale [23] and CoLoRa [24] use window-based transformations to extract time features for collision classification. (3) *Coding based methods* [25], [26], [32]–[34]: They use distinct coding schemes to assign unique chirp characteristics to different transmitters, enabling the identification and separation of signals based on predefined patterns. CurvingLoRa [25] assigns different unilinear chirp slopes to each transmitter, making signals identifiable by their unique down-chirps, while FlipLoRa [26] uses orthogonal up-chirps and down-chirps to reduce interference when there is a collision.

Fundamental limitations. Existing parallel decoding methods have two main restrictions. (1) Relying on special hardware or coding mechanisms: Many methods are closely tied to specific hardware or need applying orthogonal coding scheme, which increases both cost and deployment complexity. (2) Unable to process synchronized collisions: Current methods depend on different frequencies or time features of collision signals. The limited feature space restricts channel capacity, particularly when handling nearly synchronized collisions.

Our approach. We propose CD-LoRa, a Channel-Division LoRa parallel transmission framework, which distinguishes overlapping signals through channel characteristics inherently determined by distinct transmission paths. CD-LoRa extracts physical-layer channel characteristics from individual LoRa

TABLE I: Comparison of LoRa Parallel Decoding Approaches: Feature Utilization, Implementation Requirements, and Performance Characteristics.

Feature	Method	No Hardware Modification	No Modulation Modification	Time-Aligned Collision	Freq-Aligned Collision	Concurrency	Sensitivity
Frequency	Choir [20]	✓	✓	✓	✗	5	≈ 15 dB
	CIC [21]	✓	✓	✓	✗	10	< -5 dB
Time	FTrack [22]	✓	✓	✗	✓	10	≈ 10 dB
	NScale [23]	✓	✓	✗	✓	10	< -10 dB
	CoLoRa [24]	✓	✓	✗	✓	10	> -5 dB
Coding	CurvingLoRa [25]	✗	✗	✓	✓	10	< -10 dB
	FlipLoRa [26]	✓	✗	✓	✓	5	< -5 dB
Channel	CD-LoRa	✓	✓	✓	✓	8 (Time & Freq -Aligned Collisions)	< -10 dB

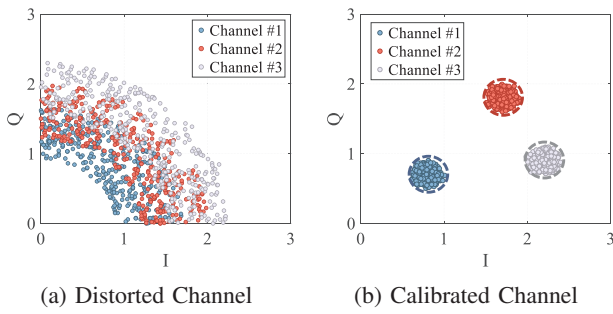


Fig. 1: Channel Division Principle of CD-LoRa.

chirp symbols, then clusters chirps with matching channel estimates into distinct groups to separate overlapping signals, as shown in Fig. 1(b). We compare CD-LoRa with typical LoRa parallel decoding methods in Table I. CD-LoRa resolves fully time- and frequency-aligned LoRa collisions by exploiting unique propagation-induced channel fingerprints, requiring no hardware modifications or modulation scheme changes.

Challenges. Putting CD-LoRa into practice, however, still faces challenges. First, extracting genuine channel characteristics from distortion sources proves challenging—hardware oscillator inaccuracies and payload modulation collectively introduce phase distortions that corrupt channel estimates, causing unstable measurements as shown in Fig. 1(a). Conventional methods often conflate these distortion components, leading to unreliable channel measurements.

Second, LoRa long-range transmission leads to ultra-low SNR at receivers. Channel features become buried in ambient noise, making channel estimation results less reliable.

Finally, device movement and environmental changes create continuous channel variations. Traditional static grouping methods misinterpret these gradual changes as distinct channel signatures, incorrectly dividing single transmissions into multiple clusters.

To address these challenges, we propose several designs in CD-LoRa. First, to recover channel distortions caused by

hardware imperfections and payload modulation, we develop a phase decomposition model that isolates genuine propagation effects from device-specific artifacts. Second, for low-SNR conditions where signals drown in noise, we develop a chirp-coherent integration method exploiting LoRa’s spectral continuity to amplify weak signals. Finally, to resolve mobility-induced channel variations, we introduce the temporal sequence clustering method, which transforms time-varying features into predictable 3D trajectories for collision resolution.

Following is a list of contributions of this work:

- We propose CD-LoRa to enable parallel transmission in LoRa without relying on hardware modifications or changing coding schemes. CD-LoRa supports large-scale IoT applications that need simultaneous transmissions with aligned time and frequencies, such as environmental monitoring and industrial applications.
- We address practical challenges to reduce channel estimation errors, along with anti-noise designs and cross-dimensional clustering to enhance signal demodulation.
- We implement CD-LoRa with commodity LoRa nodes and test its performance in real-world applications. Experimental results show CD-LoRa effectively resolves time- and frequency-aligned collisions and improves network throughput by $1.72\times$ compared to state-of-the-art methods.

II. BACKGROUND AND MOTIVATION

A. LoRa Primer

LoRa uses Chirp Spread Spectrum (CSS) modulation, where signals are modulated into chirps whose frequency changes linearly with time. LoRa chirps are characterized by their bandwidth (BW) and duration (T), with a spreading factor (SF) that determines the relationship between BW and T as $2^{SF} = BW \cdot T$. The initial frequency of a base chirp is $f_0 = -\frac{BW}{2}$, and the signal can be expressed as

$$C(t) = e^{j(2\pi(f_0 t + \frac{1}{2} \frac{BW}{T} t^2))} \quad (1)$$

To encode data, LoRa shifts the base chirp by a frequency f_i , allowing each chirp to encode up to 2^{SF} different frequency

offsets, representing SF bits of data. The initial phase of the chirp is ϕ_0 . An encoded chirp with shifted initial frequency is

$$x(t) = C(t) e^{j(2\pi f_i t + \phi_0)} \quad (2)$$

In demodulation, LoRa extracts the bit data by determining the chirp's starting frequency. The receiver multiplies the received signal by a reference down-chirp, which is the conjugate of the base up-chirp, i.e.,

$$C^*(t) = e^{j2\pi(f_1 - \frac{1}{2}kt)t} \quad (3)$$

where $f_1 = \frac{BW}{2}$ and $k = \frac{BW}{T}$ (chirp rate, i.e., frequency sweep rate). This process, called dechirping, converts the chirp signal to a single-frequency tone, i.e.,

$$C^*(t) \cdot x(t) = e^{j(2\pi f_i t + \phi_0)} \quad (4)$$

Finally, receiver applies Fast Fourier Transform (FFT) to convert the signal to the frequency domain, where the frequency peak reveals the encoded data, which is translated into SF bits.

A LoRa packet at the physical layer consists of preamble, Start Frame Delimiter (SFD), and data payloads. The preamble contains 6 to 65,536 base up-chirps, for identifying the presence of LoRa packets. The SFD is composed of 2.25 base down-chirps, for time and frequency synchronization of LoRa signals. The data payloads are up-chirps that encode the data information with frequency shifts.

