Embracing Collisions to Increase Fidelity of Sensing Systems with COTS Tags

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RFID techniques have been extensively used in sensing systems due to their low cost. However, limited by the structural simplicity, collision is one key issue which is inevitable in RFID systems, thus limiting the accuracy and scalability of such sensing systems. Existing anti-collision techniques try to enable parallel decoding without sensing based applications in mind, which can not operate on COTS RFID systems. To address the issue, we propose COFFEE, which enables parallel channel estimation of COTS passive tags by harnessing the collision. We revisit the physical layer design of current standard. By exploiting the characteristics of low sampling rate and channel diversity of RFID tags, we separate the collided data and extract the channels of the collided tags. We also propose a tag identification algorithm which explores history channel information and identify the tags without decoding. COFFEE is compatible with current COTS RFID standards which can be applied to all RFID-based sensing systems without any modification on tag side. To evaluate the real world performance of our system, we build a prototype and conduct extensive experiments. The experimental results show that we can achieve up to 7.33x median time resolution gain for the best case and 3.42x median gain on average.

CCS Concepts: • **Human-centered computing → Ubiquitous and mobile computing design and evaluation methods**.

Additional Key Words and Phrases: RFID sensing, anti-collision, channel estimation

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1 INTRODUCTION

Collision caused by simultaneous tag responses is one of the key issues in RFID systems. Typically, RFID tags respond using slotted ALOHA under existing RFID communication standards like EPCglobal C1G2 (C1G2). C1G2 uses slotted frame ALOHA to coordinate the transmissions of multiple tags. The reader initiates an inventory round by sending a Query command and the tags respond in a random slot for channel contention. Thus, tag transmissions are designed to be temporally far apart, so as to minimize collision. Even with a small number of commercial-off-the-shelf (COTS) RFID tags (with standard protocols running on them), data transmissions tend to be sparse in time.

However, the collision issue can dramatically degrade the performance of the RFID-based sensing systems. This is because, in sensing systems, the changes of environment are typically captured by measuring the channel

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fluctuations (RSSI, phase, power) experienced by a tag's transmission. Intuitively, when a sensing system can obtain these channels more frequently, it can potentially achieve higher fidelity and higher accuracy. In other words, the accuracy relies on the time interval between two channel estimates from the same tag's transmissions. More channel estimates from a tag will result in a higher activity classification accuracy. However, when collisions happen, the collided data which can not be decoded are viewed as useless and discarded and the tags are required to choose another time slot for transmission, thus reducing the time resolution of channel estimation for the tags and hurting the performance of sensing systems. For example, recent work in [29] implements fall detection system based on received signal strength indicator (RSSI) of UHF tags, which can achieve an overall accuracy of 87.5%. The authors in [40] propose a compressive dictionary-based feature representation. Most of the activities can be classified accurately. However, some similar activities–like falling left and falling right–can only achieve an accuracy of 0.55 and 0.32 respectively. We suspect that such inaccuracies are due to the lack of temporally fine grained sampling, a property inherent to RFID tag systems.

Anti-collision for RFID-based systems have recently received many attentions, which can be categorized into physical layer (PHY) and medium access control (MAC) approaches. Broadly, MAC layer approaches require new protocols for tag access to decrease the collision probability. [23] summarizes the recent Aloha-based and Tree-based anti-collision protocols. Such protocols usually can not work with COTS tags. PHY solutions overcome the collisions by enabling parallel decoding on physical layer and hence eliminating the effect of collisions. Bigroup [27] enables parallel decoding by detecting the bit boundary of collided packets for each tag. The authors in [11] also separates different stream by detecting the edges and realizes cluster-based collision detection. Fliptracer proposed in [21] obtains the transition pattern of collided signals using flip graph. Recent work [20] uses a similar method as [21] to obtain the channels and decode the tag ID of each tag. But such approaches require the tags to transmit EPC message simultaneously, which are not designed for COTS tags and can not support more than 5 tags. While anti-collision techniques try to solve the collision issue for communication, our goal is to acquire more fine-grained channel estimation for sensing based systems which deploys a large number of COTS tags.

In this paper, we propose a new approach for channel estimation, COFFEE (COllision-FrEE channel estimation), which estimates channels of concurrent transmission to improve the performance of all the existing RFID-based sensing systems which are fully compatible with COTS RFID tags. First, we retrieve the channels of multiple RFID tags from the collided data. We subtract the data stream from different tags sequentially by exploiting the characteristics of low sampling rate and channel diversity of tags. After extracting the channel information, we need to match each channel to the corresponding tag. To tackle this problem, we propose a tag identification algorithms which utilize the history channel information to identify the tag without decoding the tag ID.

We build a prototype with COTS UHF RFID tags and a software-defined radio based reader with USRP N210 and a SBX daughterboard. We design COFFEE as an extension to the current C1G2 standard [9] which provides fine-grained channel estimation and can be applied to all RFID-based sensing systems. Our experimental results show that we can achieve median time resolution gains of 2.34x, 2.9x, 3.42x over C1G2 on average and a median gain of 4.6x, 5.04x and 7.33x for the worst tag which has the lowest time resolution using C1G2. To evaluate how our system enhances existing RFID techniques, we implement an activity recognition system based on [42]. By applying COFFEE, we are able to increase the average accuracy of 10% and 22% for the best case, thus demonstrating its practicality and performance gains over current sensing systems.

2 BACKGROUND AND MOTIVATION

Collision caused by simultaneous tag responses is an inevitable issue in RFID systems. In the design of C1G2, the reader initiates an inventory round by sending a Query command which specifies communication parameters such as tag rate and tag data encoding scheme. It also contains a Q parameter which specifies the frame size as 2^Q. For example, when $Q = 4$, there are 16 time slots in each inventory round. Each tag needs to send a 16-bit

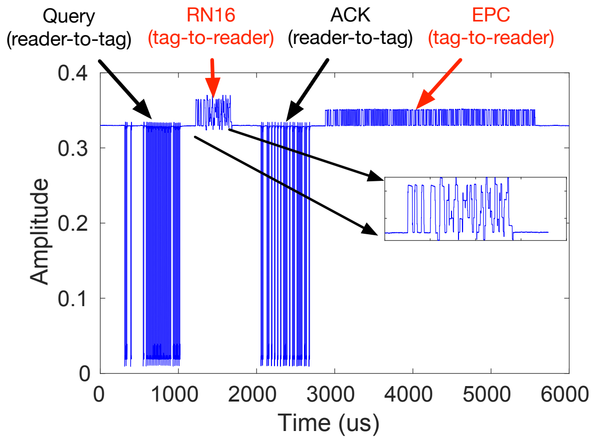


Fig. 1. Tags first respond with RN16. Collisions may happen during RN16. One tag can still transmit EPC if the reader can decode its RN16. Other collided tags need to select another time slot.

random number (RN16) at the beginning of a random slot for channel contention in each inventory round. Fig. 1 illustrates the waveform in one time slot. The reader decodes the RN16 and responds with an ACK to initiate the identification procedure with the corresponding tag. Collisions occur when multiple tags transmit RN16 simultaneously. The reader attempts to decode one RN16 if possible and send an ACK with the RN16. When a tag hears its own RN16, it responds with an EPC message which contains its identification. Otherwise, the tags need to choose another time slot to re-transmit its RN16. The RN16s of the collided tags are simply discarded. Hence, collision happens only when tags send RN16 not the EPC message. Typically, RFID systems utilize the preambles of EPC to obtain the channel information of one tag.

