Towards Fine Grained Localization of RFID Tags in Indoor Environments with Compressive Sensing

Abstract—Localization of identifiable devices has attracted much attention in recent years. In this paper, we propose a framework for Radio Frequency IDentification (RFID) localization in indoor environments, where the localization problem is much more challenging than outdoor environments due to multi-paths. The framework is based on analyzing the samples of the waveforms emitted by RFID tags with advanced signal processing techniques such as compressive sensing. It holds the potential of achieving accurate localization at much higher granularity than existing approaches. Through experiments with active RFID tags and a software-defined-radio, we find that the radio signature of RFID tag is a continuous function in the space even in the presence of multi-path, at the same time sensitive to location changes. This provides the foundation for high granularity localization. We use compressive sensing to reconstruct the continuous signal space with the samples obtained from reference tags. With the reconstructed space, we find the location of a tag by finding the best match of its radio signature in the space. We verify this framework in an office with severe multi-path in a two-dimensional scenario and show that it achieves good localization accuracy.

Index Terms—RFID localization, compressive sensing, software-defined radio.

I. INTRODUCTION

Localization of identifiable objects has attracted much attention in recent years. Many technologies exist or have been proposed, such as GPS [34], the ultrasonic technology [27], [26], wireless sensors based localization [29], [23], [3], [11], [19], [18], wireless Local Area Network (LAN) based localization [21], [36], [13], Ultra-Wide-Band (UWB) based localization [35], [32], and RFID based localization [14], [25], [5], [17], [33], [39], [38], [40], [16], [37]. In this paper, we study the problem of localization with RFID tags, because they are small, inexpensive, and easy to maintain. We focus on localization in indoor environments, because many applications take place indoors. We note that existing RFID based localization techniques are capable of delivering coarse-grained localization in the range of meters and sub-meters. However, more accurate localization, if available, will enable a large number of novel applications, such as monitoring the safety and welfare of the elderly, monitoring mouse movements and behaviors in biology/behavioral study experiments, pin-pointing the location of books in the library, etc.

The challenge in indoor localization is multi-path, which is more prevalent in the indoor environment than in the outdoor environment [28]. Fine-granularity localization must rely on fine-granularity measurements of the signals from the tags. However, wireless signals can be reflected by metal surfaces and diffracted by sharp edges of objects, such that the received signal at any given point is the summation of many different versions of the same transmitted signal with different delays and attenuations. This makes it difficult to derive the location information from the measured phase and signal strengths, because of the large number of paths and the complexity in finding the characteristics of the paths. Despite many notable attempts [3], [20], [37], [25], [21], [22], [11], the indoor fine-granularity localization is still being elusive.

In this paper, we propose a framework for indoor fine-granularity localization. Our key idea is to learn the wireless channel as a continuous system that produces the received signal without explicitly reconstructing the paths; then, given any received wireless signal, the inverse of the system is the estimate of the location. This differs from existing techniques that require explicit knowledge of the paths traveled by the signals; still, the continuous system, once learned, lends itself to fine-granularity localization. This idea bears similarities to the solutions for mitigating multi-path effects in high-speed wireless communications [31]. In wireless communications, multi-path introduces inter-symbol-interferences (ISI) among nearby symbols and limits the speed. One may reconstruct the paths explicitly and then remove the ISI; however, it is unnecessary for the purpose of communications, because to recover the symbols, it is sufficient simply to remove or to cancel the effects of multi-path from the samples with techniques such as adaptive equalization or Orthogonal Frequency Division Multiplexing (OFDM), without knowing explicitly the length of each path. We use a software-defined radio platform and verify that indoor wireless channels produce received radio signatures that are continuous in space. To learn the system, samples of the system must be obtained, where the samples are the radio signatures of the tags at known locations. Due to cost considerations, the number of samples is limited. In addition, the reference tags may not be uniformly distributed in space because it may not be feasible to mount tags at certain locations. We observe that the indoor multi-paths are typically caused by a few major objects such as metal desks and walls, such that the signal may lie in a space with a sparse representation. Therefore, we propose to use Compressive Sensing [8], [9], [12], [10], which is very effective for reconstructing sparse signals with a small number of non-uniform samples. We conduct experiments in an office with strong multi-paths and the results show that good localization accuracy can be achieved.