B. Motivation

Recent advancements in LoRa parallel decoding have demonstrated theoretical potential to enhance network capacity through concurrent packet reception. Yet, a gap persists between their theoretical capacity and practical performance, when applying those techniques in real-world LoRa deployments. The root of the gap comes from two unrealistic premises: either hardware modifications to LoRa nodes or identifiable temporal/spectral misalignment between colliding signals. Such assumptions fail to hold in event-triggered applications—such as industrial accident alarms—where distributed nodes inherently generate real-time uplink transmissions with near-zero time offsets and identical frequency parameters.

Consequently, current approaches struggle to resolve collisions under strict spatio-temporal synchronization, resulting in a persistent performance gap between theoretical decoding capacity and operational reliability in practical systems.

This paper proposes a novel collision separation paradigm that exploits wireless channels as discriminative features. Unlike conventional approaches that rely on transmitter or receiver features, the channel is uniquely determined by the physical propagation environment. This intrinsic property enables our method to disentangle overlapping signals even under perfect temporal/spectral alignment. By leveraging channel-induced signal variations inherent in existing deployments, our solution achieves practical collision recovery while maintaining full backward compatibility with standard LoRa infrastructure.

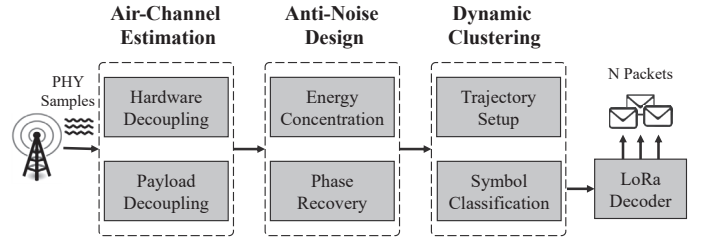


Fig. 2: Illustration of CD-LoRa workflow.

III. CD-LoRa IN A NUTSHELL

We propose CD-LoRa, a novel framework that exploits channels as discriminative fingerprints to disentangle overlapping LoRa signals. Fig. 2 delineates the architectural workflow of CD-LoRa, which comprises three principal components.

(1) *Air-Channel Estimation*: CD-LoRa first estimates the air-channel from received LoRa signals. Ideally, the air-channel is determined by propagation paths of the signal, where distinct transmission paths induce unique phase rotations and amplitude fading. In practice, however, both hardware imperfections and LoRa payload modulation will lead to phase drifts. Those drifts entangled with the channel impacts, making genuine air-channel estimation difficult. CD-LoRa addresses this challenge by introducing a hardware-payload modeling framework. It systematically decomposes phase distortion sources and compensates their impacts, enabling accurate air-channel reconstruction from received LoRa signals.

(2) *Noise-Resilient Channel Recovery*: Long-range LoRa transmissions inherently suffer from severe path loss, resulting in critically low SNR. LoRa signals may even become buried within ambient noise. Conventional channel estimation techniques prove inadequate under low-SNR conditions. CD-LoRa overcomes this limitation by exploiting the continuous frequency progression of LoRa modulation. It incorporates an energy accumulation-based phase estimation algorithm that amplifies channel features while effectively suppressing noise through coherent signal integration.

(3) *Dynamic Feature Clustering*: To accommodate potential node mobility and environmental dynamics, CD-LoRa implements dynamic feature clustering. Empirical observations reveal that channel variations exhibit temporal coherence. CD-LoRa capitalizes on this property through a three-dimensional dynamic clustering mechanism that simultaneously considers temporal and spectral feature correlations. This approach enhances clustering robustness in dynamic scenarios, where each stabilized feature cluster corresponds to an individual transmission packet, thereby enabling collision separation through persistent channel fingerprint identification.

IV. AIR-CHANNEL ESTIMATION

The air-channel can be estimated by comparing the received signal with the transmitted signal. This requires knowing the original transmitted signal. Thus, we first explain how LoRa transmitters generate chirp signals. According to Semtech's

specifications [35], LoRa nodes generate chirp signals independently for each symbol. For each symbol: 1) The transmitter calculates the instantaneous frequency based on the encoded symbol value, 2) Integrates the frequency to compute the phase, 3) Adjusts the phase at symbol boundaries to ensure it starts and ends at zero. This process guarantees continuous phase transitions across symbols in a packet.

During propagation, both the amplitude and phase of the transmitted signal $s(t)$ will change. The received signal becomes $r(t) = h \cdot s(t)$, where $h = Ae^{j\varphi}$ represents the air-channel (amplitude A , phase shift φ). In theory, all chirps in a packet should have identical channel estimation, i.e., clustered points in the I/Q plane (as shown in Fig. 3(a)). Real-world measurements, however, reveal non-constant air-channel estimates. As shown in Fig. 3(b), the estimated channel phase for different chirps vary over time, and dispersed all over the I/Q plane. Two main issues affect air-channel estimation: 1) Hardware imperfections: errors from imperfect oscillators, 2) Payload modulation: Phase shifts introduced during signal generation and demodulation. To obtain accurate channel measurements, we should precisely model and eliminate those coupled distortions. Following, we analyze how hardware and payload modulation distort channel estimation.

A. Hardware Imperfection Modeling

1) *Carrier Frequency Drifts*: We first analyze frequency drifts caused by mismatches between transmitter and receiver oscillators. These drifts induce progressive phase rotations in received signals. The distorted signal $S(t)$ can be modeled as:

$$S(t) = x(t)e^{j2\pi\Delta f t} \quad (5)$$

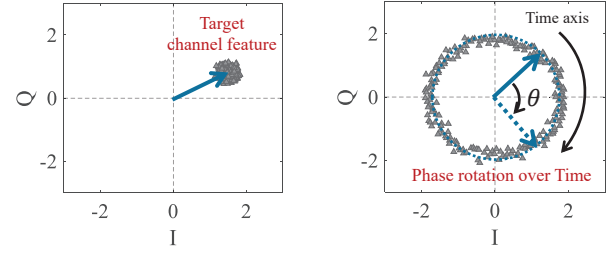
where $x(t)$ represents the ideal signal and Δf denotes the frequency drift value. The resulting phase accumulation follows $\phi(t) = 2\pi\Delta f t$, causing the initial phase of the N th preamble chirp to shift by

$$\Delta\phi = 2\pi\Delta f N \times T_{chirp} \quad (6)$$

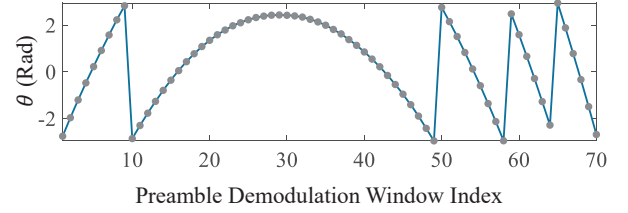
relative to its theoretical value. To estimate Δf , we extract sequential preamble chirps and apply linear regression to their initial phase measurements over time. The regression slope directly reveals the frequency drift value, enabling precise compensation during signal processing.

However, implementing this compensation mechanism for accurate channel estimation remains challenging. Our empirical observations (Fig. 3(c)) identify an unexpected behavior: while short packets exhibit phase changes consistent with the linear model, extended packet durations reveal nonlinear phase distortions. This deviation from theoretical predictions suggests additional interference sources — particularly sampling misalignment — that compound with oscillator mismatches. We now investigate how these sampling errors further perturb channel measurements.