To explore how collision affects sensing systems, we conduct experiments in the real world and we use 8 tags. We define **time resolution** of one tag as the number of channel states that can be successfully measured between itself and the reader within 1 sec. In each time slot, one tag can obtain at most one channel state. Fig. 2 plots the time resolution of 8 tags. Tag 1 has the worst time resolution of 2.94 channels/second and tag 3 can achieve a time resolution up to 11.18 channels/second. This is because when collision occurs, the tag with higher transmission power can communicate with the reader and thus transmit more. Due to the limited communication range of tags, one tag captures the channel fluctuation due to changes within a small area. Hence, in sensing systems, the features of one activity may be captured by small group of tags, where each tag's channel provides valuable, location specific information. If the time resolution of the corresponding tags is not good enough to capture the features, then the accuracy of classifying the corresponding activity will decrease. Our results indicate that there exist bottleneck tags whose time resolution is much lower than average, which can limit the performance of the sensing systems. Then, we explore the effect of choosing different Q on time resolution. As shown in Fig. 3, as Q increases, the collisions occur less often but the time resolution of average tags decreases. However, picking a large Q is not a good solution as some sensing systems require high time resolution for robust performance. Thus, for such systems, collisions need to be addressed while keeping the value of Q low.

To address the collision problem, recent works [11, 20, 21, 27] propose anti-collision systems by enabling parallel decoding. Generally, all these systems are based on clustering collided signal in IQ domain. However, clustering could fail due to the dynamics of the signal in IQ domain. As shown in Fig. 4, when the channel of two tags are similar to each other, the clusters overlap with each other which can not be separated. Fig. 5 shows an

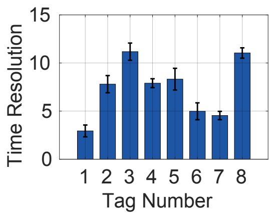


Fig. 2. Different tags have different time resolution due to the diversity of channel gains.

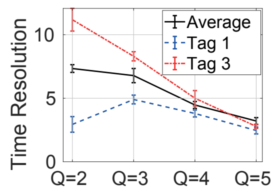


Fig. 3. For monitoring systems, Q can not be too large. Otherwise the average time resolution will decrease.

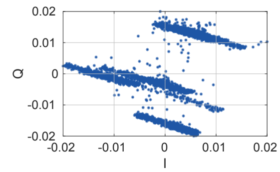


Fig. 4. 2-tag collision case. When the channels of two tags are close in IQ domain, the clusters overlap.

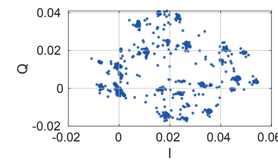


Fig. 5. 5-tag collision case. When the number of collided tags increases, it is hard to separate all clusters.

example of 5-tags collision with 32 clusters. Clusters are more closed to each other and there are more points between clusters. Separating clusters become challenging when the number of collided tags increases. Such problems limit the scalability and feasibility of parallel decoding approaches which are based on clustering signal in IQ domain. Typically, such systems can only support 3-5 tags simultaneously. In addition, current approaches assume that the tags can transmit EPC concurrently, which can not be tested with COTS tags.

Furthermore, existing approaches are designed for parallel decoding, and do not focus on acquiring the channel information. For sensing systems, it is more important to obtain the channel information than to decode the packets. Typically, to obtain clean channel for a tag, a system needs a dedicated time slot where a tag can transmit collision-free. Hence, we ask, can we design a system which can obtain the channel for multiple collided tags **without extra time slots** and **without modification on COTS tags**? Although the existing approaches can not achieve such goal, their design of utilizing the collided data on physical layer inspires our work. Instead of decoding all the transmitted data, COFFEE aims to acquire the channels of all the collided tags, which can be used for all RFID-based sensing system.

3 COFFEE OVERVIEW

Our system can be compatible with C1G2, and can potentially benefit all the RFID-based sensing systems, especially for dense sensing systems. Previous sensing systems achieve the channel profiles based on traditional C1G2 standard and mainly focus on improving the signal processing procedure and activity classification algorithms. Instead of directly extracting channel profiles from the reader, COFFEE collects the raw samples from the reader and recovers missing channel information from the collisions, thus increasing the time resolution of the channel profiles for tags.

Fig. 6 illustrates the detailed work flow of COFFEE. Upon receiving transmitted data from RFID tags, the reader feeds all the data into the software part for data analysis. First, the data streams are categorized into two parts, RN16 and EPC message. The EPC part follows C1G2 standard for decoding. The channel and the corresponding tag ID which can be obtained from EPC message can be used to assist separating the collided data. The RN16 messages are forwarded into the processing procedure. First step is detecting whether collision has occurred or not. If a collision has occurred, then the channels of the collided tags can be extracted. We map an extracted channel to the correct corresponding tag based on historical channel information of the signal. If a newly estimated channel does not map to a known tag based on the historical channel data, then the channel estimate is discarded, as it may be erroneous. Only the channel estimates that pass the error detection stage will be stored in channel profiles.

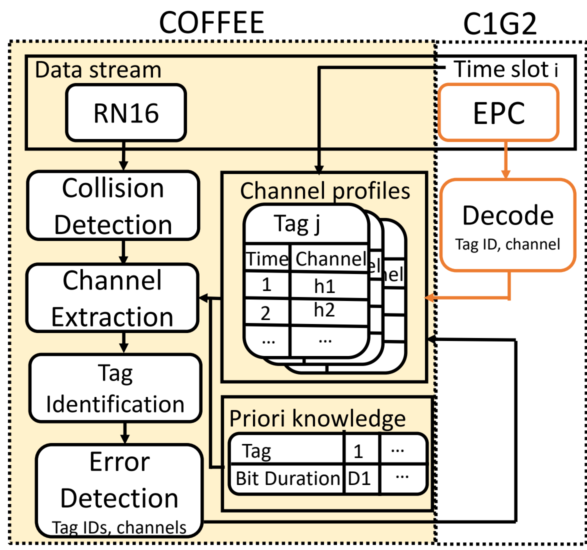


Fig. 6. Work flow of COFFEE, which works as an extension of C1G2 without modification on the tag side.

4 DESIGN

We define the channel profile as the history channel information of passive tags in this paper. In the channel profile of one tag, each channel state is labeled with the time when captured and whether it is extracted from EPC or RN16. Traditionally, in C1G2 the channel information and the tag ID of one specific RFID tag can be measured by the preambles of EPC and decoded from the data field of EPC message. Since no collision happens during EPC transmission, these channels can be viewed as certain information which can be directly restored in channel profiles. In C1G2 standard when the reader receives the collided RN16, it discards the collided data since it can not distinguish the transmitted data of different tags. Instead, COFFEE utilizes these information which seems useless. In this section, we give a detailed demonstration of how COFFEE recovers the missing channel information for each tag from the collisions.

4.1 Detecting Collisions

In this section, we discuss how to detect collisions. Passive tags encode the data by changing states between reflecting and absorbing signal. After subtracting the DC component which is delivered by reader for supplying power for tags, the data that received on the reader side can be viewed as the superposition of transmitted signal from collided tags. We categorize all the received samples into zero bits and non-zero bits by measuring the amplitude of the data. If all the tags are in the absorbing state, the total received signal only contains noise and can be viewed as zero bits. Furthermore, as long as there is at least one tag that is in the reflecting state, the received signal should be non-zero bits. Fig. 7 illustrates the constellation domain of all the samples contained in RN16 message when there is no collision. The variation of all the non-zero bits is close to noise floor because they are generated by one single tag. As shown in fig. 8, the variation of the non-zero bits during the collision should be close to signal level which is much larger than noise floor.

