AlignTrack: Push the Limit of LoRa Collision Decoding

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Abstract*—LoRa has been shown as a promising Low-Power Wide Area Network (LPWAN) technology to connect millions of devices for the Internet of Things by providing long-distance low-power communication in a very low SNR. Real LoRa networks, however, suffer from severe packet collisions. Existing collision resolution approaches introduce a high SNR loss, i.e., require a much higher SNR than LoRa. To push the limit of LoRa collision decoding, we present AlignTrack, the first LoRa collision decoding approach that can work in the SNR limit of the original LoRa. Our key finding is that a LoRa chirp aligned with a decoding window should lead to the highest peak in the frequency domain and thus has the least SNR loss. By aligning a moving window with different packets, we separate packets by identifying the aligned chirp in each window. We theoretically prove this leads to the minimal SNR loss. In practical implementation, we address two key challenges: (1) accurately detecting the start of each packet, and (2) separating collided packets in each window in the presence of CFO and inter-packet interference. We implement AlignTrack on HackRF One and compare its performance with the state-of-the-arts. The evaluation results show that AlignTrack improves network throughput by 1.68× compared with NScale and 3× compared with CoLoRa.

I. Introduction

Recent years have witnessed the rapid development of Internet of Things (IoT) technology [1]. LPWANs have been shown as a promising technology to provide low-power long-distance communication for IoT applications [2] such as health monitoring [3], smart agriculture [4], smart traffic light congestion monitoring [5], intelligent parking space allocation [6]. LoRa, as a representative LPWAN technology, has attracted both academic and industrial attention in the world [7] [8]. LoRa can communicate for a distance of up to tens of kilometers with very low energy consumption and a very low SNR. The operational lifetime of battery-powered LoRa nodes can reach up to ten years.

However, real LoRa networks suffer from severe packet collisions. The vision of LoRa is to support connections with a large number of low-cost and low-power devices. LoRa network adopts a star network topology for communication. However, a typical LoRa gateway can only receive LoRa packets from eight channels. While in practice, a gateway is supposed to connect with thousands of nodes or even more. This leads to severe packet collisions in real LoRa deployments. Moreover, to reduce control overhead, typical LoRa networks use Aloha [9] based MAC protocols (e.g., LoRaWAN [10]), in which LoRa nodes send packets without detecting the channel status. This further exacerbates the collision problem in practice [11].

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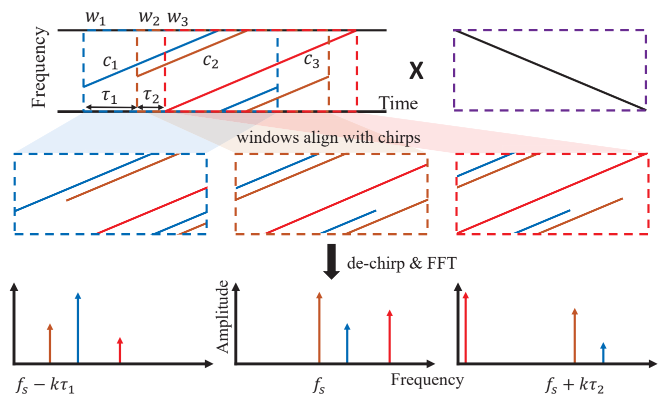


Fig. 1. An example of AlignTrack to decode a 3-packet collision. AlignTrack moves a window to align with different chirps, and finds the aligned chirps to separate packets.

Existing approaches. Different approaches are proposed to address the collision problem for LoRa. mLoRa [12] can decode three collided LoRa packets using Successive Interference Cancellation (SIC). FTrack [13] calculates the continuity of instantaneous frequency to separate collided packets. However, those approaches are based on time-domain signal analysis and do not leverage features of LoRa encoding. Thus, they require a high SNR of the packets (e.g., $SNR > 0$ dB) in decoding, which deviates from LoRa application scenarios. Further, CoLoRa [14] leverages the time offset among packets and translates the time offset to frequency-domain features to separate different collided packets. NScale [15] uses a non-stationary scaling method to translate the time offset to more robust features. They need to partition a chirp (symbol in LoRa) and therefore still introduce inevitable SNR loss in practice. In summary, existing approaches require a much higher SNR in decoding collision than traditional LoRa [14] [15]. Thus, those approaches cannot work in many practical scenarios.

Our design. To push the limit of LoRa collision decoding, we propose AlignTrack, a novel LoRa packet collision decoding approach to minimize SNR loss. AlignTrack can decode collisions with the same SNR requirement of LoRa. LoRa modulates data with chirps of linearly *increasing* frequency with different start frequency shifts to encode data bits. The start frequency shift f_s is decoded by de-chirp: a chirp is multiplied with a standard linearly *decreasing* down-chirp, which leads to a single tone at frequency f_s.

Figure 1 shows three collided packets. Assume we have a moving window aligned with the chirps of those three packets. The length of the moving window is equal to the length of a chirp. Figure 1 shows the decoding result of three windows w_1, w_2 and w_3 aligned with three chirps. We can see multiple peaks in each window due to multiple chirp segments, leading to decoding failure. The key step in collision decoding is to separate those peaks in each window to different packets.

Our main idea is to find the peak of the chirp *aligned* with each window and thus separate peaks for different packets based on those aligned chirps. We first detect the start of each packet and align a moving window with each packet. A chirp in each packet will appear in three consecutive windows. We find that the frequency of peaks corresponding to the same chirp is proportional to the time offset between the chirp and the window. For example, chirp c_2 leads to three peaks in window w_1, w_2 and w_3 with frequency $f_s - k\tau_1$, f_s and $f_s + k\tau_2$, respectively. Meanwhile, the peak of a chirp in different windows reaches its highest height when the chirp is aligned with the window. AlignTrack leverages this to determine the peak of the chirp aligned with each window and then separate packets. For example, AlignTrack first finds peaks at $f_s - k\tau_1$, f_s and $f_s + k\tau_2$ in window w_1, w_2 and w_3 for the same chirp, and then determines the peak at f_s corresponds to the chirp c_2 aligned with window w_2 *iff* it is the highest compared with the other two peaks. Then, we can group peaks to different packets based on aligned chirps and decode those packets.

Challenges. (1) How to find the accurate start of each packet in the collided signal under the impact of Central Frequency Offset (CFO)? Intuitively, we can detect the start of a packet based on the preamble. However, this leads to non-negligible errors due to the impact of CFO and inter-packet interference. We leverage the preamble and SFD in each packet. The preamble contains baseline up-chirps of linearly increasing frequency, while the SFD contains baseline down-chirps of linearly decreasing frequency. CFO introduces frequency shifts to the up-chirp and down-chirp, and we can estimate the CFO by combining up-chirps and down-chirps. Further, we find the above CFO estimation method fails in collided packets due to the challenge of finding SFD and preamble that are for the same packet. We propose a method to identify up-chirps and down-chirps that belong to the same packet, and thus estimate the accurate CFO in collisions.

(2) How to accurately detect all peaks under low SNR? The peak height for a low SNR signal is close to the noise. Thus, using a pre-determined height threshold may fail to identify all peaks. We design an iterative peak search method to find all peaks in each window. In each iteration, we calculate a dynamical threshold based on the statistic information of existing FFT results in the window, and iteratively find all peaks.