2) *Sampling Misalignment*: To explain the observed nonlinear phase variations, we investigate the fundamental signal generation mechanisms. Oscillator mismatches not only induce carrier frequency drifts but also create discrepancies between



(a) Ideal channel feature cluster (b) Actual channel phase change



(c) Channel phase change with time

Fig. 3: Illustration of channel phase changes.

the transmitter's and receiver's sampling clocks. Specifically, when using identical sample counts, the actual signal durations differ between transmission (DAC) and reception (ADC) due to unequal sampling intervals. This temporal scaling distortion accumulates progressively over time, fundamentally altering the perceived phase evolution.

Suppose transmitted chirps are systematically shorter than reception windows by Δt per symbol, temporal misalignment accumulates progressively. As demonstrated in Fig. 4, consider N consecutively received chirps with perfect initial alignment—the first chirp precisely matches its reception window. By the N th chirp, the accumulated timing advance reaches $N\Delta t$, forcing the $(N+1)$ th window to capture the misaligned chirp $C(t + N\Delta t)$. This temporal misalignment alters the received signal as:

$$r_N(t) = e^{j2\pi[f_0(t+N\Delta t) + \frac{k}{2}(t+N\Delta t)^2]} \quad (7)$$

yielding an initial phase at window start:

$$\angle r_N(0) = 2\pi f_0 N\Delta t + \pi k(N\Delta t)^2 \quad (8)$$

Expanding the expression reveals two critical components: a linear phase term $2\pi f_0 N\Delta t$ proportional to both time and chirp index N , and a quadratic phase term $\pi k(N\Delta t)^2$ intrinsic to the LoRa chirp modulation. The linear term directly links temporal misalignment to progressive frequency deviations, while the quadratic term explains the experimentally observed nonlinear phase evolution. This formulation demonstrates how fixed sampling clock mismatches systematically convert temporal offsets into measurable phase nonlinearities. To address this, we first estimate Δt through preamble analysis, then subtract the modeled nonlinear phase component $\pi k(N\Delta t)^2$ from received signals. This compensation isolates genuine

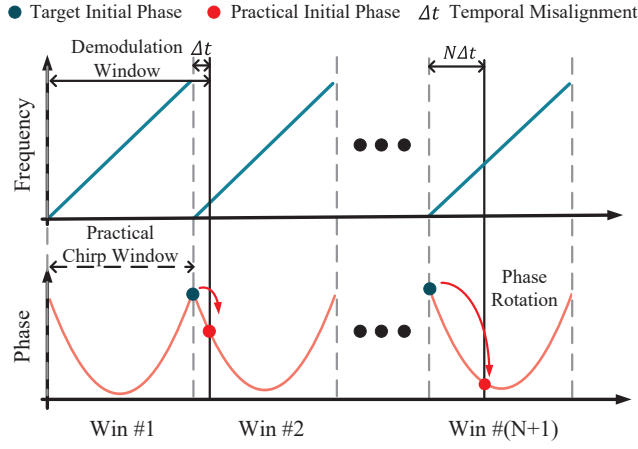


Fig. 4: SFO induces a linear time drift between symbols and the demodulation window, consequently resulting in a quadratic trend in the initial phase variation of symbols.

channel effects, enabling precise air-channel measurement despite sampling clock mismatches.

Experimental validation across different node hardware confirmed that these two factors account for the majority of phase variations, while other hardware imperfections have negligible impact on phase stability.

B. Payload Influence Modeling

Till now, we have modeled and eliminated the impact of hardware imperfections on channel estimation. Another intricate challenge for channel estimation is the payload-dependent phase variations. As presented in Fig. 5(a), while preamble-based channel estimates remain stable, the channel estimated from payload symbols exhibited significant fluctuations. Our further examination reveals systematic coupling between encoded payload values and phase distortions. The channel phase trajectory (black line) precisely mirrors the encoded value sequence (blue line) across payload windows (Fig. 5(b)). This persistent correspondence demonstrates that payload encoding actively modulates channel measurements, rather than merely introducing random noise.

This phenomenon arises from the interplay between timing offsets (TO) and LoRa's frequency-shift encoding scheme. Consider a demodulation window misaligned by TO relative to a payload symbol with encoded frequency shift f_{code} . The captured signal becomes

$$S(t) = e^{j2\pi[f_{code}(t+TO) + \frac{BW}{2T}(t+TO)^2]} \quad (9)$$

yielding an initial phase:

$$\varphi(0) = 2\pi \left(f_{code}TO + \frac{BW}{2T}TO^2 \right) \quad (10)$$

The quadratic TO term explains baseline phase distortion, while the f_{code} -linear term directly ties phase shifts to encoded values. Ideally, we can estimate the TO for each packet and use it to compensate phase drifts for payload symbols. However, two fundamental barriers hinder direct application of this

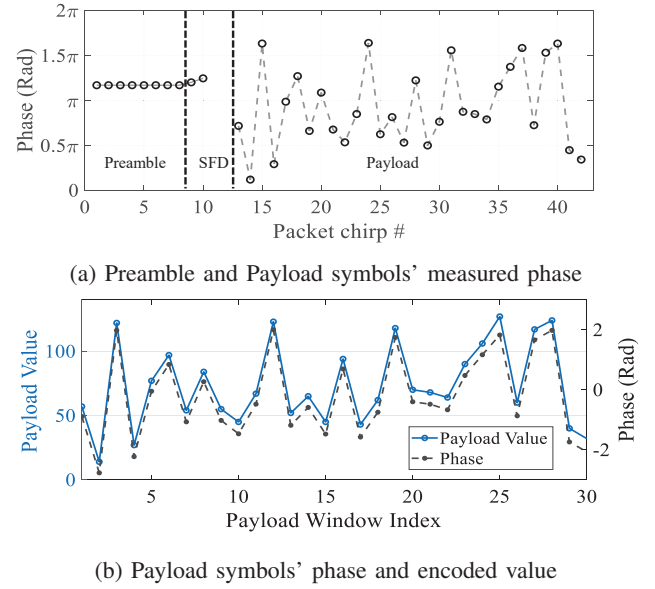


Fig. 5: Symbols' initial phases measured after eliminating hardware effects.

model: 1) TO estimates from preamble analysis contain errors due to finite frequency resolution. 2) Real-time TO tracking becomes impractical under dynamic channel conditions.

Our solution leverages embedded pilot chirps with known encoding values to bypass these limitations. Pilots provide anchor points for empirical phase modeling. For example, given two consecutive symbols with initial frequencies f_1 and f_2 , their phase difference simplifies to:

$$\Delta\varphi = 2\pi(f_2 - f_1)TO \quad (11)$$

establishing a linear relationship between encoded value differentials and observed phase variations. Therefore, by measuring the phase slope $\Delta\varphi/(f_2 - f_1)$ across pilots, we can accurately estimate TO through the linear relationship of Eq. 11. This differential approach inherently cancels resolution-induced errors and achieves high-accurate TO estimation. This methodology decouples payload-induced artifacts from genuine channel effects, enabling reliable phase-based fingerprinting even for high-mobility nodes.

V. NOISE-RESILIENT CHANNEL RECOVERY

This section describes how CD-LoRa combat the high noise interference and recovers accurate channel features.

A. Cross-Domain Energy Concentration

Standard LoRa decoding leverages the chirp's spectral compactness. It applies FFT to transform the time-domain chirp signal to the frequency domain, and thus focuses the signal energy into a single FFT bin. By the mean time, the energy of noise distributes uniformly across the spectrum. This energy-concentration property enables robust symbol decoding by identifying the frequency of a dominant energy peak in the frequency domain.

