SenSync: Real-time and Accurate Passive Sensing

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***Abstract*—SenSync tackles key challenges in RFID-based differential sensing systems, including temporal misalignment, phase ambiguity, and environmental sensitivity. Traditional techniques are limited by sequential data processing, which introduces time shifts, and arbitrary phase jumps injected by commercial RFID readers, which obscure accurate differential measurements. These issues, compounded by multipath effects and dynamic environments, hinder the deployment of robust RFID sensing systems at scale. To address these challenges, we propose innovative algorithms and signal processing techniques to align and interpret time-shifted data from multiple ICs. Our approach mitigates the effects of temporal misalignment and phase ambiguity, ensuring reliable differential sensing in real-world applications. By improving data alignment and robustness, we accelerate the sensory resolution by 5x. Furthermore, we developed a user interface capable of automatically detecting sensors within the system's field of operation and displaying their readings in real-time, demonstrating the practical applicability and versatility of our proposed solution.**

***Index Terms*—Algorithm, Passive System, Real-Time Sensing**

I. Introduction

RFID has gained widespread adoption in large-scale logistics, and asset management, owing to its desirable traits such as simplicity, low manufacturing costs, battery-free operation, minimal maintenance, and the ability to query hundreds of tags per second. These characteristics, coupled with the extensive deployment of RFID infrastructure—including antenna readers, tags, and protocols—point to a compelling opportunity to re-purpose this infrastructure for applications like ubiquitous sensing. Consequently, there is growing interest in expanding RFID's capabilities to ubiquitous sensing of quantities like force, temperature, and moisture [1]–[5]. However, the system requirements for sensing go beyond those of simple identification and tracking. It must accurately and consistently infer changes in the sensed parameter in a dynamic environment, operate in real-time, and be scalable to achieve ubiquity.

RFID tags lack inherent sensing capability and need an additional interface to read sensor outputs. This interface can be realized by digitizing the sensor output using a low-power Microcontroller [1], and then communicating to the RFID reader. However, battery-free RFID tags rely on harvested energy due to which they cannot meet the power requirements of such an interface without additional energy sources or large, making it unsuitable for wide-scale deployment. The second approach involves re-purposing existing RFID tags by cleverly embedding sensor information into the complex-valued channel (both RSSI/Phase) between the RFID tag and reader [2]. However, all these methods utilize "differential sensing" by deploying a reference tag, separate from the sensor-modulated tag, to counter the multipath effects when deployed in a dynamic channel [6]–[8]. Fundamentally, this technique of differential sensing generates two streams of data per deployed sensor to measure the stimulus reliably. This raises the question: How can we reliably process the channel data stream from two differential tags in near real-time to infer sensor readout meaningfully?

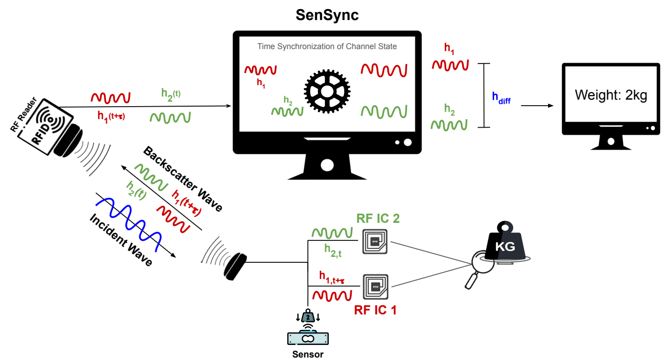


Fig. 1: Illustration of SenSync for sensing stimuli

Consider the channel state signals of the two differential tags shown in Fig. 1; for reliable differential sensing in a dynamic environment, the reader must process the information (RSSI or Phase) from both tags synchronously. However, modern RFID readers, such as the Impinj R700, process each RF Integrated Circuit (IC) individually and sequentially [9], [10]. This introduces a time shift (τ) in the data received from the reader. Furthermore, the backscatter from each IC is dependent on its energy harvesting capability and modulation power requirements. This dependency can result in significant time gaps between received signal parameters for different ICs, as one IC may require extended energy harvesting periods while another transmits multiple backscattered signals. These temporal misalignments pose a significant challenge to the effectiveness of differential sensing techniques. The **time shifts** and **gaps** between signals from different ICs can lead to substantial deviations from the true differential measurements, potentially negating the benefits of this approach.

SenSync aims to address these critical issues by proposing innovative methods to mitigate the effects of temporal misalignment and phase ambiguity in RFID-based differential sensing systems. Our research focuses on developing a robust signal processing algorithm that can accurately align and interpret the time-shifted data from multiple ICs, thereby preserving the advantages of differential sensing in real-world RFID applications. We show that our approach can improve the latency of sensory resolution by $5\times$ compared to current state-of-the-art systems. In addition, we have developed an application capable of automatically detecting sensors within the system's field of operation and displaying their readings in real-time as shown in Fig. 1.