(3) How to alleviate the interference among peaks and recover the precise peak information (position and height)? For

Fig. 2. LoRa packet structure.

example, the sidelobes of one peak can distort the position and height of other peaks. Moreover, due to the near-far problem, sidelobes of strong signals can be higher than peaks of weak signals, leading to mis-identified peaks. Typically, a filter (e.g., Hamming window) can be applied to the received signal to reduce the amplitude of sidelobes. However, there are still high sidelobes after filtering. Further, we find that sidelobes are symmetric with the real peak and exploit this to iteratively remove those symmetric sidelobes.

Main results and contributions.

- We propose AlignTrack to push the limit of decoding low SNR LoRa packet collisions. AlignTrack leverages the entire chirp in LoRa, and thus introduces very small SNR loss while existing approaches introduce non-negligible SNR loss due to the use of partial chirp.
- We address non-trivial practical challenges such as inter-packet interference and the impact of CFO in the practical design of AlignTrack.
- We implement AlignTrack on the HackRF One platform. AlignTrack sits at the gateway side and can decode collisions for COTS LoRa end nodes without any hw/sw change. The evaluation results show that AlignTrack improves the network throughput by $1.68\times$ compared with NScale [15] and $3\times$ compared with CoLoRa [14].

II. Background

A. Chirp Modulation/Demodulation

LoRa modulates signals using the Chirp Spread Spectrum (CSS). The basic symbol is a chirp with linearly increasing/decreasing frequency occupying a certain bandwidth. A baseline chirp is represented as $C(t) = e^{j2\pi(f_0 + \frac{1}{2}kt)t}$, where $|k| = BW/T_{chirp}$ is the frequency changing rate, f_0 is the start frequency at time 0, and T_{chirp} is the time duration. T_{chirp} is usually determined by the spreading factor (SF) and frequency bandwidth (BW), i.e., $T_{chirp} = 2^{SF}/BW$. A chirp is an up-chirp when $k > 0$, and otherwise is a down-chirp. A chirp is a baseline up-chirp if $f_0 = -BW/2$ with frequency linearly increasing from $-BW/2$ to $BW/2$.

CSS modulates data bits by shifting the start frequency f_0, i.e.,

$$C(t, f_s) = C(t)e^{j2\pi f_s t} \quad (1)$$

where f_s is the frequency to encode data bits. Note that the frequency above $BW/2$ is rounded by BW to fit in the range $[-BW/2, BW/2]$.

To demodulate $C(t, f_s)$, LoRa first multiplies it with the baseline down-chirp $C^{-1}(t)$ ($C^{-1}(t)$ is the conjugate of the

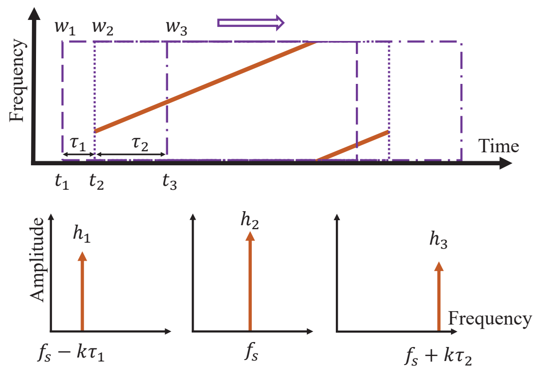


Fig. 3. The peak frequency and height in the moving window.

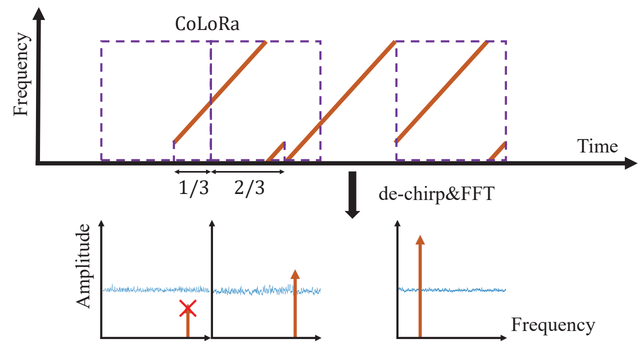


Fig. 4. The SNR loss comparison for different methods. Our method uses the entire chirp while existing methods use partial chirps.

$C(t)$). This de-chirp operation can concentrate the signal power in the time domain to a single frequency, and we obtain

$$C(t, f_s)C^{-1}(t) = e^{j2\pi f_s t} \tag{2}$$

By applying FFT to the result, we can derive f_s and decode the chirp.

B. LoRa Packet Structure

As shown in Figure 2, a LoRa packet is usually comprised of three parts: preamble, start frequency delimiter(SFD), and payload. The preamble contains 6∼65535 baseline up-chirps to determine the start of the LoRa packet and 2 up-chirps with modulated data to carry extra information. The SFD contains 2.25 baseline down-chirps. The payload contains data bits modulated with up-chirps.

III. Motivation

A. Basic Observations

For multiple collided packets, we first find the start of each packet. Then, we apply a moving window (the smallest decoding unit containing the collided LoRa signal) aligned with each packet to the signal. As shown in Figure 3, we consider three consecutive windows, each containing multiple partial chirp segments and a particular aligned chirp (i.e., a chirp completely included in the window). The aligned chirp in the middle window leads to the peak with local maximum amplitude after de-chirp and FFT. Meanwhile, a portion of this chirp is also contained in its preceding window and the following window, leading to two corresponding peaks. We first show the frequency constraint of peaks for the same chirp in consecutive windows.

Assume the chirp aligned with the middle window w_2 is $R(t) = A \cdot C(t, f_s)$, where A is the signal amplitude. The segment of $R(t)$ contained in window w_1 can be written as

$$\begin{aligned} r_1(t) &= R(t - \tau_1) \\ &= Ae^{j2\pi f_s(t-\tau_1)}C(t - \tau_1), t \in [\tau_1, T_{chirp}) \end{aligned} \tag{3}$$

The time offset can be translated to the frequency shift, i.e., $C(t - \tau_1) = e^{-j2\pi k\tau_1 t}C(t)$. Thus, we have

$$\begin{aligned} r_1(t) &= Ae^{j2\pi(f_s(t-\tau_1)-k\tau_1 t)}C(t) \\ &= Ae^{-j2\pi f_s \tau_1}e^{j2\pi(f_s - k\tau_1)t}C(t), t \in [\tau_1, T_{chirp}) \end{aligned} \tag{4}$$

Frequency constraint: The frequency of the peak p_1 for the chirp segment of $R(t)$ in window w_1 is $f_1 = f_s - k\tau_1$, and the frequency of the peak for the chirp segment of $R(t)$ in window w_3 is $f_3 = f_s + k\tau_2$. This indicates that based on the frequency constraint, we can find the peaks corresponding to the same chirp in consecutive windows.

Denote h_1, h_2 and h_3 as the height of peaks in window w_1, w_2 and w_3. Thus h_1 can be calculated as

$$h_1 = \sum_{n=0}^{N-1} r_1[n]e^{-j2\pi \frac{nT_{chirp}}{N}} = A(T_{chirp} - \tau_1)S_r \tag{5}$$

where S_r is the sampling rate and N is the total sample points of $r_1(t)$, i.e., $N = (T_{chirp} - \tau_1)S_r$.

Height constraint: The height of the peak is proportional to the chirp segment length, i.e.,

$$h_1 : h_2 : h_3 = T_{chirp} - \tau_1 : T_{chirp} : T_{chirp} - \tau_2. \tag{6}$$

The peak height reaches the highest when the chirp is aligned with the window.