To detect collisions, we use the normalized standard deviation (*nstd*), which is denoted in the Eq. 1, to measure the variation of N non-zero bits within the duration of one RN16 duration. x_i denotes the complex value of *i-th* sample and $\bar{x}$ is the mean of N samples. We use the mean to normalize the deviation of N samples. We denote

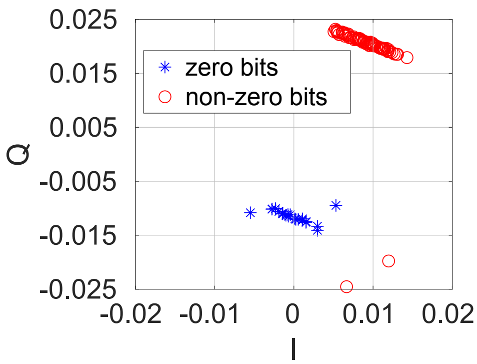


Fig. 7. When one tag transmits, the variation of non-zero bits is close to noise floor.

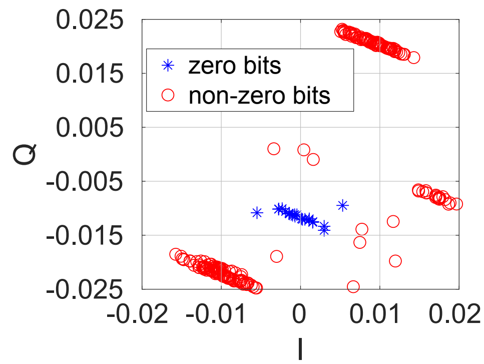


Fig. 8. When multiple tags collide, the variation of non-zero bits is much larger than noise level.

a threshold that when *nstd* is larger than the threshold, we determine that collision happens. Otherwise, no collision is detected.

$$nstd = \frac{\sqrt{\frac{1}{N}\sum_{i=1}^{N}\|x_i - \bar{x}\|_2^2}}{\|\bar{x}\|} \tag{1}$$

4.2 Extracting Channel from Collided Data

In this section, we describe how we extract the channels of multiple tags from the collided data sequentially. Our core idea is to separate one data stream of collided tags based on the order of arriving time and cancel the transmitted data after channel estimation with the known preamble bits of RN16. Then, we repeat this procedure until all collided data is subtracted. We first describe the key observations which support our idea and then introduce the details of the design.

4.2.1 Key Observations. The first observation is various response delay. The response delay is defined as the time interval between the reader's Query command and the tag's RN16. The length of response delay is determined by many factors such as the tags and readers' locations, energy harvesting efficiency, the manufacture of the tag and so on [8]. Typically, such variation of response delay can be captured by the reader because the reader usually has a much higher sampling rate compared to tags. Fig. 9 illustrates the procedure when multiple tags join. The authors in [27] also have similar observation.

The second observation is stable bit duration. The bit duration is defined as the time for one tag to send one bit. The bit duration of different tags can vary a lot since the bit duration of one tag is related to its own clock. However, for one tag, the clock is only related to the environment such as temperature and moisture, and it does not change across the time or space. Fig. 10 illustrates the bit duration of 5 tags from two manufactures. Our experimental results show that the bit duration of one tag does not change across time and space which satisfies our expectation. The average fluctuation is around 0.4 usec which is 4 samples when the sampling rate is 10 MHz. This is because the bit duration is mainly determined by manufacture factors rather than the deployments of the tags. Hence, if we know the tag ID of one RFID tag, the bit duration of this tag can be easily known by mapping from the prori knowledge.

The third observation is continuous channel change. The channel of one tag is defined as the channel between the tag and the reader in time domain. As is known, channels dynamically change across time and space due to

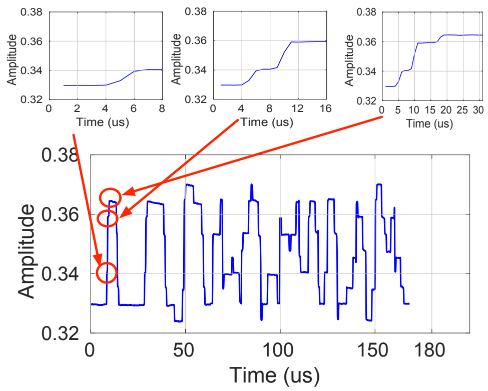


Fig. 9. Tags join the transmission at different time, which can be captured by the reader in time domain.

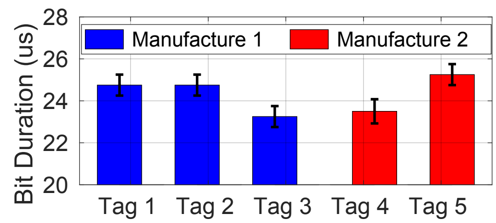
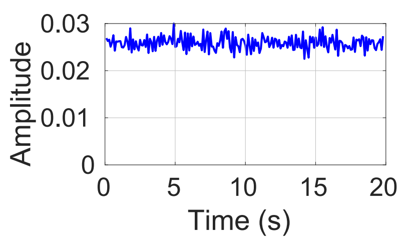
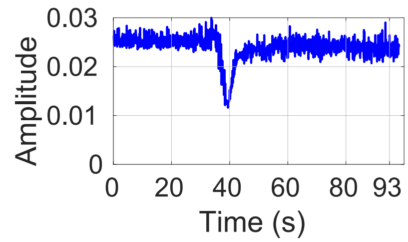


Fig. 10. Error bar of bit duration. Bit duration of different tags can be various. For one single tag, the bit duration only fluctuates within several bits.



(a) Stable environment



(b) Hands move in-between

Fig. 11. Channels change continuously in time domain. Even in mobile environment, adjacent channels change within some range.

multipath and noise. However, based on our observations, the channel of one tag usually changes within some range during coherence time. Fig. 11 illustrates the change of one tag's channels in time domain. IR represents one inventory round. Even when there exists human activity between the tag and the reader, the adjacent channels still change within some range, which indicates channels change continuously across the time line.

Since the channel of one tag can be missing due to collision or transmission failure, we also need to take such circumstance into consideration. Furthermore, the channel between tags and the reader can change due to the human motion in RFID-based monitoring system. We want to explore how rapidly the channel changes under such scenarios. We use a difference metric Δ to measure the changes between two channels $h1$, $h2$. As represented in Eq. 2, $h1$, $h2$ are the complex values of two channels.

$$\Delta = \frac{||h_2 - h_1||_2}{\sqrt{||h_1 \cdot h_2||_2}} \tag{2}$$

Taking the effect of human activity into consideration, we conduct experiments under the scenarios of both small motions like moving hands or feet and big motions like jumping or running. Figure 12 illustrates the change of channels vs. different time intervals. The difference between the adjacent channels increases when the time intervals increase from 2 inventory rounds to 4 inventory rounds. Furthermore, big motions can cause a larger

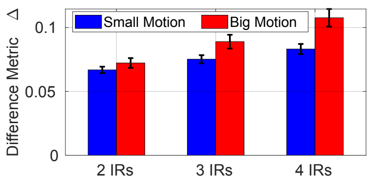


Fig. 12. Error bar of Δ between two channels vs. the time interval between the time duration of capturing two channels. Δ is small, which indicates the continuous change of channel.

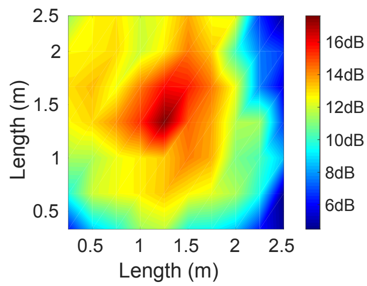


Fig. 13. In reality, various placement of tags can achieve sufficient diversity of channel gain.