II. Related Works

RFID-based sensing systems over the years have presented various mechanisms for measuring stimuli such as impedance [2], [11], RSSI [3], [6] and phase [5], [7] while some works have also shown to use multiple parameters to perform sensing [8]. While both the parameters of a tag (RSSI and Phase) can be used to accomplish sensing, Phase demonstrates greater granularity and real-time sensitivity to the sensed parameter compared to RSSI [5]. However, the sensitivity of the phase also poses significant challenges as highlighted below.

Commercial RFID readers are required to hop frequencies to reduce burdening the channels [9], [10]. While this minimizes interference, it induces abrupt phase shifts in multiples of π during frequency transitions [7], [8]. These phase discontinuities make it difficult to distinguish between changes caused by external stimuli and those introduced by the channel-switching mechanism [12]. Consequently, phase becomes an unreliable parameter for sensing applications. While [5] tries to address this by using time-interval phase changes, its assumption of channel stability fails in dynamic environments with moving sensors, limiting its usefulness. Impedance measurement [11], an alternative to phase-based sensing, is constrained by the need to match the sensor's impedance values to those of the RFID IC, while also maintaining the On-Chip RSSI within strict bounds [13]. It also requires frequent recalibration due to sensitivity to tag-reader distance and may misidentify causes when similar impedance values occur [2].

To solve these hurdles, [6] proposed attaching a secondary tag to act as a reference which can eliminate channel effects. It shows that the tags when kept close, would experience the same multipath effects. An extension of this work, [3], [14] illustrates that using separate tags without explicitly attaching sensors can also be used to estimate phenomena like soil moisture, material properties. These solutions however fail to adequately address the robustness and reliability issues faced by traditional RFID-based sensing systems. When tags are placed very close to each other, they interfere with each other leading to significant collisions[15]. Conversely, placing tags farther apart, fundamentally alters the wireless channel perceived by the tags and the phase information is corrupted the angle of arrival of the wireless signal [16]. This creates a challenging trade-off in tag placement for optimal system performance.

Work shown in single-antenna topologies like [7], [8] have instead emerged as promising solutions for mitigating multipath effects and channel variability issues. They demonstrate theoretical robustness by assuming a consistent physical channel, considering only a single origin for the backscattered signal. However, these approaches rely on critical assumptions:

1) Simultaneous data reception and transmission from multiple RF ICs.
2) Perfectly alternating responses from the RF ICs.

Additionally, these works acknowledge the presence of ambiguous π phase jumps [7], [8] but do not propose methods to resolve these ambiguities effectively. Moreover, their read rates are limited to around 100 RF ICs per second [7], [8], whereas modern RFID readers, such as the Impinj R700, can process 800-1000 RF ICs per second under regular conditions. Since we are talking about differential sensing using two RF ICs, two data points give one sensory sample, which means that existing solutions work at about 50 sensory samples per second, while commercial readers would be capable of generating 400 samples per second. This demonstrates that current applications significantly under-utilize commercial readers' capabilities.

In the following sections, we will model these challenges and provide a comprehensive insight into the caveats of differential sensing using commercial RFID readers and tags. We will then propose signal processing techniques to solve for the ambiguities and leverage the reader's full read-rate.

III. System Model

This system model outlines the operational characteristics of RFID readers, highlighting key issues in sensing reliability, and motivates the need for a software-driven approach to overcome these challenges.

A. Operational Characteristics of RFID Readers

RFID readers, such as the Impinj R700, are designed to process key signal parameters, including the RSSI, phase, and operational channel frequency. These readers operate under constraints imposed by the FCC based on the EPC UHF Gen2v3 Protocol [9], which mandates that commercial radios utilize a defined frequency range to prevent channel congestion [10]. In the United States, RFID readers function within the frequency band of 902 MHz to 928 MHz. This range is divided into 50 frequency channels [10]. Frequency hopping between these channels is governed by a pseudo-random algorithm, ensuring that no single channel becomes overcrowded. During it's operation, the reader transmits on each channel for about 200 milliseconds [9] before switching to a new frequency. This channel-hopping mechanism ensures fair utilization of the spectrum but introduces complexities in the signal processing pipeline due to the arbitrary artifacts in phase produced by the reader.