The rest of the paper is organized as follows. Section II
gives the definition of radio signature. Section III discusses measurements of radio signatures with RFID tags. Section IV discusses our framework for localization with compressive sensing, and presents localization results. Section V discusses related works. Section VI concludes the paper with a summary and discussion.

II. RADIO SIGNATURE FOR LOCALIZATION

To achieve localization, each location in space should be identifiable with a unique signature. For RFIDs, the signature is derived based on radio signals. Therefore, we first discuss wireless transmissions and give definition of radio signature.

A. Wireless Transmissions

Typical wireless signals are modulated on a carrier frequency. The received carrier is a sinusoidal wave and has certain phase at any given time instant depending on the path the signal travels. Suppose two receiving antennas are available. In the ideal case when the transmitted signal has a single Line of Sight (LOS) path to the receiver, the received baseband signals at Antenna 0 and Antenna 1 are:

\[
\begin{align*}
y_0(t) &= A_0 e^{j(2\pi f t + \phi)} \\
y_1(t) &= A_1 e^{j(2\pi f t + \phi + \Delta \phi)}
\end{align*}
\]

respectively, where: \(A_i\) denotes the signal amplitude at antenna \(i\), \(\Delta f\) the carrier frequency difference between the tag and the receiver, \(\phi\) the phase at Antenna 0, and \(\Delta \phi\) the phase difference of the signals received between Antenna 0 and Antenna 1. \(\Delta \phi\) is determined by the path length difference from the tag to the antennas, which clearly depends on the location of the tag.

Multi-path can significantly increase the complexity of location estimation. For example, in a very simple case, when there are two paths and the receiver has two antennas, the baseband signals received at Antenna 0 and Antenna 1 are the summation of the signals from the two paths:

\[
\begin{align*}
y_0(t) &= A_{00} e^{j(2\pi f t + \phi_0)} + A_{01} e^{j(2\pi f t + \phi_1)} \\
y_1(t) &= A_{10} e^{j(2\pi f t + \phi_0 + \Delta \phi_0)} + A_{11} e^{j(2\pi f t + \phi_1 + \Delta \phi_1)}
\end{align*}
\]

where: \(A_{ik}\) denotes the signal amplitude of path \(k\) at antenna \(i\), \(\phi_k\) the phase of path \(k\) at Antenna 0, and \(\Delta \phi_k\) the phase difference of path \(k\). Note that the number of unknowns significantly increases compared to the case when there is only one path. Also, more importantly, the phase difference \(\Delta \phi_0\) and \(\Delta \phi_1\) represent the path length differences from the different paths to the antennas where a path may include some reflecting surface such as a metal door, and cannot be translated directly to the distance from the tag to the antennas. Therefore, although received signals carry the information about the tag location, it is much more challenging to infer the location.

B. Radio Signature

The radio signature is based on the received wireless signal, and should satisfy the following requirements:

- It should capture the characteristics of the wireless channels at this location.
- It should only be relevant to the location and should be invariant to the characteristics of individual tags, i.e., the carrier frequency offset and transmission power.

Suppose two receiving antennas are available at the receiver. We therefore define the radio signature as

\[
\frac{y_1(t)}{y_0(t)}
\]

where \(y_0(t)\) and \(y_1(t)\) are the signal received at Antenna 0 and Antenna 1, respectively, because the division cancels the carrier frequency offset and transmission power.

We refer to the signature as a function of locations the radio signature function, or simply the signature function. The radio signatures of the same location at different receivers are different because wireless channels are different. Therefore, multiple receivers can be deployed to resolve possible ambiguity, i.e., two locations producing the same signature at one receiver.

III. MEASUREMENTS OF THE SIGNATURE FUNCTION

We conduct experiments with RFID tags and software-defined radio to study the properties of the radio signature, and assess the possibilities of using it for localization in multi-path environments.

A. Measurement Methodologies

In our experiments, the tags are the M100 asset tags from RF Code\(^1\), shown in Fig. 1(a), and the receiver is a software-defined radio (SDR) platform shown in Fig. 1(b) from Ettus Research LLC\(^2\) along with software modules and packages from the GNU software-defined radio project\(^3\).