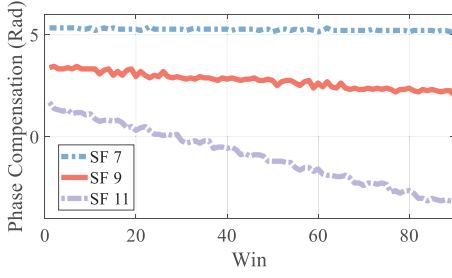


Fig. 6: Phase compensation change curve under different SFs.

CD-LoRa adapts this mechanism for noise-resilient channel recovery. Consider a received chirp $r(t) = h \cdot e^{j(2\pi f_i t + \phi_0)}$ within a demodulation window, where $h = Ae^{j\varphi}$ represents the air-channel. After FFT processing:

$$R(f) = h \cdot \delta(f - f_i) * \text{FFT}\{e^{j\phi_0}\} \quad (12)$$

The peak bin's phase directly reveals the initial phase ϕ_0 , as the Fourier shift property dictates:

$$\angle R(f_i) = \varphi + \phi_0 \quad (13)$$

By estimating the phase and height of the dominant FFT peak, we can estimate the channel-induced phase φ .

B. Inner-Chirp Phase Compensation

The energy concentration mechanism achieves noise resilience by coherently integrating entire chirp durations. However, LoRa's payload modulation through cyclic frequency shifting introduces intra-chirp discontinuities, where each payload symbol contains two chirp segments. This spectral bifurcation creates dual energy peaks in the frequency domain:

$$\begin{cases} P_1 : f_{code} \\ P_2 : F_s - BW + f_{code} \end{cases} \quad (14)$$

where f_{code} denotes the chirp initial frequency determined by the encoded data and F_s represents the sampling rate. The two energy peaks have distinct phases, necessitating phase difference compensation to enable coherent integration of the entire chirp's energy. Conventional phase compensation requires exhaustive search across possible segment phase offsets, which incurs significant computational complexity and introduces substantial processing latency. In contrast, our innovative methodology systematically exploits the deterministic phase coupling between signal segments.

Fig. 6 presents experimental measurements of the compensation phase across demodulation windows and system configurations. These empirical results reveal a consistent pattern: the phase compensation exhibits linear-varying behavior. Based on this observed regularity, we systematically derive a mathematical model to eliminate systematic phase discontinuities at symbol transitions. The model quantifies the phase shift relationship between consecutive symbols through rigorous analysis, explicitly linking the compensation value to both the instantaneous symbol window index and its system configurations. Finally, it can achieve full coherent energy

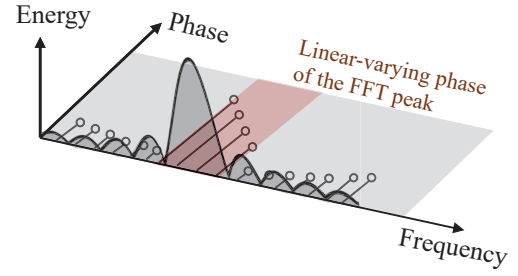


Fig. 7: Linear varying phase in the main lobe of an FFT peak.

aggregation of chirp symbols, resulting in enhanced noise resistance compared to empirical search-based methods.

For multiple overlapping packets, the model leverages preamble symbols to compute multiple potential phase compensation values, effectively reducing the computational overhead of brute-force search while providing more precise correction.

C. Linear Phase Fitting

To further enhance the noise resistance of CD-LoRa, we propose a phase-fitting approach to refine channel estimation in low SNR conditions. Our key observation is that the phase of the main lobe of the FFT frequency domain peak exhibits a linear variation. According to the time-shift property of Fourier transform, a time delay τ in the signal $s(t - \tau)$ manifests as a linear phase term $e^{-j2\pi f\tau}$ in frequency domain. The phase $\phi(f) = -2\pi f\tau$ exhibits linear variation with frequency f , where the slope corresponds to the time delay. This linear relationship is particularly evident in the main lobe region of the spectrum, as shown in Fig. 7. Therefore, by fitting a curve to the phase values of sampling points around the main lobe, we extract the phase at the peak vertex from the fitted curve instead of directly using the phase at the FFT peak position. This reduces the measurement error of the peak phase and improves estimation accuracy.

VI. DYNAMIC FEATURE CLUSTERING

A. 3D Helical Trajectory Modeling

Building upon the stable channel features extracted through our noise-resilient estimation, a critical challenge persists in dynamic environments: node mobility and environmental fluctuations induce progressive channel drift. As illustrated in Fig. 8(a), symbols from the same packet become dispersed across the I/Q plane, rendering conventional clustering methods (e.g., k-means) ineffective.

Through empirical observations, we discovered temporal coherence in channel variations. Rather than random scattering, consecutive symbols form smooth trajectories in the combined I/Q-time space (Fig. 8(b)). This motivates extending clustering into three dimensions, where the time axis captures channel evolution patterns. CD-LoRa uses a three-dimensional dynamic clustering mechanism that transforms previously disadvantageous channel variations into valuable distinguishing features that enhance the separation of conflicting LoRa data

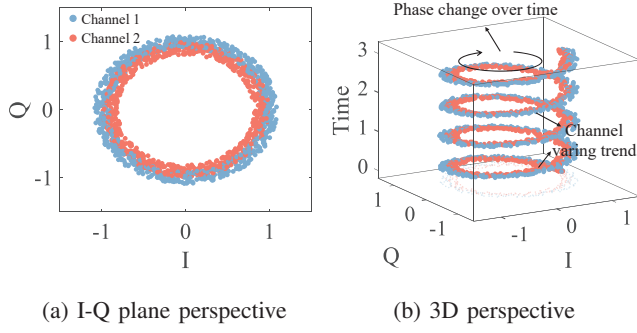


Fig. 8: Three-Dimensional Clustering Model.

packets. Specifically, CD-LoRa leverages the unique channel trajectories in the three-dimensional space, as shown in Fig. 8(b).

Each LoRa packet forms a distinct helical trajectory in the I - Q -Time space. The I - Q plane captures phase rotation and amplitude, while the time axis reflects temporal evolution, enabling our system to track the progression of channel dynamics in real-time.

Mathematically, let $\mathbf{c}_i = [I_i, Q_i]^T$ denote the 2D channel estimate for symbol i . The 3D feature vector becomes:

$$\mathbf{v}_i = [I_i, Q_i, t_i]^T \quad (15)$$

Cluster centroids evolve as parametric curves $\mathbf{h}_j(t)$ rather than fixed points, governed by:

$$\mathbf{h}_j(t) = \mathbf{m}_j + \mathbf{w}_j t \quad (16)$$

where $\mathbf{m}_j$ is the initial channel state and $\mathbf{w}_j$ captures drift velocity. Based on the unique channel varying pattern, the clustering algorithm (1) establishes n reference helical trajectories (from Pkt_1 to Pkt_n) based on the expected signal characteristics; (2) classifies each symbol by calculating its minimum Euclidean distance to each reference trajectory; (3) assigns the symbol to the packet whose helical trajectory it is closest to.