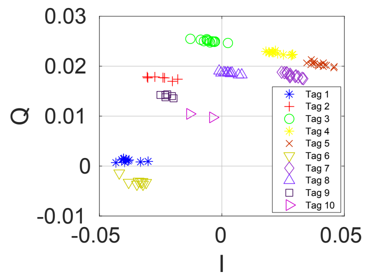


Fig. 14. When we have 10 tags, we can still obtain good separation among different tags.

variation than small motions. Even for the channels which are four inventory rounds away, δ is around 0.08 under small motions and 0.1 under big motions. The result indicates that the channels of one tag can be tracked within a short duration.

4.2.2 Design. Our core idea is to extract channel information from collisions in sequence according to different arriving time and then identify the corresponding tag. Since RN16 bits are unknown random bits, we can only utilize the preamble bits to extract the channel information of collided tags. After collision is detected, COFFEE extracts the first channel of the collided tags in the order of arrival time utilizing the preamble bits of RN16. After obtaining the channel of one tag, we identify the channel with its tag ID based on the channel profiles. Then we examine whether the residual data still contains samples from other tags. If so, we repeat the procedures from the first step until the residual data only contains noise.

The first step is separating one channel. Based on our first observation, the signals of different tags usually arrive with different response delay. Typically, the reader has a much higher sampling rate and thus can capture such difference. Before the data stream of the first tag arrives at the reader, the reader only receives the zero bits. After one tag joins, the signal steps to non-zero bits. Hence, we can obtain the "clean" channel of the first tag by extracting the samples when only the first tag is transmitting. Because at this time the bit duration of the first tag is unknown, after receiving the transmitted signal of the following tags, we can not determine whether the first tag is in reflecting or absorbing state. Therefore, we can not directly extract the channels of the following tags without cancelling the transmitted data of the first tag.

The second step is identifying the corresponding tag. In this step, our goal is equivalent to acquiring the corresponding tag ID based on the "fingerprints" of the signal without decoding. Intuitively, we want to use the channel information of each tag for identification. First, we want to validate the uniqueness of this feature. We mount the antennas of the reader at a fixed location and attach the tags at the different locations on the walls. Fig. 13 plots the SNR of the backscatter signal by the tags at different locations captured at the reader. The result indicates that the diversity of channels can be achieved by various placement in reality. Then, we explore the separation between the channels of different tags when the number of tags are large. Fig. 14 illustrates the channels of 10 tags in constellation domain, which indicates that we can still achieve good separations between different tags. Furthermore, as aforementioned, the channels of one tag can change continuously within a short time, which means that the channels can be used as a unique and robust feature for tag identification.

Although channels can be viewed as continuously changing within a short duration, due to the dynamics of wireless link, channels can vary a lot beyond the coherence time. To solve this problem, we propose a weighted streaming nearest neighbour classification algorithm (WSNN) as summarized in Algorithm 1. We apply a sliding

Algorithm 1: Weighted streaming nearest neighbour classification (WSNN)

Input: h: the unlabeled channel;
w: sliding window length;
cur: current inventory round
$CP = \{CP_1, ...CP_N\}$: channel profiles of all tags
Output: Res: estimated tag ID
Initialization:
$C_i \leftarrow \frac{\sum_{j=1}^{n} h_{i,j} \cdot w_{i,j}}{\sum_{j=1}^{n} w_{i,j}}$ //update centroid of i class
$D_i \leftarrow 0, \forall i \in [1, n]$ //Distances btw tag and centroids
for $i \leftarrow 1$ *to* N **do**
  tmp $\leftarrow$ the channels from $cur - w$ to $cur - 1$ inventory round in CP_i
  $C_i \leftarrow \frac{\sum_{j=1}^{n} h_{i,j} \cdot w_{i,j}}{\sum_{j=1}^{n} w_{i,j}}$ //update centroid of i class
  if $C_i == 0$ **then**
    $D_i \leftarrow Inf$ //No validate history
  else
    $D_i \leftarrow \|h - C_i\|_2$ //Calculate l2 distance
$Res \leftarrow arg\ min\ \{D_i$: tag i not send EPC in this IR$\}$

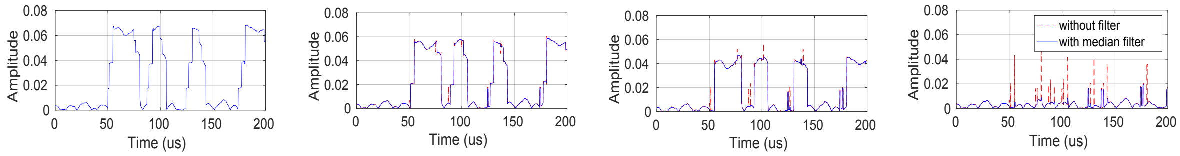
window with length L in WSNN. We choose 200 msec as the window length according to our empirical results. Furthermore, each class stands for one tag. Only the history records of channels within the sliding window are taken into consideration. The valid records for $i\text{-}th$ class are denoted by $H_i = \{h_{i,j}\}, j = 1, ..., n$. n is the total number of valid records. The centroid of $i\text{-}th$ class is calculated with $\{h_{i,j}\}$ and different weights $\{w_{i,j}\}$ as expressed in Eq.3.

$$C_i = \frac{\sum_{j=1}^{n} h_{i,j} . w_{i,j}}{\sum_{j=1}^{n} w_{i,j}} \tag{3}$$

The weight $w_{i,j}$ for $j\text{-}th$ channel record in $i\text{-}th$ class contains two parts, $w_{ci,j}$ and $w_{ti,j}$ as denoted in Eq. 4. $w_{ci,j}$ is related to the type of the channel record. If the channel is extracted from EPC message, $w_{ci,j}$ is assigned as W_{EPC}. If it is obtained from RN16 packets, $w_{ci,j}$ equals to W_{RN16}. Typically, W_{EPC} is larger than W_{RN16} since the channel extracted from EPC is more trustable than RN16. $w_{ti,j}$ is involved with the time interval $\Delta t_{i,j}$ between the time that $j\text{-}th$ channel record in $i\text{-}th$ class is captured and the current time. The unit of $\Delta t_{i,j}$ is the number of time slots. We simplify the modified logistic weight function proposed in [17]. g represents the level of penalization for the points with larger time interval. The larger $\Delta t_{i,j}$ is, the smaller $w_{ti,j}$ is. This is because the larger time interval can give rise to a bigger variation of channels as aforementioned. We pick $g = 0.25$ when the weight function follows a sigmoid pattern.

$$w_{i,j} = w_{ci,j} \cdot w_{ti,j} \quad , \quad w_{ti,j} = \frac{1}{1 + e^{g \cdot \Delta t_{i,j}}} \tag{4}$$

Overall, WSNN comprises of the following three steps. First, after we extract one channel h, we find all the valid records in channel profiles within the sliding window. The second step is to update the centroid C_i of each class based on Eq. 3-4. In the last step, we use *l2 distance* to evaluate the difference between the channel h and the the centroid of different classes. The class with the smallest *l2 distance* is chosen as the predicted class of the channel. Note that there is a constraint when picking possible tag IDs. According to C1G2, one tag needs to be silent after successfully transmitting EPC within one inventory round. Hence, the predicted class can not belong to the tags that have already sent EPC in current inventory round.



(a) Original collided preambles. (b) Cancel tag 1 transmission. (c) Cancel tag 2 transmission. (d) Cancel all collided data.