B. RFID Reader Constraints on Differential Sensing

In practical RFID systems, readers process RF ICs sequentially as per the EPC Protocol [9] guidelines, using framed Slotted ALOHA for communication [10]. Each tag is assigned a random slot within a time frame as a means to mitigate collisions. Tags are read sequentially, introducing time lags (δt) between IC signals. Varying energy harvesting and modulation power further contribute to time mismatches, with some ICs transmitting multiple signals while others harvest energy. These time differences significantly impact differential sensing reliability, causing deviations from true signals. Additionally, if the reader does not estimate tag population, it defaults to a 16-slot time frame, potentially wasting resources with fewer tags present [17]. Furthermore, reader-induced π phase jumps obscure the link between phase changes and stimuli, making it challenging to separate artificial jumps from meaningful phase changes without additional processing.

C. Overcoming system challenges

The ambiguous π phase jumps during the channel switch necessitate using the phase time series only from a single channel when performing the differential. Couple this with the slow read rate of 50 samples per second [7], [8], we only get about 10 samples from a single channel since the dwell time per channel is only 200ms as discussed earlier [10]. However, the two data sources may transmit asynchronously, potentially resulting in an uneven distribution of samples. For instance, we might receive 7 values from the first source, 3 from the second, then 3 again from the first, and 7 from the second. During this alternating sequence of reads, the frequency channel could change, leaving only the overlapping samples (in this case, the middle 3 values) as usable data for differential analysis.

The data collection process imposes constraints that require an extended time window to accurately calculate a sensor's response to stimuli. Despite claims of real-time operation, these systems typically need a 5 to 10-second delay to reliably measure and report quantities. This latency between stimulus occurrence and detection undermines the claim of true real-time sensing capabilities. By resolving the limitations of current approaches, SenSync paves the way for next-generation RFID-based sensing systems that can operate effectively even in dynamic and noisy environments.

IV. Design

In this section, we present the design contributions of SenSync that address the roadblocks experienced in differential sensing using a single antenna interface as discussed in §III. We use the same hardware tag configuration as given by ZenseTag in [7] but make significant improvements in the software.

A. Addressing the Temporal Mismatches

Previous works [7], [8] fail to address temporal mismatches from sequential tag reading and caveats of energy harvesting and backscatter consumption. Our studies reveal significantly higher phase variation when differentially analyzing unmatched sequences as shown in §VI.

To address this mismatch, we developed SenSync, an algorithm that extracts signal parameters from individual channels, temporally matches them, and computes phase differences. We employ Dynamic Time Warping (DTW), a dynamic programming algorithm originally designed for synchronizing time series of varying speeds and lengths in speech recognition [18]. The algorithm (Algo. 1) is depicted in Fig. 2.

1) Mathematical Model of Backscatter from SST

Consider the response that the reader receives from individual tags as independent channel (both RSSI and Phase) states h_1, h_2 for a given channel c :

$$h_1^c = |h_1^c| e^{-j\Phi_1^c}, \quad h_2^c = |h_2^c| e^{-j\Phi_2^c} \quad \ldots \Phi_1^c, \Phi_2^c \in (-\pi, \pi)$$

The differential amplitude (RSSI) and Phase can be represented as:

$$RSSI_{\text{diff}}^c = |h_1^c| - |h_2^c|, \quad \Phi_{\text{diff}}^c = \Phi_1^c - \Phi_2^c$$

The two sequences Φ_1 and Φ_2 represent phase values captured by the reader for the two tags over multiple channels. The input sequences are defined as:

$$\Phi_k = \{\Phi_k^1, \Phi_k^2, \ldots, \Phi_k^C\}, \quad k \in \{1, 2\},$$

where C is the number of channels, and $\Phi_k^c = \{\Phi_k^c(t_1), \Phi_k^c(t_2), \ldots, \Phi_k^c(t_N)\}$ is the phase sequence for channel c at different time instances $t_1, t_2, \ldots, t_N$.

The number of channels, C has been fine-tuned based on hyperparameter optimization of the channel state for phase stability during the channel hops. Empirical data has shown that the arbitrary phase jumps of π happen approximately 15% of the time. Now, we have observed that having at least 3 stable channels is sufficient for our algorithm to correctly detect the response from the sensor and remove the effects of these arbitrary non-idealities. From binomial probability, 90% of 4 channel hops yield at least three reliable channels. Thus, we define each DTW time frame to 4 channels, which computes to 0.8s of data collection, resulting in our sensory response time to become $5\times$ faster than current state-of-the-art differential sensing algorithms [7], [8]. This aligns with both natural stimuli variation speeds and human perception thresholds.

The temporally misaligned phases can be represented as $\Phi_1(t+\tau)$,$\Phi_2(t)$ where τ represents the time shift introduced between the two streams in the same channel. Note that as the RFID reader hops channels, and communicates with the two tags, not necessarily in a sequential/deterministic order, the time-shift τ will also vary. Consequently, the objective is to align Φ_1 and Φ_2 by removing the shift τ over the minimum frame size (Algo. 1) within which the DTW algorithm computes the phase difference Φ_{diff}. The phase difference is given by:

$$\Phi_{\text{diff}}(t_i) = |\Phi_1(t_i) - \Phi_2(t_i)|, \quad \forall t_i \in W,$$

where W is the warping path obtained using DTW [1].