This clustering approach leverages several key advantages. First, symbols from the same packet follow a consistent trajectory pattern. Second, different packets create distinct trajectories due to their unique phase rotation patterns, amplitudes, and dynamic environments. Third, the time axis provides enhanced discriminative features by temporal progression. The classification decision is formulated as:

$$\text{class}[i] = \arg \min_{j \in 1,2} d(\text{point}[i], \text{trajectory}_j) \quad (17)$$

where $d(\text{point}[i], \text{trajectory}_j)$ represents the minimum Euclidean distance between point i and the j -th helical trajectory. This method offers more robust classification than traditional k-means by combining temporal evolution and modulation characteristics in a unified 3D model. By tracking the unique helical trajectories, CD-LoRa effectively identifies and separates overlapping transmissions despite channel dynamics.

TABLE II: Packet Transmission Durations for Different LoRa Configurations

Configuration	Symbol Duration	30-Symbol Packet
SF=7, BW=500kHz	0.256ms	~7.68ms
SF=9, BW=250kHz	2.048ms	~61.44ms
SF=12, BW=125kHz	32.768ms	~983.04ms

B. Clustering Robustness Analysis

We further investigate the impact of channel dynamics on the robustness of our 3D clustering method, specifically examining three categories of dynamic factors:

(1) *Abrupt obstructions and malicious interference*: These create instantaneous channel variations affecting individual symbols rather than degrading overall coherence time. Such disturbances typically last for several symbols, with longer symbol durations experiencing fewer affected symbols. For instance, a 10ms obstruction would impact only 0.3 of a symbol duration in SF 12, BW = 125kHz (32.768ms/symbol). CD-LoRa's symbol-level clustering ensures that transient disruptions corrupt only affected symbols while maintaining packet-level integrity.

(2) *Mobile nodes*: Mobile nodes introduce Doppler effects that systematically reduce coherence time. The coherence time under mobility can be calculated as:

$$\tau_c \approx \frac{1}{2\pi f_{D,\max}} = \frac{\lambda}{2\pi v} \quad (18)$$

where $f_{D,\max} = \frac{v}{\lambda}$ represents the maximum Doppler frequency shift due to node velocity v and wavelength λ . For different mobility scenarios at 900MHz: pedestrian movement (5 km/h) yields $\tau_c \approx 1.2$ s, urban vehicular (60 km/h) yields $\tau_c \approx 100$ ms, and highway speeds (120 km/h) yield $\tau_c \approx 50$ ms. Even at highway speeds, the coherence time significantly exceeds packet transmission durations for SF 7 (7.68ms from Table II) and can maintain SF 9 with reduced packet sizes. However, SF 12 configuration faces challenges under high mobility as its 983.04ms packet duration exceeds the coherence window. CD-LoRa's adaptive clustering mechanism accounts for these timing relationships by prioritizing faster configurations in high-mobility scenarios.

(3) *Weather Conditions*: Weather-induced channel variations exhibit different temporal characteristics. Gradual changes such as humidity and pressure variations maintain coherence times of several seconds to minutes, allowing almost all LoRa configurations to operate reliably within the coherence window. Rapid environmental changes from scenarios like fires create coherence times of 50-200ms, where faster configurations (SF 7, SF 9) maintain robust operation while SF 12 becomes vulnerable as its packet duration exceeds the coherence time.

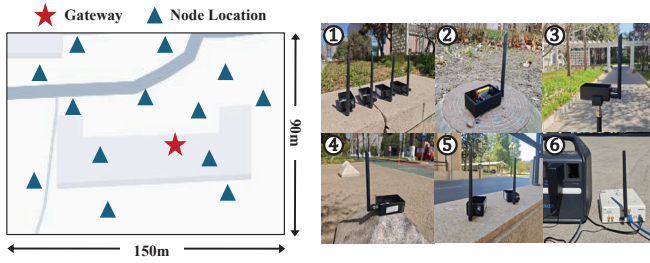


Fig. 9: The outdoor deployed LoRa network. Each triangle represents a deployment location housing 1-5 LoRa nodes.

VII. IMPLEMENTATION

We implement the CD-LoRa system using commodity LoRa nodes based on SX1278 [36] and a software-defined radio (SDR)-based gateway. We prototype CD-LoRa gateway with a USRP N210 [37] working at 470MHz carrier. The implementation of CD-LoRa is hardware-agnostic, enabling deployment on any commercial LoRa gateway as long as it can provide physical layer samples. By default, we use configuration of SF = 9, CR = 4/5, BW = 250 kHz, and sampling rate = 1MHz in the following evaluations.

Experiment Settings. We evaluate the performance of CD-LoRa with both indoor and outdoor experiment settings. The indoor testbed deploys LoRa nodes and gateways within the same building in a confined area of approximately 10m², with all nodes connected to a central controller. To obtain groundtruth channel estimation, nodes transmit packets individually while the USRP gateway receives signals and estimates channel characteristics for each node.

The outdoor testbed consists of LoRa nodes deployed across a 150m × 90m campus area as illustrated in Fig. 9. The gateway is positioned on the upper floors of a nearby tall building to optimize signal reception and range. Nodes are strategically distributed across 13 locations with varying densities (1-5 nodes per location) to create realistic collision scenarios. The deployment encompasses heterogeneous environments including open areas, vegetated regions, roadside locations, and areas with varying obstruction levels, with environmental conditions ranging from 15-25°C and 40-80% relative humidity across different locations. This diverse setup tests the system's ability to separate overlapping transmissions under varying propagation and environmental conditions.

To simulate a large-scale sensor network, each node transmits at high duty cycles, resulting in frequent packet collisions that traditional LoRaWAN cannot handle effectively. We evaluate CD-LoRa's performance in improving transmission efficiency under these challenging conditions where conventional protocols experience high packet loss.

Metrics. We evaluate the performance of CD-LoRa with following metrics:

- *Symbol Error Rate (SER)*: The ratio of error symbols to the total number of transmitted payload symbols;
- *Packet Reception Ratio (PRR)*: The ratio of correctly received packets (with CRC validation) to the total number

of transmitted packets;

- *Throughput*: The aggregate data rate of all transmissions within the network;
- *Phase Deviation*: The difference between the measured channel phase value and the real phase value.

Comparison. As shown in Table I, we select three representative baselines for comparison with CD-LoRa:

- LoRaWAN - a standard LoRa packet decoder without parallel decoding capability, serving as the baseline for existing deployment practices;
- Choir [20] - representing frequency-based collision decoding methods that leverage hardware imperfections.
- NScale [23] - representing time-based collision decoding methods that exploit time offsets between different signals;

VIII. EVALUATION RESULTS

A. Phase Measurement Performance

We first evaluate the impact of Signal-to-Noise Ratio (SNR) and Spreading Factor (SF) on channel phase estimation under three SNR levels: high (20 dB), medium (10 dB), and low (-5 dB), across SF values from SF 7 to SF 12. As SNR decreases, noise interference increases phase deviations (Fig.10(a)), but higher SF mitigates this effect by extending signal duration and enhancing energy accumulation during FFT processing. Fig.10(b-d) shows that with SF 7, approximately 60% of phase deviations remain below 0.25 rad under low SNR, while with SF 11, 80% of deviations stay below 0.01 rad in high and medium SNR conditions.

We then investigate inter-packet interference effects by evaluating phase estimation across varying numbers of concurrent transmissions at different SFs. While phase measurement accuracy degrades with more concurrent packets (Fig.11(a)), the system shows remarkable resilience, especially at higher SFs. Even with 6 collision peaks, phase deviations remain small (Fig.11(b-d)).