B. Limitations of State-of-the-arts

Existing methods such as FTrack [13] and mLoRa [12] use time-domain signal amplitude to identify collided packets. Their methods can mainly work for high SNR (e.g., $SNR > 0$ dB). Further, CoLoRa [14] and NScale [15] propose to leverage features in frequency domain to identify collided packets. However, they use a portion of a chirp instead of the entire one for collision resolution, which introduces non-negligible SNR loss. For example, as shown in Figure 4, CoLoRa partitions a chirp into two parts and leverages the ratio of height between those two parts to decode collisions. It proposes a method to guarantee that both parts are larger than 1/3 of the entire chirp. To decode a chirp, the peak after de-chirp should be higher than noise. The height of a peak is mainly determined by the

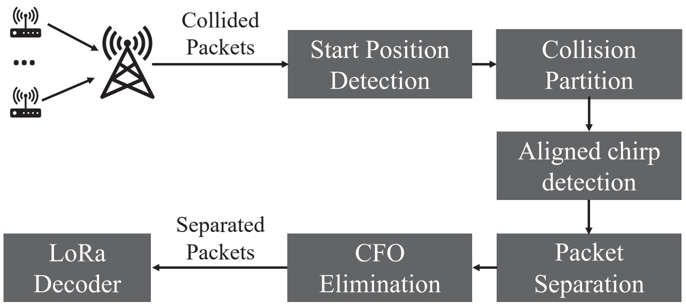


Fig. 5. Overall design of AlignTrack.

length of the chirp segment in a window. A long chirp segment can lead to a high peak. When the peak of an entire chirp is higher than the noise, the peak height in CoLoRa, which corresponds to only a portion of the chirp, can be under the noise. Thus, the peak cannot be identified, and the collision cannot be decoded. Our approach leverages the entire chirp in the aligned window to retain the peak height to the greatest extent to avoid the SNR loss.

C. Summary

- Collisions result in multiple peaks in a window. The key step in collision decoding is to separate those peaks into different packets. The state-of-the-art collision decoding approaches in LoRa have a high SNR loss as they use parts of a chirp to separate peaks.
- For consecutive windows on the collided signal, the peaks for the same chirp in different windows have peak frequency offset proportional to window offset.
- The peak height reaches the highest when the chirp is aligned with the window. For each peak in the window, we can determine whether it corresponds to the aligned chirp as follows. First, we find the peaks corresponding to the same chirp in consecutive windows. Then, the peak corresponds to the aligned chirp *iff* the peak is highest compared with the peaks in the preceding window and following window.

IV. AlignTrack Design

A. Overview

As shown in Figure 5, the design of AlignTrack mainly consists of the following steps. (1) Start position detection: For the received signal, we detect the number of collided packets and the start position of each packet. (2) Collision partition: Then, we apply a moving window to align with each packet and extract peaks after de-chirp and FFT. (3) Aligned chirp detection: By comparing the peak information with adjacent windows, we find the peak of the chirp aligned with each window. (4) Packet separation: We group peaks of aligned chirps based on the position of each packet. (5) CFO elimination: We eliminate the impact of CFO to decode peaks of each packet.

B. Challenges

- How to find the accurate start for all collided packets?
- How to recover all peaks in each window as the chirps for different collided packets will interfere with each other?
- How to find the peak of the aligned chirp in each window?

C. Peak Extraction

Collision brings the following challenges in peak extraction.

1) Typically, peaks can be identified by a pre-determined threshold. Due to the uncertainty of packet time offset and the variation of signal strength and SNR, the height of peaks for different packets can vary significantly. A fixed pre-determined threshold cannot work.
2) Due to the limited resolution of FFT, the accurate frequency of the peak is difficult to derive, and the height for surrounding points of a peak is also high.
3) The sidelobes of a peak can distort the position and height of other peaks. Even worse, the sidelobes of high peaks may be mis-identified as peaks.

1) Iterative Peak Extraction: To address challenges 1 and 2, we propose an iterative peak extraction method by adopting a dynamic threshold. Denote the result of FFT as $H[i]$ ($1 \leq i \leq N$) where H is the amplitude, and N is the total number of points in FFT. In each iteration, we first find the highest peak $H[i_m]$ in $H[\cdot]$. Then, we need to determine whether it is a real peak based on the combination of $mean(H)$ and $std(H)$, where $std(H)$ is the standard deviation of H. In traditional outlier detection algorithm, data points that exceed $mean(H) + k \cdot std(H)$ (k = 3) are considered as outliers. We find that a larger k leads to more false negative peaks, and a smaller k leads to more false positive peaks. We evaluate the performance for different k and find that $k = 6$ leads to the best performance in peak identification. Thus, we choose $r = mean(H) + 6 \cdot std(H)$ as the threshold. If $H[i_m] < r$, the iteration terminates. If $H[i_m] \geq r$, we set the point at i_m as a peak and add i_m to the peak array I. Due to limited frequency resolution in FFT results, the points surrounding i_m may also have a high height and can be mis-identified as peaks in following iterations. We remove those surrounding points as follows. We find the closest local minimum before and after i_m, i.e., $H[i_m - a]$ and $H[i_m + b]$. Then, we remove all points between $i_m - a$ and $i_m + b$ from H. In the next iteration, we update r based on the remaining points in H.

2) Sidelobe Elimination: To address challenge 3, a straightforward method is to apply a Hamming filter to the received signal to reduce the amplitude for the sidelobes of each peak. However, the remaining high sidelobes (e.g., sidelobes of very high peaks) can still be mis-identified as peaks. We find that sidelobes are symmetric around a certain peak in terms of frequency and height. Based on this, we design the following method to remove sidelobes. In practice, due to the impact of noise and limited FFT bin resolution, the frequency (height) of two symmetric sidelobes cannot be exactly the same. Therefore, we derive symmetric sidelobes as follows: If two

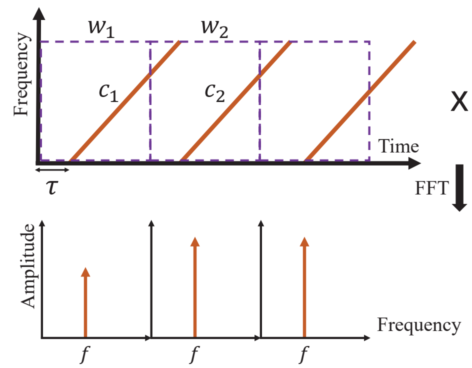


Fig. 6. Preamble detection process: the peaks of baseline up-chirps in preamble appear at the same frequency.

peaks have similar height and frequency, we consider them as symmetric peaks. We sort the peak array I in ascending order of height. For each peak i in I, we find if there exist symmetric peaks centered at i. If yes, we remove those symmetric peaks from I. Finally, we use the remaining peaks in I as the extracted peaks. The detailed algorithm of peak extraction is shown in Algorithm 1.