In Fig. 2, the left side of the diagram represents unprocessed input sequences from two tags (Φ_1 and Φ_2) across four channels:

$$\Phi_1 = \{\Phi_1^1, \Phi_1^2, \Phi_1^3, \Phi_1^4\}, \quad \Phi_2 = \{\Phi_2^1, \Phi_2^2, \Phi_2^3, \Phi_2^4\}.$$

Each sequence is time-indexed and contains noisy or misaligned data. Dynamic Time Warping is applied to each pair of sequences Φ_1^c and Φ_2^c per channel c, aligning the sequences and ensuring that the indices t_i match optimally.

After alignment, the processed output on the right side of the diagram represents the computed phase differences $\Phi_{\text{diff}}(t_i)$ for all aligned timestamps:

$$\Phi_{\text{diff}}^c(t_i) = |\Phi_1^c(t_i) - \Phi_2^c(t_i)|, \quad c \in \{1, 2, 3, 4\}$$

The final output is a consolidated matrix of Φ_{diff} values for all channels, ready for subsequent analysis.

This algorithm is effective because the sequences, though time-misaligned, still represent channel and stimuli effects. SenSync demonstrates that it solves the hidden caveats of differential sensing using a single antenna interface. Importantly, this algorithm is not limited to phase but can be easily extended to other signal parameters like RSSI or impedance. As a consequence of using a deterministic algorithm, our proposed solution does not necessitate the need for creating a training dataset, thus generalizing it to any environment for precise operation. Accordingly, SenSync reliably addresses the issue of channel variability that differential sensing was meant to solve which will become evident from the wide range of evaluations presented in §VI.

SenSync truly enables differential sensing by solving the ambiguities that arise due to the caveats of commercial RFID readers as shown in §III. Because this algorithm can be

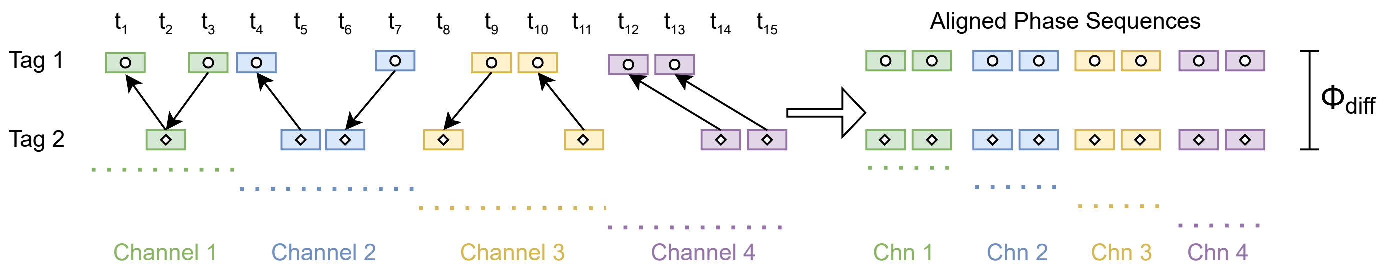


Fig. 2: Pictorial representation of data packets received from the different RF ICs and matching them temporally.

Algorithm 1 Dynamic Time Warping (DTW)

Require: Two sequences $\Phi_1 = \phi_1(t_1), \phi_1(t_2), \ldots, \phi_1(t_N)$ and $\Phi_2 = \phi_2(t_1), \phi_2(t_2), \ldots, \phi_2(t_M)$

Ensure: The DTW distance and the optimal warping path W

Initialize the cost matrix D of size $N \times M$:
$D(0,0) = 0$
$D(i,0) = \infty$ for all $i > 0$
$D(0,j) = \infty$ for all $j > 0$
for each i from 1 to N **do**
  for each j from 1 to M **do**
    Calculate the cost $d(\phi_1(t_i), \phi_2(t_j)) = |\phi_1(t_i) - \phi_2(t_j)|$

    Update the cost matrix:

$$D(i,j) = d(\phi_1(t_i), \phi_2(t_j)) + \min\Big(D(i-1,j), D(i,j-1), D(i-1,j-1)\Big)$$

  end for
end for
Initialize the warping path $W = \{(N, M)\}$
Set $i = N, j = M$
while $i > 1$ or $j > 1$ **do**
  Find the direction of the minimum cost:

$$(i', j') = \arg\min\Big\{D(i-1,j), D(i,j-1), D(i-1,j-1)\Big\}$$

  Update $(i,j) \leftarrow (i', j')$
  Append (i,j) to W
end while
Reverse W to obtain the final warping path
return $D(N,M)$ and W =0

extended to other signal parameters, SenSync becomes a universal solution for enabling differential sensing based on RFID technology. The increased throughput has also reduced the time taken for inferring stimuli to sub-second values which is a stark 80% improvement over the existing state-of-the-art sensing systems [7].