The results demonstrate that CD-LoRa exhibits strong resilience to both noise and inter-packet interference, with higher SF values consistently improving phase measurement accuracy through enhanced signal energy accumulation.

B. End-to-End Transmission Performance

We then evaluate the end-to-end transmission performance by investigating the impact of SNR on Symbol Error Rate (SER), comparing against NScale and Choir as practical baselines that work with existing commercial LoRa nodes without hardware modifications. Coding-based approaches like CurvingLoRa require hardware changes incompatible with commodity devices, while ML-based methods impose significant energy overhead through on-node computation, making them impractical for low-power IoT scenarios.

The performance is assessed at SF 9, with SNR varying from -10 dB to 20 dB. Fig. 12 shows that CD-LoRa demonstrates significant advantages: Under high SNR conditions (≥ 15 dB), CD-LoRa achieves the lowest symbol error rate (SER approximately 10^{-2}), significantly outperforming SOTA

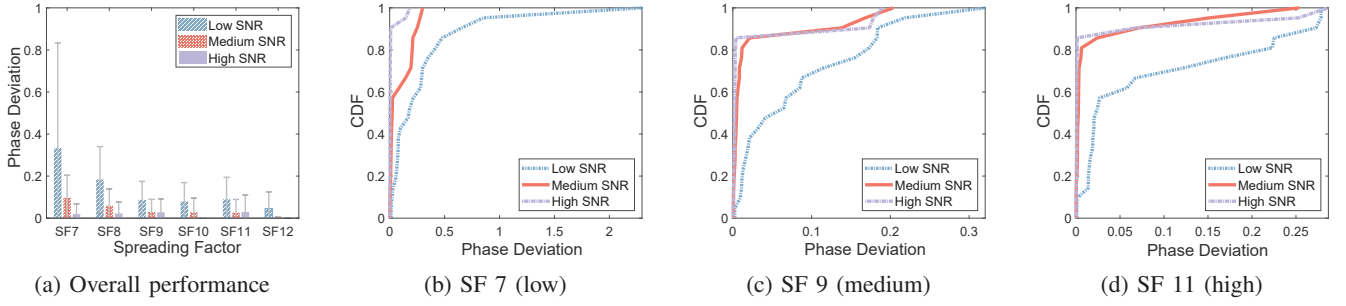


Fig. 10: Deviation of the channel phase measurement under different SFs.

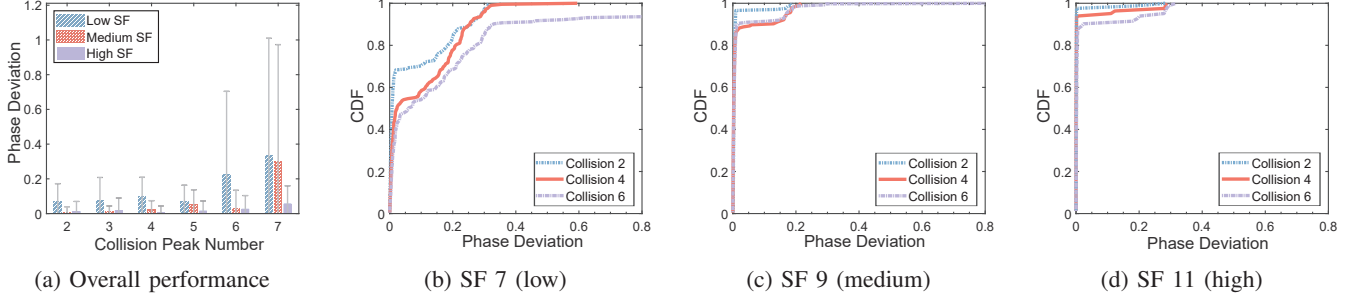


Fig. 11: Deviation of the channel phase measurement when colliding.

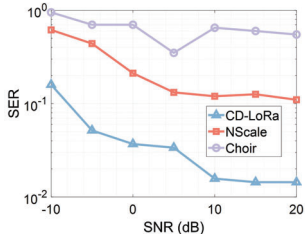


Fig. 12: Impact of SNR on SER compared with SOTA works.

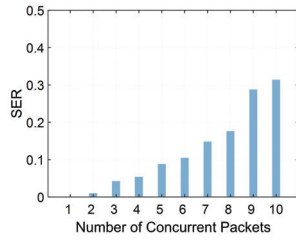


Fig. 13: Impact of Concurrency on SER.

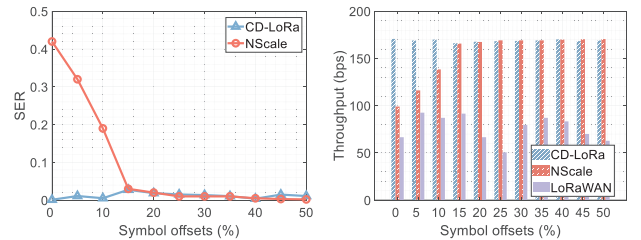


Fig. 14: Impact of Inter-Packet time offset.

methods. As SNR decreases, CD-LoRa exhibits stronger robustness compared to other schemes. Even under low SNR conditions (-5 dB), CD-LoRa maintains a relatively low SER (approximately 5×10^{-2}), while the performance of SOTA methods degrades significantly, highlighting CD-LoRa's superior noise resistance performance.

C. Impact of Concurrency

We evaluate the impact of node concurrencies on SER at SF 9. From Fig. 13, when the number of concurrent packets is low (1-5 packets), the SER remains at an excellent level, staying below 10% and demonstrating minimal interference effects. As concurrency increases to moderate levels (6-8 packets), the SER shows a gradual but controlled increase, indicating that CD-LoRa can effectively manage interference within this range. When the number of concurrent packets reaches high levels (9-10 packets), the SER increases due to inter-packet peak interference and feature space confusion that compromise

the signal discrimination capability. This result highlights the robust performance of CD-LoRa in maintaining relatively low error rates under varying concurrency conditions.

D. Impact of Inter-Packet Time Offset

We evaluate the relationship between time offset and system performance under concurrent transmission, comparing CD-LoRa with SOTA LoRa collision decoding methods and traditional LoRaWAN. As shown in Fig. 14, we evaluate the system's SER and throughput across 11 different time offset regimes ranging from 0 to $0.5 \times T_{chirp}$ at SF 9.

Our phase-based approach demonstrates remarkable resilience to timing offsets, maintaining a consistent SER of approximately 10^{-2} and stable throughput (~ 170 bps) across the entire range of time offsets. This indicates that CD-LoRa remains largely unaffected by timing variations, enabling reliable concurrent transmissions even with near-zero inter-packet time offsets. In contrast, SOTA methods exhibit significant

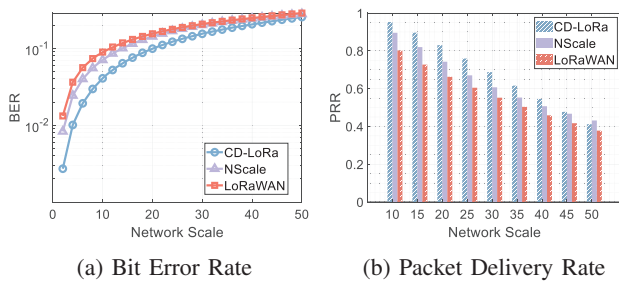


Fig. 15: Performance in real-world LoRa deployments.

performance degradation when time offsets are small, with worsening SER and sharply dropping throughput as time offset decreases.