The carrier frequency of the tags is 433.92 MHz with typical transmission range over 90 meters. Using a compact replaceable battery (Lithium CR2032), a tag typically lasts over seven years. A tag transmits signal in the form of bursts at almost regular intervals such as 2 or 10 seconds. Each burst lasts about 100 ms, and consists of 40 pulses where each pulse is basically a sinusoidal wave for a short period of time (around 35 \(\mu s\)) on the carrier frequency. The pulses are separated by certain intervals where the values of the intervals, as they seem, are unique to the tag and are used for identification. We therefore refer to the list of interval values as the tag ID. For example, Fig. 2(a) and (b) show a burst and a pulse from a tag, respectively.

The SDR has two antennas, and takes samples of the baseband waveform. It captures the pulses transmitted by the tag and stores the raw baseband samples in a log file. The log file is passed to a processing program written in Matlab.

---

2 http://www.ettus.com/.
which finds the radio signature. The radio signature is simply the average ratio of the sample from antenna 1 over the sample from antenna 0 during a pulse period. For example, Fig. 2(c) shows the samples taken by the two antennas during one pulse period, where samples from the same antenna are represented in the same color.

![Image](image1.png)

**Fig. 1.** (a). The RFID tags. (b). The USRP and laptop.

To expedite the measurements, we let the SDR capture the signals from multiple tags simultaneously such that the radio signatures of multiple locations can be obtained with one reading. This poses some technical challenges, as the bursts from the tags may overlap in time, i.e., the pulse of tag A may be immediately followed by a pulse from tag B, thus breaking the interval structures. To solve this problem, we adopt a simple algorithm which separates the composite signal from multiple tags into separate files, one for each tag. We first conduct measurements and obtain a database of the tag signatures of all the tags we have. Given a log file, we search for the first pulse after a long idle period, where an idle period is long if it is longer than 100 ms, the length of a burst. This pulse, with high probability, is the first pulse of a burst, and is referred to as the reference pulse. For each tag, we cast pulses according to its tag ID onto the time axis, aligning the first pulse with the reference pulse. We then calculate the distance of this tag defined as \( \sum_{i=1}^{30} |p_i - q_i| \), where \( p_i \) is the time when pulse \( i \) should occur according to the tag ID, and \( q_i \) is the time of the pulse in the log file that is closest to \( p_i \). The tag with the smallest distance is picked as the tag that generates the reference pulse, and all its pulses belonging to this burst are removed from the composite log file and stored in the file only for this tag. This process is continued until no pulse is left in the composite log file.

**B. Measurement Results**

Our experiments are conducted in a typical 12 by 12 feet office room. In each experiment, we lay 15 RFID tags on a row on a table and measure the radio signature of each tag location, and repeat this for a total of 15 rows. In total, 20 experiments are carried out with different receiver locations and, in some cases, artificially introduced multi-paths. For example, one experiment setting is shown in Fig. 3.

Figure 4 shows the measured radio signatures in three typical experiments. The experiment in Fig. 4(a) was conducted when the row of the tags directly faced the receiver. The experiment in Fig. 4(b) was conducted with the same receiver location as Fig. 4(a), except that a large metal cabinet was placed close to the receiver to create strong multi-paths. The experiment in Fig. 4(c) was conducted when there was no artificially created multi-path, but the receiver was at a different location. For simplicity, only the phases of the radio signatures are shown. We make the following important observations:

- The signature is sensitive to locations, because a change in location results in clear visible changes in radio signature. This should enable fine-grained, signature-based localization.
- The function is relatively smooth in space. This is also
a very nice property which reduces the complexity in reconstructing the function.

- Multi-path can significantly influence the signature function, which shows the challenges in indoor localization.

IV. TOWARDS INDOOR ACCURATE LOCALIZATION

In this section, we discuss our framework towards accurate, fine-grained localization.

A. Challenges

The key to localization is to learn or reconstruct the signature function, after which localization is basically calculating the reverse the function. To achieve this, samples of the function can be taken, i.e., the radio signatures of certain locations can be measured. Samples can be obtained by deploying reference RFID tags at chosen locations. The signal received from each tag carries information about the wireless environment, even for locations where no tag is deployed. Theoretically, if a signature function can be described by no more than $N$ parameters where $N$ is the number of samples, it can be uniquely determined. However, the challenge is that the reference tags, hence the samples, are often limited and non-uniform in space, as explained earlier in Section I.