Algorithm 1 Peak Extraction

Input: H: the amplitude result of FFT
Output: I: the index array for peaks after removing sidelobes

```
while true do
    i_m = arg_i max(H);
    r = mean(H) + 6 · std(H); //in each iteration, recalculate i_m and r according to a new H
    if H[i_m] > r then
        add H[i_m] to I
        find closest local minimum before and after i_m, i.e.,i_m − a and i_m + b;
        remove points between i_m − a and i_m + b from H; //H is changed after each iteration
    else
        break;
    end if
end while
sort I by ascending order of their peak height;
while i < I.length do
    for j = i + 1; j++; j < I.length do
        find k such that I[j] − I[i] == I[i] − I[k]; //frequency symmetric at i
        if H[I[k]] == H[I[j]] //height symmetric then
            set isSidelobe[k] and isSidelobe[j] to TRUE;
        end if
    end for
    i = i + 1;
end while
I = I[isSidelobe≠ TRUE];
```

D. Packet Start Detection

We leverage the structure of the LoRa packet to detect the accurate start position of each packet in a collision. The preamble of a LoRa packet consists of N_p (6∼65535) baseline up-chirps with $f_s = 0$. As shown in Figure 6, we apply a non-

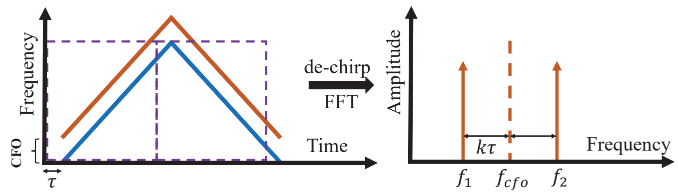


Fig. 7. Calculate CFO by combining preamble and SFD.

overlapped moving window to the received signal with moving step T_{chirp}. In each window, we multiply it with a baseline down-chirp and calculate the FFT result. For the preamble, we should have N_p peaks of the same frequency in N_p consecutive windows.

In Figure 6, assume the time offset between the start of the moving window and the start of the packet is τ. Given two windows w_1 and w_2, the peak for the segment of a chirp c_1 in w_1 is $f_1 = f_s - k\tau$, and the peak for the segment of chirp c_1 in w_2 is $f_2 = f_s + k(T_{chirp} - \tau)$. $kT_{chirp} = BW$ and the frequency of peak varies from 0 to BW. Thus, f_2 should be $f_2 = f_s - k\tau$. Similarly, for chirp c_2 and other baseline up-chirps in a LoRa preamble, the frequency of each peak should be $f = f_s - k\tau$.

By finding N_p consecutive peaks at the same frequency f, we can find the preamble and calculate the start of the packet. When there are multiple collided packets, we can find multiple groups of peaks, each group corresponding to a packet. Then we can calculate the start of each packet.

In practice, the existence of CFO introduces errors in packet start detection. Thus, we need to estimate the CFO under collision. We use both the preamble (baseline up-chirps) and SFD (baseline down-chirps) in each LoRa packet to estimate CFO [14]. Figure 7 shows a pair of baseline up-chirp and down-chirp without CFO (blue line) and with CFO (yellow line). For the baseline up-chirp in the first window with time offset τ, it results in a peak at position $f_1 = f_{cfo} - k\tau$. For the baseline down-chirp in the second window, it results in a peak at position $f_2 = f_{cfo} + k\tau$. We can see the time offset leads to the opposite shift to the peak frequency shift centered at CFO. Therefore, CFO can be calculated as $f_{cfo} = \frac{f_1+f_2}{2}$ and the time offset can be calculated as $\tau = \frac{f_2-f_1}{2k}$.

Then, we consider the case with collision. The key challenge here is that there are multiple peaks in each window, and we need to find the preamble and SFD to the same packet to calculate CFO. When multiple packets collide, we first find the preamble for each packet by finding N_p peaks at the same frequency. Meanwhile, as shown in Figure 8, there are multiple peaks of SFDs as SFDs of different packets are mixed together, leading to difficulty in calculating CFO. Given a peak P of a preamble PRE, we find the peak of SFD corresponding to the same packet pkt as follows. For a peak P_{SFD_i} of SFD_i in the mixed peaks of SFDs, we calculate the CFO and τ by combining P_{SFD_i} with P. We then check whether P_{SFD_i} and P are from the same packet based on the CFO and τ as shown in Figure 9. We shift the moving

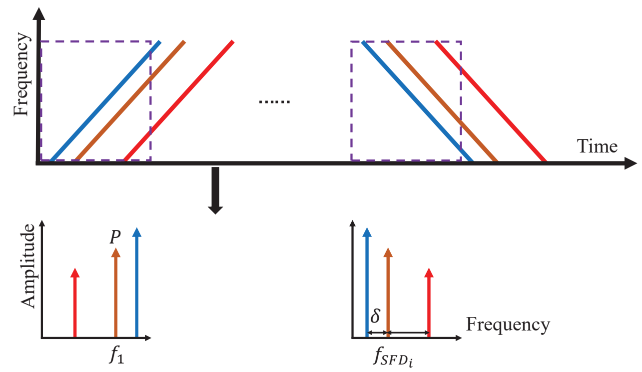


Fig. 8. Peaks for preambles and SFDs in a collision. Given a peak for a preamble, there are multiple peaks for collided SFDs.

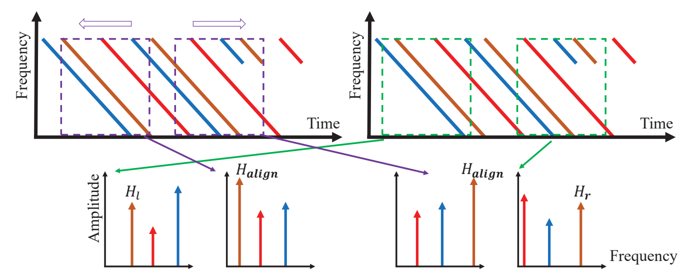


Fig. 9. Calculate CFO in packet collisions.

window by a time offset τ to align with the packet pkt. If SFD_i is from pkt, SFD_i should be accurately aligned with the window, and the height of its peak H_{align} should reach its highest height; otherwise, SFD_i should not be aligned with the window. Thus, we slightly shift the moving window by δ to the left and right, and then calculate the height of peaks corresponding to SFD_i. Denote the peak height in the left window and right window as H_l and H_r, respectively. SFD_i is from packet pkt *iff* $H_l < H_{align}$ and $H_r < H_{align}$. Otherwise, SFD_i is not from the packet pkt, and we should test other SFDs. Note that the value of δ should be smaller than $abs(f_{closest} - f_{SFD_i})/k$ to guarantee that only SFD_i can be aligned with the window, where $f_{closest}$ is the frequency of the closest SFD peak to SFD_i, f_{SFD_i} is the frequency of P_{SFD_i}, and k is the frequency changing rate of a chirp.

E. Aligned Chirp Detection

After detecting the exact start of each packet in the received signal, the positions of all chirps are known. We use a collision moving window to align all chirps in the received signal. In each window, we extract all peaks after de-chirp and FFT. Then, we identify the peak of the chirp aligned with the window. When there is no collision, the only peak in the window is the peak of the chirp aligned with the window.

Then, we consider the case with collision. Given a window w_i aligned with chirp c_i in the payload of packet A, assume w_{i-1} and w_{i+1} are the preceding and following window in the moving window sequence. We calculate all peaks in those three windows. As shown in Figure 10, there should be $2N-1$ peaks for N collided packets in each window. We first group peaks belonging to the same chirp based on the frequency constraint. For all groups of peaks, we need to identify the peak corresponding to the aligned chirp (i.e., c_i) based on the height constraint. For example, assume p_{i-1}, p_i and p_{i+1} are three peaks in the same group and H_{i-1}, H_i and H_{i+1} are their height, respectively. The peak p_i corresponds to the aligned chirp c_i *iff* the height constraint is satisfied, i.e., $H_{i-1} \leq H_i$ and $H_i \geq H_{i+1}$.