Fig. 15. Waveform after sequentially cancelling signals of collided tags in time domain. Wrong bit duration leads to spikes. Applying filter can remove most of the spikes. Noise accumulates after cancelling signals of each tag.

The last step is canceling signal of one tag. Since the tag is identified at this time, we can obtain the bit duration of this tag using the priori knowledge as discussed in the second observation. Furthermore, the preambles of RN16 are predefined and the channel is estimated. Hence, the data transmitted by i-th tag can be predicted in sample level and subtracted from the residual data. The length of each symbol is the bit duration of the corresponding tag. COFFEE uses a 6 bit preamble which is around 150 usec as specified in C1G2. Hence, COFFEE is able to distinguish the collided data within the duration of preamble symbols.

Bit duration for one single tag can fluctuate within several samples based on our previous observation. Wrong bit duration can result in some spikes in the residual data after cancellation. To solve this problem, we apply a median filter to remove the random peaks after cancelling the collision data of one tag. Median filter can smooth the data while preserving the edges of the signal and reserving the variation of the residual data. Fig. 15 illustrates the procedure of cancelling the transmitted signal of collided tags in sequence. We find that the noise accumulates after subtracting the signal sequentially. Figure 15d plots the amplitude of the residual signal after cancelling all the collided data. The red dot lines stand for the signal without filtering, where there exists many spikes caused by wrong duration estimation and the transitions points at the edge. The result implies that if the difference between the predicted and actual bit duration is small, we can remove the spikes by filtering.

Assuming all the collided samples can be cancelled, the residual data should only contain noise. If the average amplitude of the residual signal is smaller than the threshold, we can determine that all the collided channels are separated. If not, we will repeat the previous steps. However, there is possibility that errors can occur in the previous steps, which can result in failure of collision cancellation, thus leading to unlimited loop. Hence, we set an upper bound for the number of the collided tags as N_{max}. After cancelling N_{max} tags, we restore all the channels extracted from the collision data, the corresponding tag ID and also the residual data into temporary file. Before stored into channel profiles, the temporary file needs to pass the error detection block, as discussed in the following section.

4.3 Error Detection

Due to the dynamics of wireless channel and the noise, errors are inevitable when extracting channels and identifying tags. The errors can lead to either missing or unwanted channel information. Then we discuss the reasons and present the possible methods to avoid the problems. Firstly, wrong channel estimation can be caused by the wrong collision separation. If the signal of different tags arrive in same sample, it is hard for COFFEE to separate the collided data. Generally, the reader has much higher sampling rate than tags, which enables the reader to distinguish different arrival time among multiple signals. Also, the tags are typically located separately in sensing systems, thus resulting in sufficient wireless channel dynamics. To decrease the occurrence of missing collision separation, we can either increase the sampling rate or the diversity of tags' channel. Secondly, wrong tag identification can be caused by low SNR or similar channel information. We can increase the distance between tags or use tags from different manufactures to increase the diversity of the channel features of the tags. Furthermore, when two tags are closed by, the signal can bounce back and forth between tags, thus resulting in non-linear addition. Since the transmitted power of backscatter signal is weak, the interference signal will die out quickly. Typically, in most sensing systems, the tags are required to be located half wavelength away to obtain uncorrelated channel measurement, where the non-linearity effect can be neglected, thus satisfying our requirements.

The error detection of COFFEE is twofold. First step is to detect whether we successfully separate all collided data by examining the average power of residual data. After cancelling N_{max} tags, if the average amplitude of residual signal is still much larger than noise level, it indicates failure of extracting collided data. Secondly, we compare the difference between the channel and the adjacent channels restored in channel profiles. When the difference is large, the channel estimation can be wrong. When error detected, we discard the wrong channel information. Otherwise, we restore the extracted channel in the channel profile of the corresponding tag.

5 EVALUATION

In this section, to evaluate COFFEE in practice, we build a prototype and run experiments in the real world. We first introduce the system settings. Then we run some micro-benchmark experiments to validate the components of COFFEE separately. We also conduct system level tests to illustrate the time resolution gain of our system in practice.

5.1 System Setting

5.1.1 Hardware. We build a prototype of COFFEE using COTS C1G2 UHF tags [14] and software-defined reader. The reader is built on USRP N210 equipped with a SBX daughterboard. We adopt a USRP2 implementation of C1G2 RFID reader [22]. The reader operates at a carrier frequency of 910 MHz and a sampling rate of 10 MHz. We deploy two circularly antennas with 8.5 dBiC gain (ALIEN ALR-8696 RFID ANTENNA [13]), one transmitter for sending reader commands and one receiver for capturing tags signal which work in full duplex mode. We use 100 RFID tags from three manufactures, Alien Squiggle ALN9740 UHF tags [14], Alien AZ9634 UHF tags [15] and Impinj H47 UHF tags [16].

5.1.2 Software. In terms of data collection, we use Gnuradio and UHD to extract the low-level data stream from the receiver antenna. We implement COFFEE with MATLAB programming on the PC.

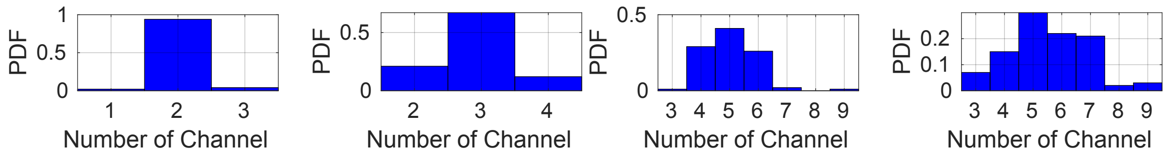
5.1.3 Deployment. COFFEE is based on assumption of the diversity of channels. To achieve sufficient diversity, tags need to be located separately. Passive tags are attached on the wall and separated by 15-30cm apart which is larger than half wave length at the carrier frequency of 910 MHz. The antennas are mounted on the cell of a lab which can be easily rotated and moved. The distance between the tags and reader is between 150 and 250 cm.

Threshold	Miss Detection	False Alarm
0.2	0.005	0.335
0.25	0.02	0.1675
0.3	0.065	0.09
0.35	0.11	0.0575
0.4	0.14	0.0275
0.45	0.185	0.0125
0.5	0.22	0.0125

Fig. 16. Table of miss detection and false alarm rates for collision detection vs. threshold. Considering performance balance, we choose threshold as 0.3.

5.2 Micro-benchmark

5.2.1 Validating Collision Detection. In Sec 4.1, we propose a collision detection approach. By measuring the variation of all the non-zero bits using *nstd*, we can determine whether collisions occur or not. We set a threshold that if *nstd* is larger than the threshold, we determine that collision is detected. Fig. 16 illustrates the miss detection and false alarm rates when choosing different thresholds. Miss detection is denoted as failing to detect collisions



(a) 2 tags collide. (b) 3 tags collide. (c) 6 tags collide. (d) 8 tags collide.

Fig. 17. PDF of the number of channels extracted from collisions. When the number of tags increases, the performance can degrade. When there are 8 tags, we can still obtain sufficient channels from collisions.

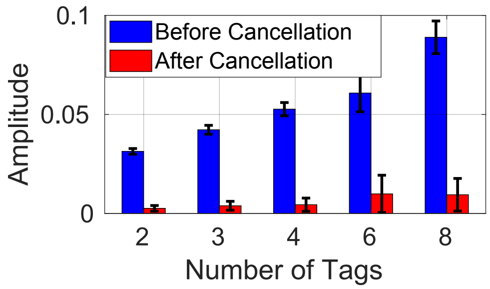


Fig. 18. Error bar of the average amplitude of original signal and residual signal after cancellation.