B. The Sparsity Conjecture

We note that multi-path is typically caused by just a few major obstacles and reflecting surfaces, such as office walls and metal doors. Signals may bounce back and forth between such surfaces, which makes it difficult to reverse engineer the physical characteristics of the walls and doors. However, with actually just few root causes of multi-path, it is likely that the signature function resides in a sparse space, i.e., can be described as a linear combination of only a few features.

C. Localization with Compressive Sensing

If the sparsity conjecture holds, recent developments in signal processing lend efficient reconstruction methods, such as Compressive Sensing. Compressive sensing is very efficient in reconstructing functions of sparse nature, and requires far less number of samples than traditional methods [8], [9], [12], [10]. Compressive sensing models a function as a linear combination of column vectors of a dictionary matrix. Given samples of the function, it attempts to find a set of columns that produce the same values at the sample points, while minimizing the cardinality of the set. Minimizing the cardinality is to reflect the sparse nature of the function. This minimization problem, however, is NP-hard, but can be approximated by relaxing it into a linear programming one. In addition, it does not require the samples to be taken uniformly from the space. These properties perfectly fit our need of localizing with limited, non-uniform samples.

To be more specific, we assume there are $L$ discrete locations. The dictionary matrix $A$ is a $L \times T$ matrix, where $T$ is the total number of columns. The linear combination of columns can produce values at different locations. We are
given the measured values at \( S \) locations where \( S < L \), and we wish to use compressive sensing to recover the values at other locations. Denote the measured values as a vector \( y = [y_{l_1}, y_{l_2}, \ldots, y_{l_S}] \), where \( \{l_1, l_2, \ldots, l_S\} \) are the indices of the locations with measurements. We construct matrix \( A' \) by taking rows \( \{l_1, l_2, \ldots, l_S\} \) from \( A \), and attempt to find a vector \( x \) such that

\[
\min \sum_{i=1}^{r} |x_i|
\]

subject to

\[ A' x = y. \]

With \( x \), the values at all locations are obtained by \( Ax \). An element in \( x \) is referred to as a coefficient. The optimization problem is solved with the package at [1].

Clearly, to apply compressive sensing for localization, the major problem is to obtain a good dictionary matrix. This can be achieved by running extensive experiments and pass the data to the k-SVD program [4] available at [2] to learn a dictionary that is likely to result in a sparse representation of the signal.

**D. Experimental Results**

One practical challenge is that an experiment takes a substantial amount of time to carry out with our current equipment, and we have in total 20 sets of data from our measurement experiments. On the other hand, to be able to effectively represent the signal space, the dictionary should have a sufficient number of columns, where at least one experiment is needed to generate an independent column. We therefore divide a real experiment into 9 smaller experiments, each has 5 rows and 5 columns of data from the original experiment. For simplicity, in the following, we refer to such a small experiment as an experiment unless stated otherwise. We therefore have a total of 180 experiments and we use 153 experiments to train the k-SVD program and use the rest for testing. The dictionary we generate has 128 columns. The experiments used for testing include the experiment with introduced strong multi-path. As the phase measurements have less noise than the amplitude measurements, we use only the phase measurements in the tests.

To study the effectiveness of using compressive sensing, we run the following tests. First, for an experiment, we select \( S \) locations among the total 25 locations, and pass the measured signatures at these locations as \( y \) to the compressive sensing program. We then compare the reconstructed signature function (\( Ax \)) with the measured signature function. Figures 5 and 6 show the reconstruction results for three typical experiment when \( S = 8 \) and 12, respectively. The function constructed by compressive sensing is shown in dashed green lines along side of the measured signatures shown in solid blue lines. They are rearranged into one-dimension by displaying the rows consecutively for easy comparison; each row is a saw tooth in the figure. We can see that compressive sensing can usually reconstruct the data reasonably well, and the reconstruction, of course, is better with more samples.

To quantitatively measure the accuracy of the reconstruction, we define **reconstruction error** at a location as the difference between \( Ax \) and the measured value. We apply the above reconstruction method to all test experiments, and measure the distribution of reconstruction errors. Figure 7 shows the histogram of the reconstruction errors among all experiments when \( S = 8, 12 \). We can see that for most locations, the reconstruction error is very small. There are,
however, some outliers.