E. Performance in a Real Network

We finally evaluate the performance of CD-LoRa in real-world deployments using the outdoor testbed. Concurrent LoRa transmissions are collected from nodes deployed in various environments. To assess CD-LoRa's ability to handle concurrent transmissions, we create collision scenarios by introducing randomized temporal offsets to the collected packets. Each LoRa node transmits periodically with a 7% duty cycle, and we simulate different network scales by varying the number of active nodes.

Fig. 15 compares CD-LoRa's performance with LoRaWAN. As shown in Fig. 15(a), CD-LoRa achieves less than 10% BER with 20 concurrent transmissions, significantly outperforming LoRaWAN's around 15% of PRR and NScale's around 13% of PRR. PRR measurements further highlight this advantage (Fig. 15(b)), with CD-LoRa achieving around 80% PRR with 25 concurrent transmissions, compared to LoRaWAN's less than 60% of PRR and NScale's around 70% of PRR. These results demonstrate CD-LoRa's enhanced ability to handle dense network deployments in real-world deployments.

IX. RELATED WORK

Parallel LoRa Transmission. *Frequency-based methods* extract concurrent signals by exploiting distinguishable features in the frequency domain, such as spectral energy peaks or frequency clustering patterns. *Choir* [20] clusters spectral peaks based on inherent frequency variations across device. *CIC* [21] iteratively identifies the strongest frequency peak in each window, decodes the corresponding signal, and subtracts it from the received mixture to expose weaker overlapping signals. *mLoRa* [27] leverages the linear chirp structure of LoRa to infer encoded symbols from non-overlapping segments.

Time-based methods distinguish concurrent signals using arrival time misalignments and the temporal evolution of chirps. *FTrack* [22] reconstructs a spectrum-time distribution to track symbol boundaries via time-varying peak shifts. *NScale* [23] introduces a non-uniform scaling function to amplify amplitude differences and refine symbol peaks via iteration. *CoLoRa* [24] infers symbol-level misalignments by evaluating energy ratios between neighboring FFT bins, then

realigns symbols adaptively. *Pyramid* [28] and *AlignTrack* [29] track the temporal continuity of signal trajectories in the frequency-time domain to detect symbol boundaries and separate overlapping transmissions.

Coding-based methods modify the chirp encoding process to achieve inherent signal separability. *CurvingLoRa* [25] replaces linear chirps with nonlinear ones, assigning each node a unique spreading curve to enable orthogonal channeling. *FlipLoRa* [26] encodes each symbol using up- or down-chirps to increase modulation diversity, while using frequency-domain interference cancellation. *NetScatter* [38] assigns each device a unique starting frequency and uses silence for '0', relying on orthogonality across frequencies. *PushLoRa* [32] proposes a re-encoding and projection strategy to isolate overlapping symbols through time-frequency domain manipulation.

Channel Estimation. Recent advancements in wireless channel estimation address diverse scenarios through distinct technical approaches [39]–[45]. Molisch et al. [39] pioneered multi-path clustering models using ultra-wideband (UWB) time-domain channel sounding, enabling high-resolution delay profile extraction. Rappaport et al. [40] combined directional horn antennas with rotating platforms to measure angular spreads and path loss exponents. AI integration methods [41] use LSTM networks to predict mmWave beamforming vectors. Chowdhury et al. [42] further unified channel measurements via software-defined radios with programmable up/down-conversion chains. However, two limitations persist: 1) hardware imperfection and payload modulation effects remain unconcerned; and 2) existing frameworks fail to process LoRa's chirp-modulated signals under ultra-low SNR. These gaps highlight the need for hardware-aware and modulation-robust channel measurement paradigms.

X. CONCLUSION

We propose CD-LoRa, a method to support LoRa concurrent transmission in large scale IoT systems. CD-LoRa leverages distinct channel signatures to separate overlapping LoRa signals, without hardware changes or modulation modifications. We extract genuine channel features from hardware imperfections and payload modulation distortions. We improve low-SNR LoRa signals' performance by energy-concentration techniques and employ dynamic temporal sequence clustering method to address channel variations in mobile scenarios. We implement CD-LoRa on commodity LoRa devices and evaluate its performance in multifarious scenarios. Experimental results reveal that CD-LoRa effectively processes up to 8 packets with identical time-frequency allocations, outperforming existing solutions with a $1.72\times$ throughput gain.