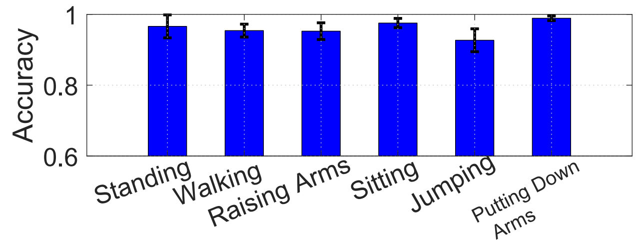
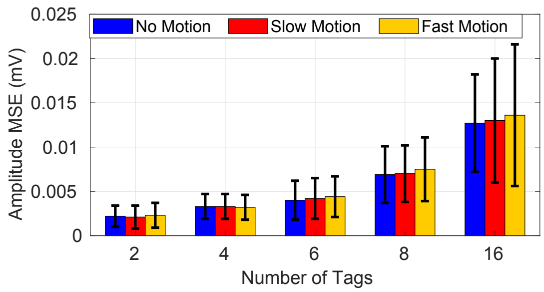


Fig. 19. Error bar of accuracy of tag identification. It is effective even when human moves around.

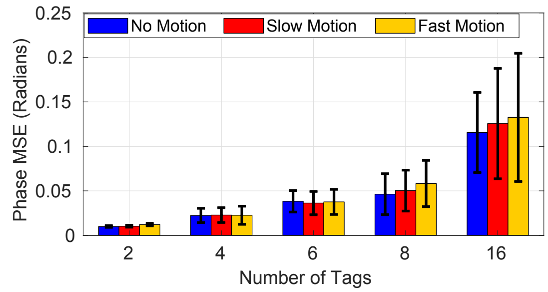
when it happens and false alarm is when we determine a collision but no collision happens, both of which are inevitable in reality due to the noise. Miss detection can result in missing channel information, but false alarm can give rise to unwanted outputs and error factors. Hence, we aim to pick a threshold to decrease false alarm while keeping miss detection within an acceptable range. According to the result, we choose 0.3 as the threshold in the real world experiments.

5.2.2 Validating Collision Separation. The separation of collided channels depends on the sufficient diversity of wireless channels. Transmitted data of different tags should arrive with various response delay. However, when the number of tags increases, the ambiguity between the channels of different tags also increases, which can lead to missing channel extracted from collision. In this section, we investigate how efficient COFFEE can separate and extract channels from collision when the number of tags increases. We run experiments in a total of 40 randomly chosen topologies with 2,3,6,8 RFID tags being employed. For each trace, we set $Q = 0$ to control the number of collided tags in each time slot since every tag needs to transmit in one time slot. Note that even when $Q = 0$, we can not guarantee that each tag transmits packets in each slot. Fig. 17 illustrates the probability density function of the number of channels extracted from collision. Y axis stands for the occurrence ratio. de, we can extract the 2 collided channels over 94% time slots. As is shown in Fig. 17b, 17c and 17d, we can extract 2.91, 5.03, 5.53 channels from collisions on average when 3, 6 and 8 tags transmit simultaneously. The results indicate that our system can extract more channels when the number of collided tags increases. Previous clustering based systems, like [21, 27], needs to cluster 2^n states in IQ domain for n, where each tag is either in transmitting or absorbing state. They decode the collided signal by detecting the transition of states. The ambiguity of clusters can lead to missing states or misclassified states thus resulting in the failure of decoding. That is why they can not support a large number of tags. In contrast, our system leverages the channel information of each tag, where for n tags, we only need to classify n channel states. Hence, our systems can support a larger number of tags.

5.2.3 Validating Cancellation. In this part, we do experiments to evaluate the average power of residual signal after cancelling all the transmitted data from collision tags. Each time after cancellation, the noise and the



(a) MSE of amplitude estimation.



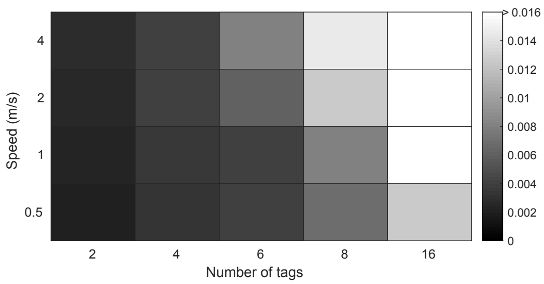
(b) MSE of phase estimation.

Fig. 20. Channel estimation for device-free sensing systems under different mobility. The performance degradation caused by motions can be negligible for indoor activities. Error remains relatively low when multiple tags collide.

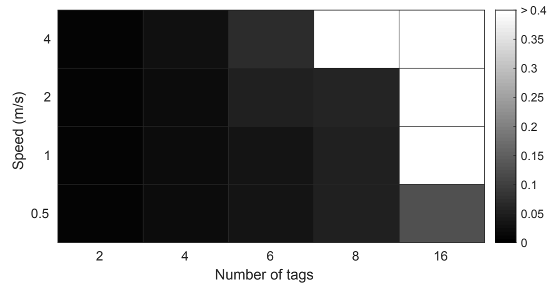
interference signal caused by wrong bit duration estimation accumulates, thus increasing the residual signal power level. This can lead to unlimited loop of collision separation since COFFEE regards as there still exists transmitted signal from other RFID tags. Hence, the residual noise level can limit the maximum number of collided tags that can be separated by COFFEE. Fig. 18 plots the average power for residual signal vs. the number of collided tags. The results indicate that our system can still work when there are 8 tags transmitting simultaneously. Here we set $Q = 0$ to control the number of the collided tags. Whereas in practice, Q is usually set larger than 0 and the total number of time slots increases exponentially which means that COFFEE can potentially support a large number of tags.

5.2.4 Validating Channel Estimation. In this part, we do experiments to evaluate the channel estimation accuracy. We use the channel from EPC as benchmark and calculate the mean square error (MSE) of the estimated channel which is obtained from RN16 using COFFEE. Channel estimation is a key component of our system. The experiments are conducted in 20 randomly chosen topologies under each setting. We classify the RFID sensing systems into device-free sensing and with-device sensing. In device-free sensing systems, the location of the reader and RFID tags are fixed and the objects move in between. On the contrast, in with-device sensing systems, tags are attached to moving objects and the reader captures the channel variations of direct path between the reader and the tags, where the channel could change rapidly. We evaluate the channel estimation accuracy for both device-free and with-device sensing systems.

Fig. 20 plots Mean Square Error (MSE) of amplitude and phase vs. the number of collided tags under different mobility levels for device-free sensing. We conduct experiments under scenarios of no motions, slow motions when the objects move with a walking speed of 0.5 - 1.5 m/s and fast motions with a running speed of 2.5 - 5 m/s. We observe that the indoor human activities, like walking, running, waving hands and so on, do not affect the performance a lot. The mean and variance of error may slightly increase when the objects move faster but the increment can be ignored. This could be caused by that the transmission bandwidth is greater than the coherence bandwidth under the indoor activities. Furthermore, device-free sensing systems extract the channel changes of the multi-paths among the reader, the tags and the objects where such variation can be relatively small compared to with-device sensing. When 8 tags collide, the MSE of amplitude and phase estimation is around 0.007 and 0.05 rad under all scenarios. The results indicate that our system can still work well when there are multiple tags transmitting simultaneously. Note that the error goes up when the number of tags increases. When 16 tags transmit simultaneously, the MSE of amplitude and phase increase to 0.013 and 0.126 rad. This is because noise and error accumulate each time after cancelling the signal from one tag. Hence, the residual noise level can limit the maximum number of collided tags that can be separated by COFFEE.