To verify the sparsity conjecture, we show in Fig. 8 the histogram of the number of significant coefficients among all experiments, where we consider a coefficient significant if its absolute value is no less than 0.001. We can see that the sparsity conjecture should likely hold, because typically there are only around 10 significant coefficients although the total number of columns in the dictionary is 128.

Finally, we test the localization accuracy after the signature function has been reconstructed. With the test experiments, we have 3 readings for each tag location (because the test experiments are partitioned from 3 larger experiments). The size of the tag is about $1.8 \times 1.2$ inches. To achieve a finer granularity than the size of the tag, we use the gridfit function available in Matlab to interpolate 15 points between adjacent tags. We adopt a simple algorithm for localization: given the measurement vector with three signatures at an unknown location, search the interpolated signal space and output a location with minimum total square error from the measured vector. Figure 9 shows the cumulative distribution function of the localization errors when $S = 8, 12$, respectively. The average estimation errors are 1.32 inch and 1.74 inch for $S = 8, 12$, respectively. We expect the localization accuracy can be further improved substantially with better a dictionary matrix learned from more experiments.

V. RELATED WORKS

Localization is usually based on analyzing the signal emitted by signal sources. The received signal waveform of a radio source is affected by the paths the signal travels, and carries the raw information about the paths and thus the location. Due to the readily availability to the upper layers,
a large percentage of localization techniques rely on coarse information, such as the detection rates of RFID tags [14], [17], the received signal strength (RSS) [6], [25], [5], [39], [36], [24], or both [16]. The processing of such information is also often based on simplified assumptions or empirical equations [25], [39]. Algorithmic optimizations in the upper layers have been adopted, such as Bayesian inference [5], [30], [22], [40], nearest neighbor search [25], [17], [40], and kernel-based learning [7], [24], [40]. However, working on coarse information, such systems usually offer granularity at the meter or sub-meter’s level. High granularity can only be achieved by passing the raw signal waveform to the upper layers and designing algorithms that understand the intricate relations between the wireless environment and the signal.

Indeed, the possibility of localization with RF waveform information has been studied recently in [23], [3], [20], [11], [19], [18], [18], and has been shown to be successful for the outdoor channels [23] and is able to achieve error in the order of 0.1m at long range, because the signal phase carries the information of the line-of-sight (LOS) path which can be used to infer locations. Indoor localization based on the signal phase has been attempted in [3], [20], however, it remains challenging because of the difficulties in coping with the indoor channels with multi-path.

In [15], we showed the potential of using the phase knowledge for fine-grained localization; however, no specific localization technique was proposed and it was unclear how to cope with multi-path. In this work, we propose a framework for localization with the presence of multi-path, and conduct localization experiments to validate our idea.

VI. CONCLUSIONS AND FUTURE WORK

In this paper, we have proposed a framework for fine-grained, accurate localization in indoor multi-path environments with RFID tags. We found through our experiments that location information can be reflected in tag-agnostic radio signatures, which is continuous in space while still sensitive to location changes. Our idea is to learn the continuous signature function with samples obtained from reference tags, without explicitly reconstructing the paths the signals travel, and therefore avoiding the complexity in calculating the paths. Once the function is learned, the localization is simply to reverse the function which can be computed efficiently with numerical methods. We assume that the signature function lies in a sparse space, and use compressive sensing to reconstruct the signature function. Our experiments in a 2-D space in a typical office show that good localization accuracy can be achieved. The effectiveness of the localization results in the
2-D space will further motivate our future research along this direction to tackle more challenging cases. Currently, the dictionary is learned with limited sets of experiments. We will conduct more experiments, i.e., in the order of hundreds, to further improve the localization accuracy. The quality of the dictionary has a huge impact on the localization accuracy; we tried dictionaries obtained with synthesized data and the results are worse. With more experiments and a better dictionary, we should be able to attack the localization problems in much larger areas and further in the 3-D space at higher accuracy. We will also try using other types of RFIDs. The RFID tags used in our current experiments are at the 433.92 MHz carrier frequency which in some sense limits the size of the area in which we carry out our localization experiments; as its wavelength is about 30 inches, a complete phase cycle can be observed within 30 inches. We will try RFIDs operating on lower carrier frequencies which have longer wavelengths such that a larger area can be covered with the same number of tags. However, longer wavelength will also lead to larger estimation errors, and the tradeoff between estimation error and covering range will be further studied.

REFERENCES