We start decoding from the first window to the last window in the collision moving window sequence based on the above process. For the first (last) window in the sequence, there is no preceding (following) window. Thus, we should find the aligned chirp only based on two windows. Note when there are multiple consecutive identical chirps in a collided packet and the position of the moving window is after the start of these chirps, there will be two peaks satisfying the frequency and height constraint. One is the peak P_a of the aligned chirp, and the other is the peak P_m of multiple consecutive identical chirps. However, we have already find the peak P_m in the last window. And thus we can remove P_m in the current window and correctly find the peak of the aligned chirp.

Ideally, the above process assumes that peaks of segments in w_{i-1}, w_i, w_{i+1} should be higher than noise. However, when the SNR is low, or the length of chirp segments in w_{i-1} or w_{i+1} is short, the peak height can be lower than the noise. In this case, existing approaches such as CoLoRa and NScale cannot work as they require to identify all peaks. AlignTrack can deal with this case as follows. For an N-packet collision with chirp c_i aligned with w_i, assume we can extract p_i but cannot extract p_{i-1} and p_{i+1} in w_{i-1} and w_{i+1}, as p_{i-1} and p_{i+1} corresponds to a segment of of c_i. There should be $2N-1$ chirp segments in w_i. The peak p_i corresponds to c_i, and other $2N-2$ peaks correspond to segments of the other $2N-2$ chirps, of which $N-1$ chirps c_l^b $(1 \leq l \leq N-1)$) are before c_i and $N-1$ chirps c_l^a $(1 \leq l \leq N-1)$ are after c_i. Assume $p_l^{b'}$ and p_l^b $(1 \leq l \leq N-1)$ are peaks of c_l^b in w_{i-1} and w_i, and $H_l^{b'}$ and H_l^b are their height. As the length of the chirp segment of c_l^b in w_{i-1} must be longer than that in w_i, we have $H_l^{b'} > H_l^b$. If p_l^b can be extracted in w_i, $p_l^{b'}$ can be extracted in w_{i-1}. However, $H_l^{b'}$ and H_l^b do not satisfy the height constraint. Thus, p_l^b are not the peak corresponding to the aligned chirp c_i and can be removed. Similarly, We can remove peaks of c_l^a. After removing peaks of those unaligned chirps, the remaining peak is one corresponding to aligned chirp c_i.

Example. Figure 10 shows a 3-packet collision, and w_1,w_2 and w_3 are three windows aligned with three chirps. Chirp c_2 is aligned with w_2 and we can derive p_2 from w_2. p_1, p_2 and p_3 are peaks of c_2 in w_1, w_2 and w_3. Suppose p_1 and p_3 can not be extracted in w_1 and w_3 due to the impact of noise. In w_2, there are five chirp segments from three LoRa packets and assume we can extract all those five peaks, where p_2 corresponds to c_2, p_1^b and p_2^b correspond to c_1^b from packet

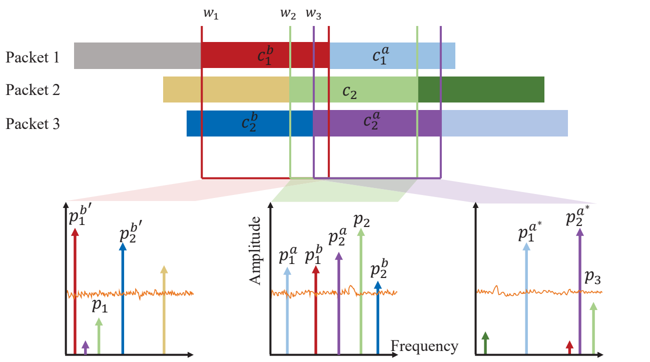


Fig. 10. Aligned chirp detection when peaks of chirp segments cannot be detected: we can remove the peaks of unaligned chirps to derive the right one

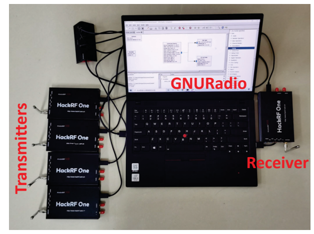


Fig. 11. Experiment setup.

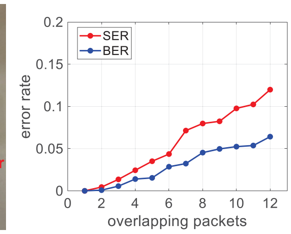


Fig. 12. SER and BER with different number of overlapping packets.

1 and c_2^b from packet 3, p_1^a and p_2^a correspond to c_1^a from packet 1 and c_2^a from packet 3. c_1^b and c_2^b are before c_2 while c_1^a and c_2^a are after c_2.

$p_1^{b'}$ and p_1^b are peaks corresponding to c_1^b in w_1 and w_2. $H_1^{b'}$ and H_1^b denote their height. The segment of c_1^b in w_1 is longer than that in w_2, i.e.,$H_1^{b'} > H_1^b$. p_1^b can be extracted in w_2. Thus, $p_1^{b'}$ can be extracted in w_1. However, $H_1^{b'}$ and H_1^b do not satisfy the height constraint. Thus, we can identify p_1^b as a peak for unaligned chirp and then remove it. Similarly, p_2^b, p_1^a, and p_2^a can be removed.

Therefore, we can remove all peaks for unaligned chirps from w_2, and the remaining peak is the one for the aligned chirp. Note that in a very low SNR, the peak height of a complete chirp is close to noise amplitude. The peak height of any chirp segment (i.e., a portion of a chirp) can be lower than noise. Thus, only p_i corresponding to c_i in w_i can be extracted. AlignTrack can work in this scenario by removing unaligned chirps. Thus it can work at the same SNR as that of LoRa.

The above method mainly works for collisions with a time offset among packets. In practice, the probability for concurrent transmission with no time offset should be very low. Thus, our method can address most of the cases in practice. Even in the case of concurrent transmission, we can extend our method by leveraging existing techniques. For example, we can leverage the small frequency distortion due to hardware imperfection [16]. Thus, we can divide those peaks according to the fractional part of the frequency distortion and then separate into different packets.

F. Packet Separation and CFO Elimination

Till now, we have detected 1) the aligned chirp in each window and 2) the exact start position of each packet. Then, we can group chirps into different packets. We can obtain the length of different collided packets. When there is no peak satisfying the frequency and height constraint, it means there is no chirp aligned with the window. Thus, the corresponding collided packet ends in the last window aligned with the packet. And we can obtain the length of this packet by calculating the position of the last window. Then we can decode chirps for each packet. Then, we chirps belong to the same packet, we first compensate the CFO and then decode the packet. Assume the demodulated frequency for a chirp $f_s{}^*$, then the real modulated data after remove CFO is

$$f_s = (f_s{}^* - f_{cfo}) \mod 2^{SF} \tag{7}$$

V. Implementation and Evaluation

A. Implementation

Hardware: We implement our gateway on the HackRF One platform. The HackRF One can run at a frequency range of 30 MHz-6 GHz. and supports the use of GNURadio. The maximum sampling rate is 20 M samples per second (Msps), and We only use 1 Msps due to the limited bandwidth. In order to better control the LoRa nodes, we implement the function of LoRa nodes on HackRF one. Therefore, we can use GNURadio+HackRF One as a LoRa transceiver to create packet collisions.