V. Implementation

A. General Compute Specifications

We have implemented SenSync as a software package atop the hardware given by [7]. SenSync can be installed on any general purpose compute machine, having any of the commonly used operating systems. We deployed this as a standalone Java program using the Impinj Octane SDK. We developed a frontend application with Java Swing for plotting real-time sensory outocmes on a Graphical User Interface (GUI) and an auto-detector for nearby sensors. The GUI also allows users to select from multiple detected sensors. Additionally, we created a Python program using the JPype library to demonstrate our software package's language agnosticism.

We specifically used our application with a Windows 11 system having an Intel(R) Core(TM) EVO i7-1355U CPU having a peak clocking speed of 3.7GHz. The system usage during operation is lower than 20% peak speed and consumes less than 2 GB of memory due to its efficient nature. We also used an Ubuntu 20.04 machine running on an Intel(R) Core(TM) i7-1165G7 CPU having a peak clocking speed of 2.8GHz just as effectively. This shows the cross-platform operability of SenSync. The code for the implementation can be found here: https://github.com/ucsdwcsng/SenSync [19]

B. Reader - Compute Interface

Most recently published works rely on Python based open-source Low Level Reader Protocol (LLRP) libraries for interfacing the RFID reader with the compute devices; however, these are bottle-necked in terms of their throughput due to limited packet sizes which results in significantly reduced sampling rates of 100 RF ICs (or 50 sensory samples) per second [7], [8]. Instead, in SenSync, we interface our Impinj R700 reader with any general purpose compute device using the Octane SDK provided by Impinj. We developed a custom Java application built on the existing SDK, focusing on RFID data acquisition and processing. It implements our algorithms for improved data interpretation and visualization.

We provide preset configurations for the reader, defining expected tag population and reader mode to set the correct frame size in the *Query* field [10]. Setting the correct reader mode optimizes resource allocation, allowing the reader to focus on decoding backscattered signals containing RFID parameters instead of evaluating its environment. Using this direct approach, throughput has been boosted to 800 RF ICs (or 400 sensory samples) per second.

By tailoring the software to our system's specific needs, we have created a robust platform for RFID data collection and analysis that enhances the throughput by $8\times$ as per Table I, enabling more efficient and accurate processing of the complex data streams generated by RFID systems. We tested our application using commercial off-the-shelf RFID tags and a separate commercially available Impinj R700 RFID reader.

Algorithm	1s	2s	5s	10s	30s	60s	Average
SenSync	771	1457	3607	7204	21259	42407	786 Hz
ZenseTag	114	199	478	947	2838	5744	99 Hz

TABLE I: Data points collected from SenSync and ZenseTag for different time intervals

VI. Evaluation

To evaluate the proposed technique, we developed a Simulatory Stubbed Tag (SST) device, based on ZenseTag [7] but adapted for a rigid PCB implementation, as shown in the inset of Fig. 3a. Unlike ZenseTag's sensor- impedance dependent phase modulation, SST utilizes a transmission line stub to introduce a fixed phase shift. The PCB incorporates two-RFID ICs at known electrical lengths (calculated at effective wavelength λ_{eff} inside the substrate) from a shared antenna and Wilkinson Power Combiner, creating distinct path lengths. This induces a natural phase difference between incident and backscattered signals, enabling accurate phase-based sensing with a known ground truth. This calculated difference is $5.95°$ for each signal, resulting in a net phase difference of $11.9°$ for the backscattered signal confirmed using a Vector Network Analyzer (VNA). Using SST, we compare the performance of ZenseTag [7] and SenSync. This SST serves as a benchmark to compare both methods' performance in two scenarios: optimal conditions without multipath interference, and challenging environments with significant multipath effects.

We tested ZenseTag in dynamic conditions using our improved software and a simple differential technique on raw data in which we subtract phase of the reference without processing the phase signals, as given in [7]. We evaluated both data collection methods using SenSync's DTW algorithm, and results show that accurate real-time sensing in dynamic conditions requires SenSync's complete system.

A. Performance under Static Conditions

In optimal conditions, we positioned the SST at 50cm from the RF Antenna in an environment having static metallic and non-metallic objects in its vicinity but not in the Line of Sight (LOS) path.

We evaluated the performance of both SenSync and ZenseTag using the SST under optimal conditions as defined above. Based on our observations, we can safely say that SenSync has much better accuracy and gives significantly more precise results when compared to ZenseTag. Fig. 3a reveals that the median error in computing phase difference is $0.2°$ lower when the algorithm proposed in SenSync is used when compared to one suggested in [7] making a strong case for enhanced accuracy when using SenSync. Thus SenSync is more reliable and robust compared to state-of-the-art.