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REFERENCES

- [1] Usman Raza, Parag Kulkarni, and Mahesh Sooriyabandara. Low power wide area networks: An overview. *IEEE Communications Surveys & Tutorials*, 19(2):855–873, 2017.
- [2] Shuai Tong and Jiliang Wang. Progress and challenges of lora low power wide area networks. *Acta Electronica Sinica*, 52(10):3623–3642, 2024.
- [3] Leiyang Xu, Xiaolong Zheng, and Liang Liu. Vortex em wave-based rotation speed monitoring on commodity wifi. *Chinese Journal of Electronics*, 2025.
- [4] Shuai Tong, Jiliang Wang, Jing Yang, Yunhao Liu, and Jun Zhang. City-wide lora network deployment and operation: Measurements, analysis, and implications. In *Proceedings of ACM SenSys*, 2024.
- [5] Marco Cattani, Carlo Alberto Boano, David Steffebauer, Stefan Kaltenbacher, Markus Günther, Kay Römer, Daniela Fuchs-Hanusch, and Martin Horn. Adige: an efficient smart water network based on long-range wireless technology. In *Proceedings of the 3rd International Workshop on Cyber-Physical Systems for Smart Water Networks*, pages 3–6, 2017.
- [6] Yidong Ren et al. Aeroecho: Towards agricultural low-power wide-area backscatter with aerial excitation source. In *Proceedings of IEEE INFOCOM*, 2025.
- [7] Sunnyeo Park, Shinhye Yun, Hyunjin Kim, Ryunhwan Kwon, and John Ganser. Forestry monitoring system using lora and drone. In *Proceedings of the 8th international conference on web intelligence, mining and semantics*, pages 1–8, 2018.
- [8] Ana Maria Claudia Drăgulinescu, Adrian Florin Manea, Octavian Fratu, and Andrei Drăgulinescu. Lora-based medical iot system architecture and testbed. *Wireless Personal Communications*, pages 1–23, 2020.
- [9] Jie Jiao, Yongsheng Qi, Liqiang Liu, Yongting Li, and Zhaoxia Wang. A scene-adaptive dual-branch efficient cattle face recognition algorithm. *Acta Electronica Sinica*, 52(9):3251–3261, 2024.
- [10] Zhipeng Song, Shuai Tong, and Jiliang Wang. Losense: Integrated long-range sensing and communication with lora signals. In *2023 IEEE 31st International Conference on Network Protocols (ICNP)*. IEEE, 2023.
- [11] Harsha V Madhyastha and Chinedum Okwudire. Remotely controlled manufacturing: A new frontier for systems research. In *Proceedings of the 21st international workshop on mobile computing systems and applications*, pages 62–67, 2020.
- [12] Fei Tao, Qinglin Qi, Ang Liu, and Andrew Kusiak. Data-driven smart manufacturing. *Journal of manufacturing systems*, 48:157–169, 2018.
- [13] Xin Ma, Quanyi Huang, Quanyi Liu, Xueming Shu, and Quanlai Zhao. Dynamic fire monitoring method for buildings based on internet of things. *Journal of Tsinghua University (Science and Technology)*, 52(11):1584–1590, 2012.
- [14] Satyajit Sinha. State of iot 2024: Number of connected iot devices growing 13% to 18.8 billion globally, September 2024.
- [15] Jothi Prasanna Shanmuga Sundaram, Wan Du, and Zhiwei Zhao. A survey on lora networking: Research problems, current solutions, and open issues. *IEEE Communications Surveys & Tutorials*, 22(1):371–388, 2019.
- [16] Boris Solomonovich Tsybakov and Viktor Alexandrovich Mikhailov. Free synchronous packet access in a broadcast channel with feedback. *Problemy peredachi informatsii*, 14(4):32–59, 1978.
- [17] Piyush Gupta and Panganmala R Kumar. The capacity of wireless networks. *IEEE Transactions on information theory*, 46(2):388–404, 2002.
- [18] Branden Ghena, Joshua Adkins, Longfei Shangguan, Kyle Jamieson, Philip Levis, and Prabal Dutta. Challenge: Unlicensed lpwans are not yet the path to ubiquitous connectivity. In *The 25th Annual International Conference on Mobile Computing and Networking*, pages 1–12, 2019.
- [19] Martin C Bor, Utz Roedig, Thiemo Voigt, and Juan M Alonso. Do lora low-power wide-area networks scale? In *Proceedings of the 19th ACM international conference on the analysis, simulation and simulation of wireless and mobile systems*, pages 59–67, 2016.
- [20] Rashad Eletreby, Diana Zhang, Swarun Kumar, and Osman Yağan. Empowering low-power wide area networks in urban settings. In *Proceedings of the Conference of the ACM Special Interest Group on Data Communication*, pages 309–321, 2017.
- [21] Muhammad Osama Shahid, Millan Philipose, Krishna Chintalapudi, Suman Banerjee, and Bhuvana Krishnaswamy. Concurrent interference cancellation: Decoding multi-packet collisions in lora. In *Proceedings of the 2021 ACM SIGCOMM 2021 Conference*, pages 503–515, 2021.
- [22] Xianjin Xia, Yuanqing Zheng, and Tao Gu. Ftrack: Parallel decoding for lora transmissions. In *Proceedings of the 17th Conference on Embedded Networked Sensor Systems*, pages 192–204, 2019.
- [23] Shuai Tong, Jiliang Wang, and Yunhao Liu. Combating packet collisions using non-stationary signal scaling in lpwans. In *Proceedings of the 18th International Conference on Mobile Systems, Applications, and Services*, pages 234–246, 2020.
- [24] Shuai Tong, Zhenqiang Xu, and Jiliang Wang. Colora: Enabling multi-packet reception in lora. In *IEEE INFOCOM 2020-IEEE Conference on Computer Communications*, pages 2303–2311. IEEE, 2020.
- [25] Chenning Li, Xiuzhen Guo, Longfei Shangguan, Zhichao Cao, and Kyle Jamieson. Curvinglora to boost lora network capacity via concurrent transmission. *arXiv preprint arXiv:2201.05179*, 2022.
- [26] Zhenqiang Xu, Shuai Tong, Pengjin Xie, and Jiliang Wang. Fliplora: Resolving collisions with up-down quasi-orthogonality. In *2020 17th Annual IEEE International Conference on Sensing, Communication, and Networking (SECON)*, pages 1–9. IEEE, 2020.
- [27] Xiong Wang, Linghe Kong, Liang He, and Guihai Chen. mlora: A multi-packet reception protocol in lora networks. In *2019 IEEE 27th International Conference on Network Protocols (ICNP)*, pages 1–11. IEEE, 2019.
- [28] Zhenqiang Xu, Pengjin Xie, and Jiliang Wang. Pyramid: Real-time lora collision decoding with peak tracking. In *IEEE INFOCOM 2021-IEEE Conference on Computer Communications*, pages 1–9. IEEE, 2021.
- [29] Qian Chen and Jiliang Wang. Aligntrack: Push the limit of lora collision decoding. In *2021 IEEE 29th International Conference on Network Protocols (ICNP)*, pages 1–11. IEEE, 2021.
- [30] Rajoon Jung and Philip Levis. Receiving colliding lora packets with hard information iterative decoding. In *2021 IEEE Global Communications Conference (GLOBECOM)*, pages 1–7. IEEE, 2021.
- [31] Zhe Wang, Linghe Kong, Kangjie Xu, Liang He, Kaishun Wu, and Guihai Chen. Online concurrent transmissions at lora gateway. In *IEEE INFOCOM 2020-IEEE Conference on Computer Communications*, pages 2331–2340. IEEE, 2020.
- [32] Pengjin Xie, Yinghui Li, Zhenqiang Xu, Qian Chen, Yunhao Liu, and Jiliang Wang. Push the limit of lpwans with concurrent transmissions. In *IEEE INFOCOM 2023-IEEE Conference on Computer Communications*, pages 1–10. IEEE, 2023.
- [33] Yaman Sangar and Bhuvana Krishnaswamy. Wichronos: energy-efficient modulation for long-range, large-scale wireless networks. In *Proceedings of the 26th Annual International Conference on Mobile Computing and Networking*, pages 1–14, 2020.
- [34] Dimitrios Zorbas. Design considerations for time-slotted lora (wan). 2020.
- [35] Gianni Pasolini. On the lora chirp spread spectrum modulation: Signal properties and their impact on transmitter and receiver architectures. *IEEE Transactions on Wireless Communications*, 21(1):357–369, 2021.
- [36] Semtech Corporation. *SX1276/77/78/79 Datasheet*. Semtech Corporation, 2024. Accessed: December 2024.
- [37] Ettus Research. *USRP N210 Datasheet*. Ettus Research, A National Instruments Company. Accessed: December 2024.
- [38] Mehrdad Hesar, Ali Najafi, and Shyamnath Gollakota. {NetScatter}: Enabling {Large-Scale} backscatter networks. In *16th USENIX symposium on networked systems design and implementation (NSDI 19)*, pages 271–284, 2019.
- [39] A. F. et al. Molisch. Ultra-wideband propagation channels—theory, measurement, and modeling. *IEEE J. Sel. Areas Commun.*, 2005.
- [40] T. S. et al. Rappaport. Millimeter wave mobile communications for 5G: Feasibility and challenges. *IEEE Commun. Mag.*, 2013.
- [41] Y. et al. Zhang. Deep learning based channel prediction for massive MIMO systems. *IEEE Trans. Antennas Propag.*, 2020.
- [42] M. Z. et al. Chowdhury. SDR-based THz channel sounding: From sub-6 GHz to 140 GHz. *Nat. Commun.*, 2022.
- [43] Xianjin Xia, Ningning Hou, Yuanqing Zheng, and Tao Gu. Pcube: Scaling lora concurrent transmissions with reception diversities. *ACM Transactions on Sensor Networks*, 18(4):1–25, 2023.
- [44] Xianjin Xia, Qianwu Chen, Ningning Hou, and Yuanqing Zheng. Hylink: Towards high throughput lpwans with lora compatible communication. In *Proceedings of the 20th ACM Conference on Embedded Networked Sensor Systems*, pages 578–591, 2022.
- [45] Zixuan Wang, Shanhu Wang, Xin Wang, Jiafei Yao, Jun Zhang, Shanwen Hu, Zhikuan Cai, and Yufeng Guo. A fast start-up crystal oscillator based on phase error correction technology. *Acta Electronica Sinica*, 52(4):1182–1188, 2024.