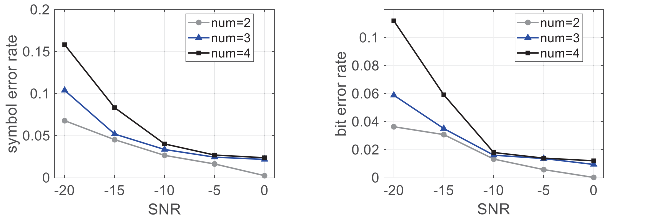
Software: The HackRF One can provide PHY layer samples of the received signal. We implement AlignTrack in MATLAB on a PC to process LoRa PHY samples. We implement the LoRa encoder and decoder using Matlab. In our experiment, each LoRa packet consists of a preamble with 10 up-chirps, of which eight are baseline up-chirps, an SFD with 2.25 baseline down-chirps, and a payload with 36 up-chirps. We use $SF = 12$ and $BW = 125$ kHz. The sampling rate is set to 1 MHz, and the central frequency is set to 471.3 MHz.

Note that AlignTrack does not depend on the specific hardware platform. It can decode collision packets as long as the PHY samples of a received signal are provided. AlignTrack sits at the gateway for collision decoding. It can work for existing COTS LoRa nodes without any modification in software and hardware.

B. Evaluation

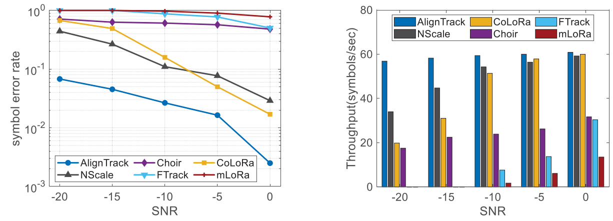
We use a HackRF One as the receiver and multiple HackRF One nodes as transmitters. We mainly measure the following metrics: (1) symbol error rate (SER), the error rate of decoding a chirp, (2) bit error rate (BER), the error rate after translating symbols to bits, and (3) throughput, the total receiving symbol rate (symbols/second) at the receiver. Note that, in LoRa the BER is usually lower than SER as it uses error correcting codes at the symbol level.

Based on those metrics, we mainly evaluate the performance of AlignTrack under (1) different number of overlapping



(a) (b)

Fig. 13. SER and BER under different SNR: (a) SER under different SNR. (b) BER under different SNR.



(a) (b)

Fig. 14. SER and throughput comparison under different SNR: (a) Averaged SER. (b) Network Throughput.

packets, (2) different SNR, (3) different time offset, and (4) different spreading factors among packets. Further, we compare AlignTrack with the following state-of-the-arts.

- mLoRa [12], a LoRa collision decoding approach based on SIC in the time domain.
- FTrack [13], time-domain frequency continuity based LoRa collision decoding.
- CoLoRa [14], a LoRa collision decoding approach based on the height difference of different packets in the frequency domain.
- NScale [15], a LoRa collision decoding approach leveraging a non-linear scaling function in the frequency domain.
- Choir [16], a LoRa collision decoding approach based on frequency shift due to imperfection hardware.

Packets sent by each transmitter are known in advance to calculate the SER, BER, and throughput. In order to show the collision decoding performance in real LoRa environments, our experiments are conducted in the scenario of $SNR < 0$ dB and the collision can appear at different positions, such as preamble-preamble, preamble-SFD, preamble-payload, etc.

1) Impact of the number of packets: We evaluate the performance of AlignTrack at the different number of overlapping packets. We use a HackRF One as the receiver and use 12 HackRF Ones as transmitters. We use GNURadio to control the transmit time of each transmitter to create collisions.

Figure 12 shows the averaged SER and BER with the different number of overlapping packets. We can see that the overall SER is under 4% and BER is under 2% when the overlapping number is under 6, the SER is under 10% and the BER is under 6% when the overlapping number is under 10. The maximum number of overlapping packets is 12 with BER $< 6.5\%$, which is acceptable in the LoRa network. Both SER and BER increase as the overlapping number increases from 1 to 12. It is because the time offset among packets decreases when the overlapping number increases. A smaller time offset leads to less height change among different windows and thus degrades the decoding performance.

2) Impact of SNR: We evaluate the impact of the signal-to-noise ratio (SNR) on the performance of AlignTrack. Due to the collisions of multiple packets, the actual interference intensity is higher than the ambient noise intensity. We use $3 \sim 5$ HackRF Ones, of which one is the receiver and the others are transmitters. To accurately control the SNR, we add additive white Gaussian noise (AWGN) to the received signal.

AlignTrack multiplies the entire up-chirp with baseline down-chirp in each moving window, which is the same as traditional LoRa. Figure 13 shows the averaged SER and BER of AlignTrack when SNR varies from -20 to 0. The SER and BER decrease with the increase of SNR. When $SNR \approx -20$ dB, the SER of 2-packet collision is 6.79%, and the BER is 3.64%, i.e., AlignTrack can decode most 2-packets collision successfully at an extremely low SNR. When $SNR = 0$ dB, the SER and BER of 2-packet collision are 0.25% and 0.022%. For 4-packet collisions, the SER is still lower than 10%, and BER is lower than 6% even at $SNR \approx -15$ dB. In all, AlignTrack can decode packets collision in an extremely low SNR as traditional LoRa. This also validates that AlignTrack introduces very small SNR loss.

Figure 14 shows averaged SER and throughput of different methods with the SNR varies from -20 to 0. We compare AlignTrack with mLoRa, FTrack, CoLoRa, NScale, and Choir. Figure 14(a) shows that the SER of AlignTrack is much lower than that of the other methods. When $SNR \approx 0$ dB, the SER of mLoRa reaches 77.8%, and the SER of FTrack and Choir is about 50%, while that of AlignTrack is even lower than 0.3%. When $SNR \approx -20$ dB, the SER of AlignTrack is still lower than 7%, while the SER of NScale is 44.25% and the SER of CoLoRa and Choir is about 70%. This is because AlignTrack transforms time domain information to frequency domain information and uses the entire up-chirp to demodulate. AlignTrack can concentrate the energy of the entire chirp to resist interference from other packets and noise. mLoRa and FTrack only use time-domain information and cannot work at a low SNR. The hardware offset in Choir is also hard to find in a low SNR. CoLoRa and NScale separate the entire chirp into two segments, which reduces the concentration of energy. Thus, AlignTrack introduces much less SNR loss than other approaches that are using parts of a chirp.

Figure 14(b) shows the network throughput. When $SNR \approx -20$ dB, the network throughput of AlignTrack is 57 sps, which is $1.68\times$ of NScale (34sps), $3.35\times$ of Choir (17sps) and $3\times$ of CoLoRa (19sps).

3) Impact of symbol time offset: The height of a peak is impacted by chirp segment length in the current window. A small symbol time offset among packets leads to a small

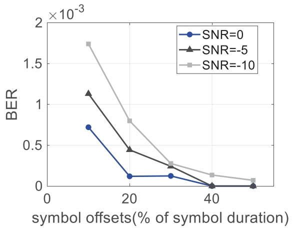


Fig. 15. BER under different symbol time offsets in collisions.

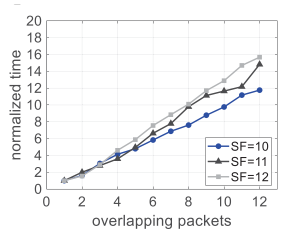


Fig. 16. Normalized time consumption under different number of overlapping packets.

difference of segment length between two windows. This leads to a very small height change of a peak. Thus, we evaluate how symbol time offset can impact the performance of AlignTrack.