B. Performance under Dynamic Conditions

For the dynamic scenario, we introduced significant disturbances in the LOS path, including moving people. Additionally, we vigorously moved the SST laterally relative to the platform it was kept on.

We evaluated SenSync and ZenseTag individually under real-world conditions, focusing on their data collection and algorithmic capabilities. Specifically, we tested ZenseTag with our channel-wise DTW algorithm (IV-A) and with our improved data collection technique (V-B), which is equivalent to evaluating SenSync without the DTW algorithm. This approach demonstrates the independent impact of SenSync's design enhancements and details the optimal method for differential sensing.

Fig. 3b shows that SenSync achieves the lowest error, with individual enhancements also providing significant improvements. SenSync demonstrates substantial accuracy gains in measuring true differential phase. Under harsh simulation conditions, SenSync's median error is only $0.79°$, marginally higher than the $0.6°$ observed in static conditions (VI-A).

ZenseTag with DTW, even though a distant second, demonstrates DTW's effectiveness in matching time sequences for each channel and managing EPC protocol [9] constraints. Next, SenSync without DTW matching (throughput-enhanced ZenseTag) shows that increasing the read-rate by $8\times$ does improve the overall error but results in a more sporadic spread of values due to the lack of temporal sequence matching.

We also studied the variability in readings for each experiment as seen in Fig. 3c. SenSync, shown by the dark green bar, outperforms others with lower error, reduced variability, and improved consistency. Its higher throughput (Table I) enables sub-second stimulus resolution, achieving a $5\times$ improvement over existing methods [2], [5], [7], [8].

C. Evaluation with Commercial Sensors

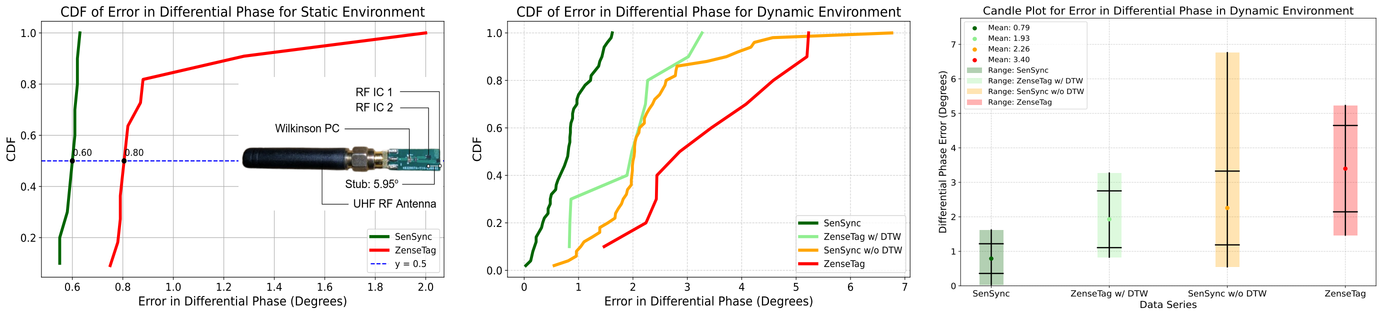
We have also evaluated SenSync in the real world using a commercial Force-Sensitive Resistor (FSR) using the setup as shown in Fig. 4a. We conducted measurements using standard weights of 20gm and 50gm respectively and plotted confusion matrices to highlight the difference between State-of-the-Art algorithms vs SenSync. Fig. 4 compares state-of-the-art differential sensing against SenSync for detecting weights using commercially available standardized metallic weights. From Figs. 4b,4c it is evident that differential sensing today struggles with inconsistent tag data and poor accuracy, while SenSync performs better even with metallic weights. This robustness highlights SenSync's capability to handle external factors and different materials compared to traditional differential sensing.

VII. Conclusion

Wireless, battery-free solutions for ubiquitous remote sensing face numerous challenges, particularly in multipath-rich environments with static and non-static objects and people. We presented SenSync, an algorithm designed to address real-world non-idealities through a theoretical approach. Being a deterministic algorithm, SenSync requires no pre-training or post-deployment recalibration, making it suitable for any environment. We demonstrate this by developing a GUI that can capture and visualize real-time sensory outcomes, offering an intuitive model for RFID-based sensing.

SenSync serves as a universal solution for RFID-based differential sensing, applicable to phase, RSSI, or impedance as sensing mechanisms. The current operation of SenSync is constrained by sensor speed. Since we define the DTW time frame based on limitations imposed by commercial RFID readers, we are restricted to detecting stimuli that do not change more rapidly than the frame size. Another potential limitation is the use of handheld RFID readers. While SenSync can account for tag movement, all our experiments have involved stationary readers.