(a) MSE of amplitude estimation v.s moving speed.



(b) MSE of phase estimation v.s moving speed.

Fig. 21. Channel estimation with different mobility. When the tags move faster, the errors increase and our system will support less concurrent sensing.

We also conduct experiments when tags are attached to moving objects for with-device sensing systems and Fig. 21 illustrates the MSE of amplitude and phase estimation v.s. different moving speed. The results indicate that when the tags move faster, the errors increase and our system will support less concurrent sensing. For instance, when the objects move slower than 0.5 m/s, for example, like finger tracking or gesture recognition systems, we can still support 16 tags concurrent transmission. However, if the objects move at walking speed around 2 m/s, we can support 8 tags. Moreover, 6 tags are preferred under running speed up to 5 m/s. This is because when the tags move, the channel variation between the reader and the tags will increase rapidly and it is harder for COFFEE to track the tags' identity with the channel information, thus increasing the channel estimation error. Another possible cause is that the "real" value of channel status in RN16 packets can be different from the "ground truth" that are extracted from EPC packets. However, there is no way to retrieve the "real" value since we can not replay the real traffic of different tags separately. To mitigate the effect of rapid channel variation, we can either increase the bit rate of RFID tags or use a smaller Q to allow the tags transmit more frequently.

5.2.5 Validating Tag Identification. In this part, we evaluate the accuracy of our tag identification algorithm. COFFEE aims to apply for sensing system where the channels between the tags and the reader can change rapidly. Those changes during the procedure of activity recognition can affect the performance of our classification algorithms. To evaluate the effect of dynamic environment on channel classification, we use 8 tags and set $Q = 3$ and let a human move around. We choose 6 different activities as shown in Fig. 19. Note that only EPC message can provide the accurate information of tag ID. So, we use the channel extracted from EPC packet to validate channel classification. The results show that our identification algorithm can still achieve a high prediction accuracy up to 0.993 where the worst case is 0.932 even when human moves around.

5.3 System Level Test

To evaluate the benefits of deploying multiple RFID tags, we measure the average time resolution gain of COFFEE over C1G2. We run experiments in a total of 150 randomly chosen topologies with 4 to 16 tags being employed. For fairness, we choose the value of Q that can maximize the average time resolution for both C1G2 and COFFEE. In Fig. 22, we can see that the median gain with 4, 8, 16 RFID tags is around 2.34x, 2.9x and 3.42x on average. As the number of tags increases, we can achieve a higher gain. This is because as the number of RFID tags increases, the collision happens more frequently which can allow COFFEE to recover more channels to boost the performance. Furthermore, we validate the improvement for the bottleneck tag which has the lowest time resolution. Fig. 23 illustrates the CDF for time resolution gain of the bottleneck tag. We can achieve the median gain of 4.6x, 5.04x and 7.33x for the worst tag which has the lowest time resolution using C1G2.

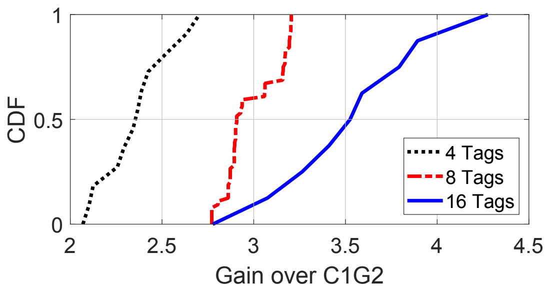


Fig. 22. CDF of the time resolution gain of COFFEE over C1G2 on average vs. the number of tags.

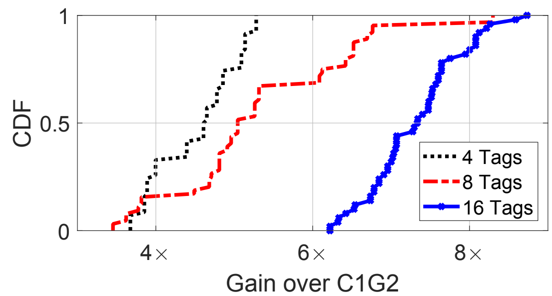


Fig. 23. CDF of the time resolution gain of COFFEE over C1G2 for the worst tag which has the lowest time resolution in C1G2 vs. the number of tags.

	Standing	Sitting	Walking	Jumping	Raising Arms	Putting Down Arms
Standing	1	0	0	0	0	0
Standing	0	1	0	0	0	0
Walking	0	0	0.86	0	0	0.14
Jumping	0	0	0	0.78	0.10	0.12
Raising Arms	0	0	0	0.12	0.64	0.24
Putting Down Arms	0	0	0.02	0.08	0.18	0.72

Fig. 24. Confusion matrix without COFFEE. Most errors happen when identifying similar activities.

	Standing	Sitting	Walking	Jumping	Raising Arms	Putting Down Arms
Standing	1	0	0	0	0	0
Standing	0	1	0	0	0	0
Walking	0	0	0.98	0	0	0.02
Jumping	0	0	0	0.92	0	0.08
Raising Arms	0	0	0	0.02	0.86	0.12
Putting Down Arms	0	0	0	0.02	0.12	0.86

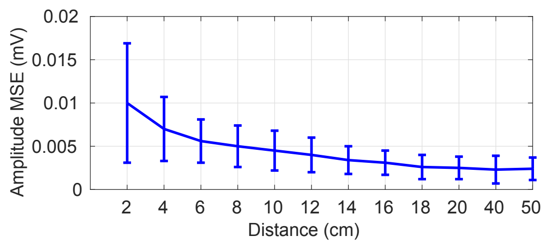
Fig. 25. Confusion matrix with COFFEE. Our system can significantly improve the accuracy.

5.4 Application

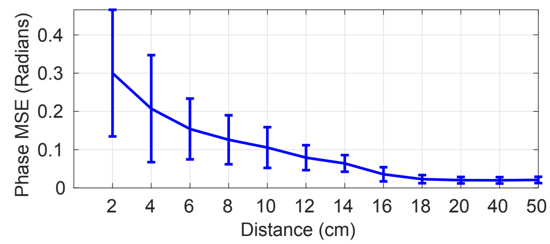
In order to understand the benefits of COFFEE in RFID-based sensing systems, we implement an activity recognition system based on the approach in [42] and apply our system on the top of it. Note that the system in [42] is designed for gesture recognition. To realize activity recognition, we deploy 8 tags separately in the environment to cover the area for human activity. We conduct 6 kinds of human activities: standing, walking, jumping, sitting, raising arms and putting down arms. Fig. 24 illustrates the confusion matrix without applying COFFEE. The most errors occur when identifying similar activities, for example raising arms and putting down arms. Same observation has been reported in the literature [40]. By applying our systems, the accuracy increases around 10% on average as shown in Fig. 24. In particular, the accuracy for classifying the activity of raising arms increases from 0.64 to 0.86 by applying COFFEE. The results show that our system can significantly improve the performance of RFID-based sensing systems.

6 RELATED WORK

RFID-based sensing systems [10, 28, 33, 36] receive a growing interest. Some recent works propose motion tracking systems [5, 18]. The authors in [24] design a wearable RFID system for monitoring hand use. Furthermore, some indoor localization systems like [37, 39] can localize the objects with RFID arrays. Also, some activity recognition systems, such as [41, 42] can monitor and recognize the human activity. Some recent sensing systems utilize new classification algorithms to increase the accuracy. Recent work in [40] proposes an activity recognition with sparse representative for RFID sensing data. [38] introduce deep learning algorithms to RFID-based systems. There are also other sensing systems which monitor the environment. A wildlife and environmental monitoring system is proposed in [7] based on sensor network. The authors in [1] presents a long-range RFID tag which can encourage more applications of sensing networks. Typically, RFID-based sensing systems capture the channel



(a) MSE of amplitude estimation v.s. distance btw tags.