We create different symbol time offsets of a 2-packet collision. Figure 15 shows the averaged BER under the impact of symbol time offset and SNR. The BER decreases with the increase of the symbol time offset, which coincides with our analysis. When the time offset is larger, it is easier for AlignTrack to find the unique peak corresponding to the aligned chirp. The smallest symbol time offset is 10% of symbol duration when $BER < 0.2\%$ and $SNR = -10$ dB. This means that AlignTrack can decode almost all overlapping packets under a very small time offset. The collision packets that cannot be decoded when the time offset is too small can be retransmitted.

4) Time consumption: AlignTrack adopts a moving window to align with all chirps in the received signal, which means the time consumption is influenced by the number of chirps. Figure 16 shows the normalized time consumption under different SF and number of overlapping packets. The normalized time consumption increases when the number of overlapping packets increases. The normalized time consumption of decoding 12 packets is 12× and 15× of decoding 1 packet when $SF = 10$ and $SF = 12$. The time consumption increases faster when the SF increases. This is due to the reason that when the SF increases, the chirp length increases, and it will spend more time on *Peak Extraction*. In the future, we will further work on how to reduce time consumption.

5) Performance in an outdoor network: We evaluate the performance of AlignTrack in a real outdoor LoRa network. We use COTS LoRa nodes with chip SX1278 as transmitters and a HackRF One as the receiver. As shown in Figure 17, we deploy LoRa nodes in 12 different places. Figure 18 shows the averaged SER and throughput of four methods when the number of overlapping packets varies from 1 to 12.

Figure 18(a) shows the averaged SER. The SER increases with the increasing number of overlapping packets. The SER of NScale, CoLoRa, and Choir increase faster than that of AlignTrack, and the SER of Choir increases the fastest. This is because Choir uses hardware imperfection which is difficult to find under low SNR, and NScale and CoLoRa partition a chirp to segments and use the height difference among packets to decode collisions. When the number of overlapping packets increases, the height difference among chirps in different LoRa

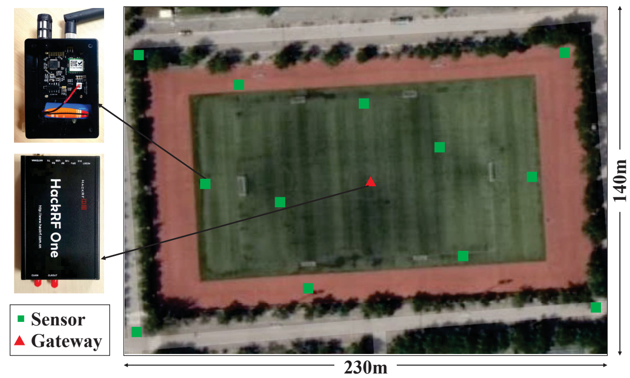
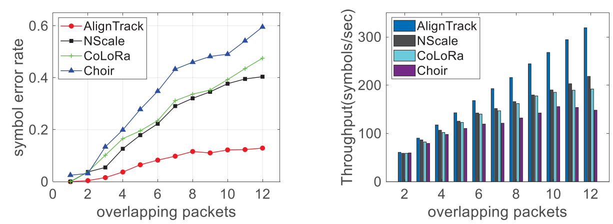


Fig. 17. Outdoor LoRa Network: LoRa nodes with radio chip SX1278 as transmitters and HackRF One as the receiver (gateway) in a campus.



(a) (b)

Fig. 18. Performance in real outdoor deployed LoRa networks:(a) Averaged SER. (b) Network Throughput.

packets decreases, and the features of different packets are more likely to be similar, i.e., not distinguishable enough to separate packets. For AlignTrack, we only focus on the peak frequency and height change of the aligned chirp at the current moving window. Thus, our approach introduces more robust features to distinguish packets. When the number of overlapping packets reaches 7, the SER of Choir is more than 40%, the SER of NScale and CoLoRa are almost 30% while the SER of AlignTrack is still lower than 10%. When the number of overlapping packets reaches 12, the SER of NScale is more than 40%, which is 3.1× of AlignTrack (12.9%). And the SER of CoLoRa (48%) and Choir (60%) are 3.72× and 4.65× of AlignTrack. Figure 18(a) shows that when there is no collision, there are still decoding errors in Choir. This is because Choir separates packets by grouping peaks with the same fractional part of the frequency of peaks. The fractional part is mainly determined by the CFO due to the hardware imperfection. However, the CFO changes with time, and the fractional part changes with time. And thus, peaks for the same packet will be divided into different packets. AlignTrack uses the integer part of the frequency of peaks, and thus can be more robust to distinguish packets.

Figure 18(b) shows the network throughput of AlignTrack, NScale, CoLoRa and Choir. When the number of overlapping packets reaches 12, the throughput of AlignTrack is 320 sps, which is 1.52× of NScale (210 sps), 1.68× of CoLoRa (190 sps), and 2.16× of Choir (148 sps).

VI. Related work

Collision resolution in LoRa. There are many works to decode collisions for LoRa. mLoRa [12] adopts SIC to separate packets and can decode collision from three nodes. FTrack [13] separates collided packets by calculating the continuity of instantaneous frequency and concentrates on the time domain features, which needs a high SNR (e.g., $SNR > 0$ dB). Choir [16] exploits the frequency shift of imperfect hardware to separate packets. CoLoRa [14] considers the height relationship of peaks in adjacent windows. NScale [15] multiples the chirp segment with a non-stationary scaled down-chirp and leverages peaks of different segments to distinguish different packets. CoLoRa and NScale need to partition a chirp and introduce inevitable SNR loss in practice. AlignTrack leverages the entire chirp in LoRa and introduces a very small SNR loss. The SNR loss introduced by CoLoRa and NScale requires LoRa nodes to transmit LoRa packets with higher strength, while AlignTrack does not need to do any redundant operations.

General methods for collision resolution. There are many traditional methods for collision resolution. One is to use multiple antennas, such as Multi Input Multi Output(MIMO) [17], [18]. MIMO uses multiple antennas to form a transceiver system with multiple channels. However, MIMO is not suitable for a single antenna device like the LoRa node. The other is to perform channel detection to avoid collision, such as CSMA/CA [19] [20] and RTS-CTS [21] [22]. However, CSMA/CA needs to detect the channel status, and RSSI based channel detect method does not work in a very low SNR like the LoRa network. Channel Activity Detection (CAD) method introduced by LoRa needs to detect the LoRa preamble, which introduces a high overhead and power consumption. Meanwhile, CSMA/CA significantly reduces the transmission efficiency especially considering the dense deployment of LoRa nodes and the long communication distance. The impact of the hidden/exposed terminal problems is exacerbated and will significantly reduce the network efficiency. SIC [23] is also a general method for collision resolution. SIC iteratively finds and reconstructs coding information based on different signal strengths and some known coding information. However, it does not utilize the features of LoRa.

Improvement on LPWANs. A variety of works have been proposed to improve the performance of LPWANs. OPR [24] uses multiple gateways to recover packets subject to CRC and/or FEC errors. Chime [25] analyzes the path signals traverse from the client to distributed and coordinated gateways to choose the optimal frequency of the LPWAN client. LiteNap [26] enables sub-Nyquist sampling and packet decoding to improve energy efficiency. EF-LoRa [27] allocates different network resources to achieve fair energy consumption among end devices. The work [28] conducts a series of experiments to verify the claims made by Semtech on LoRa.