As RFID readers improve in size, computing power, and become free of the arbitrary phase jumps introduced during frequency hopping, SenSync can become more powerful.

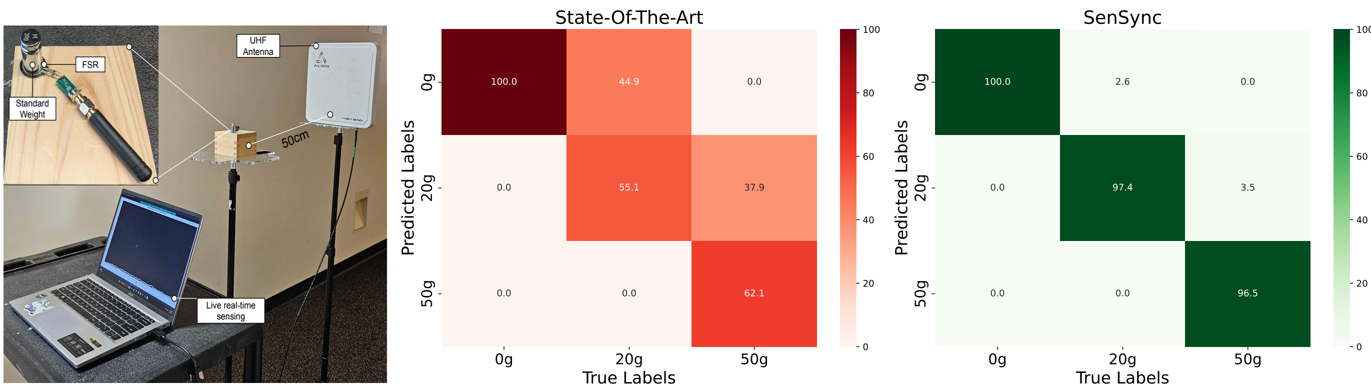


(a) CDF plot showing the error margins in static conditions. (Inset: Simulatory Stubbed Tag)

(b) CDF plot showing the error margins in dynamic conditions.

(c) Illustration of the range and variability in error in dynamic conditions.

Fig. 3: Comparative analysis of Error between SenSync and State-of-the-Art techniques.



(a) Weight measurement Evaluation setup.

(b) Weight classification accuracy for SOTA algorithms.

(c) Weight classification accuracy usingSenSync.

Fig. 4: Comparative analysis between SenSync and SOTA for measuring weights (All values in percentages).

This advancement could potentially enable truly ubiquitous passive sensing, achieving the long-sought deploy-and-forget paradigm in remote sensing.

References

[1] R. Menon, R. Gujarathi, A. Saffari, and J. R. Smith, "Wireless identification and sensing platform version 6.0," in *Proceedings of the 20th ACM Conference on Embedded Networked Sensor Systems*, ser. SenSys '22, Boston, Massachusetts: Association for Computing Machinery, 2023, pp. 899–905, ISBN: 9781450398862. DOI: 10.1145/3560905.3568109. [Online]. Available: https://doi.org/10.1145/3560905.3568109.

[2] E. Shen, W. Yang, X. Wang, S. Mao, and W. Bin, "Tagsense: Robust wheat moisture and temperature sensing using a passive rfid tag," in *ICC 2022 - IEEE International Conference on Communications*, 2022, pp. 1617–1622. DOI: 10.1109/ICC45855.2022.9838925.

[3] J. Wang, L. Chang, S. Aggarwal, O. Abari, and S. Keshav, "Soil moisture sensing with commodity rfid systems," in *Proceedings of the 18th International Conference on Mobile Systems, Applications, and Services*, ser. MobiSys '20, Toronto, Ontario, Canada: Association for Computing Machinery, 2020, pp. 273–285, ISBN: 9781450379540. DOI: 10.1145/3386901.3388940. [Online]. Available: https://doi.org/10.1145/3386901.3388940.

[4] W. Sun and K. Srinivasan, "Healthy diapering with passive rfids for diaper wetness sensing and urine ph identification," ser. MobiSys '21, Virtual Event, Wisconsin: Association for Computing Machinery, 2021, pp. 188–201, ISBN: 9781450384438. DOI: 10.1145/3458864.3466870. [Online]. Available: https://doi.org/10.1145/3458864.3466870.

[5] A. Gupta, D. Park, S. Bashar, *et al.*, "Forcesticker: Wireless, batteryless, thin & flexible force sensors," *Proc. ACM Interact. Mob. Wearable Ubiquitous Technol.*, vol. 7, no. 1, Mar. 2023. DOI: 10.1145/3580793. [Online]. Available: https://doi.org/10.1145/3580793.