(b) MSE of phase estimation v.s. distance btw tags.

Fig. 26. The non-linearity exists when two tags are close by. When the distance is larger than half wave length, it can be negligible.

fluctuation and require deploying a large number of tags. Therefore, COFFEE can potentially benefit all such systems.

Anti-collision for RFID-based systems [6, 11, 27, 35] have recently received many attentions, which can be categorized into physical layer (PHY) and medium access control (MAC) approaches. Broadly, MAC layer approaches require new protocols for tag access to decrease the collision probability. [23] summarizes the recent Aloha-based and Tree-based anti-collision protocols. Such protocols usually can not operate on the COTS tags. PHY solutions overcome the collisions by enabling parallel decoding on physical layer and hence eliminating the effect of collisions [21, 27, 35]. Such methods are not feasible for parallel sensing for large-scale COTS tags as discussed earlier. Hence, current anti-collision systems can not operate on the monitoring systems using COTS tags. In contrast, COFFEE can be compatible with such systems.

7 DISCUSSION

In this section, we discuss the potential of COFFEE and how we can further improve its performance.

7.1 Why Simultaneous Sensing Is Important In RFID Sensing Systems?

Due to the nature of low sampling rate and the inevitable collision issues, the reading rate of one RFID tag can be very low compared to other RF technology. As discussed in Sec. 2, one tag can only be interrogated several times per second under some circumstances, while the other RF systems, like WiFi and radar systems, can obtain a sampling rate up to 1 GHz. However, most sensing systems are based on detecting the changes of wireless channel, which requires fine-grained measurements of channel information. In some sensing systems, the environments may change rapidly and such systems rely on frequent channel estimations. Furthermore, some sensing applications require a dense deployment of RFID tags, where the reading rate could decrease a lot due to collision. By enabling simultaneous sensing, we can increase the reading rate by several times without any modifications on the original applications, which can potentially enhance the performance of RFID sensing systems. Moreover, COFFEE can bring another underlying benefit for COTS RFID tags that our system can encourage the tags to transmit and collide more since our goal is to retrieve more channel measurements in stead of communications. To be noticed, our scheme can extract additional channel estimation from the collided data, which is built on the top of commercial standard. Hence, our scheme can benefit all RFID based sensing systems that utilize channel variation to detect the change of environment, for example, activity recognition [2, 19, 33], motion tracking[4, 12, 26, 32], agriculture monitoring[34], robotics applications [3, 25, 30] and so on.

7.2 Limitations of COFFEE

The performance of our systems can be limited by many factors, such as the number of tags, the moving speed of the tags or the objects in the environment, the inter-tag interference and so on. In addition, the interference from other RF devices in the same frequency band can also affect the sensing accuracy. However, such problems exist extensively in all RFID based systems, which is not our focus. Hence, we focus on the effects of the following factors on the scalability of COFFEE in the rest discussions.

7.2.1 Large Population of Tags. As we discussed before, our system relies on the assumptions that we can identify the collided tags with its corresponding physical layer information. Hence, we need to make sure the channel states of collided tags can be separated in IQ domain, which means our scheme can not support unlimited number of tags. Our results has shown that we can support 16 tags transmitting simultaneously in one time slot. However, in the future, with the development of sensing technology, some systems may require hundreds of tags. Collision problem has been an open problem in such systems. We plan to evaluate how our system can benefit such applications of dense sensing and how our system perform with an extremely large number of tags. Currently, we should keep Q as a small value to make sure the probability of 16-tags collision is relatively low in each time slot. Be that as it may, our scheme can still benefit large-scale RFID systems since we can always retrieve additional channel information when few tags collide.

7.2.2 High Mobility. As stated before, our system should be able to identify the collided tags with its corresponding channel information in the varying environments where the channel states change continuously. Our previous results show that in device-free sensing systems, the changes of environment will affect the signal that traverses the multipath among the object, the tags and the reader. Typically, our system can handle such channel variation for most indoor activities where objects move within 5 m/s. For such systems, we can keep Q relatively low to make the tags transmit and collide more to get more channel measurements. However, for with-device sensing systems, where the tags are attached to an moving object, the channel estimation error will add up with an increasing speed of tag movement. When the speed is high, we should appropriately augment the value of Q to reduce the number of concurrent transmissions. Still and all, our scheme can always achieve some gains by obtaining additional channel information. In addition, the experiments in this paper are conducted in indoor environment where the objects move within running speed of 5 m/s. However, the performance of COFFEE under extremely high mobility is unknown. Our system can work based on the assumptions that the channels of one tag change continuously across the time line. Theoretically, our system can not support dramatic channel changes where the sampling rate of RFID systems is smaller than coherence bandwidth.

7.2.3 Clock Drift. In the step of collision separation, we need to cancel the transmission of collided tags sequentially. As mentioned in Sec. 4.2.2, clock drift will lead to unexpected spikes in residual signal after cancellation and we can use filter to remove some spikes. However, if the clock drift is too large, we may extract unwanted channel from the collided data and our error detection module will remove the wrong estimation and throw an exception when wrong channel estimation is detected. Furthermore, in our design, in case adding unwanted channel into channel profiles, we will periodically calibrate channel status and bit duration. If the error detection module keeps throwing exceptions even after calibration, it may indicate problems in the circuit of some tags. It could be either caused by damaged tags or working beyond nominal temperatures, and we may need to replace the corresponding tags with operational tags.

7.2.4 Inter-tag Interference. Our current method of channel estimation can be affected by the inter-tag interference. When two tags are close by, the signal can bounce back and forth between tags, thus resulting in non-linear addition. To learn how inter-tag interference effect COFFEE, we conduct experiments with one reader and two tags. The tags are co-located 0.5 meter away from the reader and we vary the inter-tag interference by changing the distances between the tags. Fig. 26 illustrates the MSE of amplitude and phase estimation v.s. the distance between the two tags. The result indicates that the non-linearity effect only exists when the two tags are close by (e.g., when the distance is smaller than half wave length). When the distance between two tags is larger than 10 cm, the MSE of amplitude and phase estimation is smaller than 0.0045 and 0.1 rads. However, some sensing systems may require a dense deployment of tags. For example, the authors in [31] build a device-free finger tracking systems with an RFID array, where the tags are located side by side. Also, to detect small motions like finger movement, a precise channel estimation is required. Hence, COFFEE may not be able to support such systems which require high channel estimation when tags are located close by. Fireworks [20] mitigates inter-tag interference by extracting the un-interfered signal samples. Their approaches assume that they can identify the tags by decoding tag IDs in parallel. However, current C1G2 UHF tags can not transmit EPC packets simultaneously and their approaches can only be used with non COTS tags. It would be our next step to learn how to extract the no-interfered samples without decoding the packets.

8 CONCLUSION

In this paper, we propose COFFEE, the first system that can harness the collision to improve the fidelity for monitoring systems using COTS tags. COFFEE can be treated as an extension to C1G2 standard, which can be applied for all the RFID-based sensing systems without modification on tag side. Unlike the previous sensing systems which focus on enhancing the performance on application level, our system is the first work to break the bottleneck of the physical layer caused by collisions. The experimental results show that our system can significantly improve the performance of existing sensing systems. We also believe COFFEE can benefit more RFID-based applications which leverage the channel information of RFID tags.

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