VII. Conclusion

LoRa has been one of the key technologies to connect millions of devices in the Internet of Things. However, the collision of LoRa packets significantly degrades its performance in practice. Existing collision decoding approaches introduce non-negligible SNR loss in collision decoding. We present AlignTrack, the first LoRa collision decoding approach that incurs negligible SNR loss and can decode collisions under a very low SNR. Unlike state-of-the-arts that leverage partial chirps to separate collided packets, AlignTrack aligns windows to each packet and leverages the aligned chirps in each window to separate packets. We address practical challenges in the implementation. We propose a method to accurately find the start of each packet under interference and CFO. We show how to accurately find the aligned chirps in each window and recover accurate peak information. We implement AlignTrack on the HackRF One platform and evaluate its performance extensively. AlignTrack totally sits at the server side without any modification to the LoRa end nodes and can be applied to existing LoRa networks. The evaluation results show that AlignTrack improves network throughput by $1.68\times$ compared with NScale and $3\times$ compared with CoLoRa.

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References

[1] Kais Mekki, Eddy Bajic, Frederic Chaxel, and Fernand Meyer. Overview of cellular LPWAN technologies for IoT deployment: Sigfox, LoRaWAN, and NB-IoT. In *2018 IEEE International Conference on Pervasive Computing and Communications Workshops (PerCom Workshops)*, 2018.

[2] Oratile Khutsoane, Bassey Isong, and Adnan M. Abu-Mahfouz. IoT devices and applications based on LoRa/LoRaWAN. In *IECON 2017-43rd Annual Conference of the IEEE Industrial Electronics Society*, 2017.

[3] Afef Mdhaffar, Tarak Chaari, Kaouthar Larbi, Mohamed Jmaiel, and Bernd Freisleben. IoT-based health monitoring via LoRaWAN. In *IEEE EUROCON 2017-17th International Conference on Smart Technologies*, 2017.

[4] Danco Davcev, Kosta Mitreski, Stefan Trajkovic, Viktor Nikolovski, and Nikola Koteli. IoT agriculture system based on LoRaWAN. In *2018 14th IEEE International Workshop on Factory Communication Systems (WFCS)*, 2018.

[5] Ruhaizan Fazrren Ashraff Mohd Nor, Fadhlan HK Zaman, and Shamry Mubdi. Smart traffic light for congestion monitoring using LoRaWAN. In *2017 IEEE 8th Control and System Graduate Research Colloquium (ICSGRC)*, 2017.

[6] Saifil Allif A'ssri, Fadhlan HK Zaman, and Shamry Mubdi. The efficient parking bay allocation and management system using LoRaWAN. In *2017 IEEE 8th Control and System Graduate Research Colloquium (ICSGRC)*, 2017.

[7] Yao Peng, Longfei Shangguan, Yue Hu, Yujie Qian, Xianshang Lin, Xiaojiang Chen, Dingyi Fang, and Kyle Jamieson. PLoRa: A passive long-range data network from ambient LoRa transmissions. In *Proceedings of the 2018 Conference of the ACM Special Interest Group on Data Communication*, 2018.

[8] Vamsi Talla, Mehrdad Hessar, Bryce Kellogg, Ali Najafi, Joshua R. Smith, and Shyamnath Gollakota. Lora backscatter: Enabling the vision of ubiquitous connectivity. *Proceedings of the ACM on Interactive, Mobile, Wearable and Ubiquitous Technologies*, 1(3):1–24, 2017.

[9] Norman Abramson. THE ALOHA SYSTEM: another alternative for computer communications. In *Proceedings of the November 17-19, 1970, fall joint computer conference*, 1970.

[10] Jonathan de Carvalho Silva, Joel JPC Rodrigues, Antonio M Alberti, Petar Solic, and Andre LL Aquino. Lorawan—a low power wan protocol for internet of things: A review and opportunities. In *2017 2nd International Multidisciplinary Conference on Computer and Energy Science (SpliTech)*, 2017.

[11] Ferran Adelantado, Xavier Vilajosana, Pere Tuset-Peiro, Borja Martinez, Joan Melia-Segui, and Thomas Watteyne. Understanding the limits of LoRaWAN. *IEEE Communications magazine*, 55(9):34–40, 2017.

[12] 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)*, 2019.

[13] Xianjin Xia, Yuanqing Zheng, and Tao Gu. FTrack: parallel decoding for LoRa transmissions. In *Proceedings of the 17th Conference on Embedded Networked Sensor Systems*, 2019.

[14] Shuai Tong, Zhenqiang Xu, and Jiliang Wang. Colora: Enabling multi-packet reception in lora. In *IEEE INFOCOM 2020-IEEE Conference on Computer Communications*, 2020.

[15] 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*, 2020.

[16] 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*, 2017.

[17] Lu Lu, Geoffrey Ye Li, A. Lee Swindlehurst, Alexei Ashikhmin, and Rui Zhang. An overview of massive MIMO: Benefits and challenges. *IEEE journal of selected topics in signal processing*, 8(5):742–758, 2014.

[18] David Gesbert, Mansoor Shafi, Da-shan Shiu, Peter J. Smith, and Ayman Naguib. From theory to practice: An overview of MIMO space-time coded wireless systems. *IEEE Journal on selected areas in Communications*, 21(3):281–302, 2003.

[19] Rafael Laufer and Leonard Kleinrock. The capacity of wireless CSMA/CA networks. *IEEE/ACM Transactions on Networking*, 24(3):1518–1532, 2015.

[20] Eustathia Ziouva and Theodore Antonakopoulos. CSMA/CA performance under high traffic conditions: throughput and delay analysis. *Computer communications*, 25(3):313–321, 2002.

[21] Peisong Lin and Lin Zhang. Full-duplex rts/cts aided csma/ca mechanism for visible light communication network with hidden nodes under saturated traffic. In *2018 IEEE International Conference on Communications (ICC)*, 2018.

[22] Kaixin Xu, Mario Gerla, and Sang Bae. Effectiveness of RTS/CTS handshake in IEEE 802.11 based ad hoc networks. *Ad hoc networks*, 1(1):107–123, 2003.

[23] Pulin Patel and Jack Holtzman. Analysis of a simple successive interference cancellation scheme in a ds/cdma system. *IEEE journal on selected areas in communications*, 12(5):796–807, 1994.

[24] Artur Balanuta, Nuno Pereira, Swarun Kumar, and Anthony Rowe. A cloud-optimized link layer for low-power wide-area networks. In *MobiSys*, 2020.

[25] Akshay Gadre, Revathy Narayanan, Anh Luong, Anthony Rowe, Bob Iannucci, and Swarun Kumar. Frequency configuration for low-power wide-area networks in a heartbeat. In *17th {USENIX} Symposium on Networked Systems Design and Implementation ({NSDI} 20)*, 2020.

[26] Xianjin Xia, Yuanqing Zheng, and Tao Gu. Litenap: Downclocking lora reception. In *IEEE INFOCOM 2020-IEEE Conference on Computer Communications*, 2020.

[27] Weifeng Gao, Wan Du, Zhiwei Zhao, Geyong Min, and Mukesh Singhal. Towards energy-fairness in lora networks. In *2019 IEEE 39th International Conference on Distributed Computing Systems (ICDCS)*, 2019.

[28] Jansen C Liando, Amalinda Gamage, Agustinus W Tengourtius, and Mo Li. Known and unknown facts of lora: Experiences from a large-scale measurement study. *ACM Transactions on Sensor Networks (TOSN)*, 15(2):1–35, 2019.