[6] J. Wang, O. Abari, and S. Keshav, "Challenge: Rfid hacking for fun and profit," in *Proceedings of the 24th Annual International Conference on Mobile Computing and Networking*, ser. MobiCom '18, New Delhi, India: Association for Computing Machinery, 2018, pp. 461–470, ISBN: 9781450359030. DOI: 10.1145/3241539.3241561. [Online]. Available: https://doi.org/10.1145/3241539.3241561.

[7] N. Bhat, A. Gupta, I. Bansal, H. Govindarajan, and D. Bharadia, "Zensetag: An rfid assisted twin-tag single antenna cots sensor interface," in *Proceedings of the 22nd ACM Conference on Embedded Networked Sensor Systems*, ser. SenSys '24, Hangzhou, China: Association for Computing Machinery, 2024, pp. 336–350, ISBN: 9798400706974. DOI: 10.1145/3666025.3699342. [Online]. Available: https://doi.org/10.1145/3666025.3699342.

[8] J. Nolan, K. Qian, and X. Zhang, "Keystub: A passive rfid-based keypad interface using resonant stubs," *Proc. ACM Interact. Mob. Wearable Ubiquitous Technol.*, vol. 7, no. 4, Jan. 2024. DOI: 10.1145/3631442. [Online]. Available: https://doi.org/10.1145/3631442.

[9] *Epc™ radio-frequency identity generation-2 v3 uhf rfid standard*, https://ref.gs1.org/standards/gen2/, Global Standards 1, 2024.

[10] M. Buettner and D. Wetherall, "A "gen 2" rfid monitor based on the usrp," *SIGCOMM Comput. Commun. Rev.*, vol. 40, no. 3, pp. 41–47, Jun. 2010, ISSN: 0146-4833. DOI: 10.1145/1823844.1823850. [Online]. Available: https://doi.org/10.1145/1823844.1823850.

[11] L. Li, B. Shang, Y. Wu, J. Xiong, X. Chen, and Y. Xie, "Cyclops: A nanomaterial-based, Battery-Free intraocular pressure (IOP) monitoring system inside contact lens," in *21st USENIX Symposium on Networked Systems Design and Implementation (NSDI 24)*, Santa Clara, CA: USENIX Association, Apr. 2024, pp. 1659–1675, ISBN: 978-1-939133-39-7. [Online]. Available: https://www.usenix.org/conference/nsdi24/presentation/li-liyao.

[12] X. Liang, Y. Ma, C. Tian, Y. Han, and K. Liu, "Moc-sar: Motion compensation for synthetic aperture-based holographic localization in uhf rfid system," *IEEE Sensors Journal*, vol. 24, no. 19, pp. 30 758–30 768, 2024. DOI: 10.1109/JSEN.2024.3408678.

[13] X. Zhang, H.-X. Li, and H. S.-H. Chung, "Setup-independent sensing architecture with multiple uhf rfid sensor tags," *IEEE Internet of Things Journal*, vol. 9, no. 2, pp. 1243–1251, 2022. DOI: 10.1109/JIOT.2021.3079448.

[14] C. Li, Z. Meng, Z. Li, N. Gao, Z. Zhang, and D. Zhen, "Uhf rfid differential sensing via the backscatter coupling between the reader-tag antennas," *IEEE Sensors Journal*, vol. 24, no. 13, pp. 21 395–21 408, 2024. DOI: 10.1109/JSEN.2024.3394969.

[15] G. Shi, Y. He, B. Yin, *et al.*, "Analysis of mutual couple effect of uhf rfid antenna for the internet of things environment," *IEEE Access*, vol. 7, pp. 81 451–81 465, 2019. DOI: 10.1109/ACCESS.2019.2923661.

[16] H. Cai, G. Wang, X. Shi, *et al.*, "When tags 'read' each other: Enabling low-cost and convenient tag mutual identification," *ACM Trans. Sen. Netw.*, vol. 18, no. 2, Mar. 2022, ISSN: 1550-4859. DOI: 10.1145/3494541. [Online]. Available: https://doi.org/10.1145/3494541.

[17] H. Vogt, "Efficient object identification with passive rfid tags," in *Proceedings of the First International Conference on Pervasive Computing*, ser. Pervasive '02, Berlin, Heidelberg: Springer-Verlag, 2002, pp. 98–113, ISBN: 3540440607.

[18] H. Sakoe and S. Chiba, "Dynamic programming algorithm optimization for spoken word recognition," *IEEE Transactions on Acoustics, Speech, and Signal Processing*, vol. 26, no. 1, pp. 43–49, 1978. DOI: 10.1109/TASSP.1978.1163055.

[19] I. Bansal, *Sensync*, https://github.com/ucsdwcsng/SenSync, WCSNG, 2025.