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uThaw: Ultra-wideband Wireless Solid-Liquid State Transition Sensor to Detect Thawing of Food

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Abstract—This paper explores the potential use of ultra-wideband (UWB) wireless sensors in detecting the transition of food items from a frozen state to thawed state (or vice-versa), marking a significant advancement in monitoring the thawing process. By exploiting the drastic change in complex permittivity at microwave frequencies (we use frequencies close to 4GHz) during the solid-liquid state transition, this paper introduces a novel approach in ensuring frozen food safety, and in enhancing the efficiency of the frozen food industry and cold chain transportation. The developed system, capable of operating through food packaging, offers a non-invasive, cost-effective solution for real-time monitoring, addressing the limitations of conventional temperature-based and timing-based methods widely used today in household and professional cooking and in the food industry. Our findings from the raw UWB channel impulse responses (CIR) and computed similarity scores indeed show significant promise and validate the feasibility of the proposed system with various real-world applications.

Index Terms—Wireless Sensing, Ultra-Wideband (UWB), Solid-Liquid State Transitions, Food Safety Monitoring, Complex Permittivity, Channel Impulse Response (CIR), IoT Sensor Systems

I. INTRODUCTION

At microwave frequencies, solid-liquid state transition of water causes a drastic change in its complex permittivity, and therefore a corresponding drastic change is also observed in its refractive index (RI). While water has a refractive index of about 8.9, ice has a refractive index of merely 1.8 at these frequencies [1]. In contrast, for visible light, refractive index does not drastically change when ice (RI = 1.31) transitions into water (RI = 1.33). Because most food has substantial amounts of water, this change in permittivity is also observed when food freezes or thaws. In an enclosed space, as in a microwave oven or freezer, where influence of the external environment is minimal, the changing refractive index dramatically changes wireless signal's reflection and absorption patterns. The core premise of this paper is that wireless reflections show a stable albeit different pattern for *both* frozen and fully thawed foodstuff, but show a changing reflection pattern while thawing or freezing is underway.

Developing a wireless sensor that detects the solid-liquid transition can have significant impact on the frozen food industry and the transportation industry that uses refrigerated trucks to transport them (called the cold chain). Today, freezers are monitored using thermometers which are only a proxy for ensuring that food remains frozen. Temperature differentials, blocking of cold-air vents, different additives in foodstuff that change the melting point, external heat sources, or other variable factors can significantly affect the temperature in different zones, meaning that thermometers alone are not enough to ensure that the food remains frozen. Reversing the context, when cooking food, ensuring that the food was fully thawed is important for maintaining both food taste and texture. Further, consuming food within a certain time after it has thawed is important for food safety as it brings a significant health risk if not properly consumed in time. Microwave ovens are particularly inefficient (due to the lower complex permittivity) when heating frozen foods, while convection heaters would be more efficient. In a completely different application, both microwaves and freezers have a defrost mode. Understanding when food has fully thawed in a microwave and when the surface frost has been removed from the freezer would be particularly useful for next generation smart freezers and microwaves. Overall, there is significant utility in developing a solid-liquid state transition sensor.

To the best of our knowledge, there does not exist a state transition detector that would work through food packaging. Opportunities of determining state are few. Density changes, changes in form, or changes in conformance of food would all require direct access to the food. However, most food is inside some form of packaging which itself could be rigid and provide enough space within itself for expanding food as it freezes, meaning, merely observing the packaging for changes is not enough. Further, infrared thermometers, which can detect differences in temperature over a certain area, would still only provide information about the external temperature of the packaging. Thus inaccessible food makes the state transition detection a difficult problem. In contrast, microwave-range frequencies easily penetrate through most packaging materials such as paper, cardboard, plastics, and glass. They can therefore directly interact with the food through the packaging. Additionally, since the complex permittivity dramatically varies between ice and water, the signal reflection also dramatically changes as the food undergoes state transition.

This paper extends our preliminary report [2] to now include a similarity score based state-transition detection methodology without touching the food, and even when the food is placed in an unstructured manner inside an enclosed space. Note that we have not developed an ice or water detector, but rather only a state-change detector.

II. BACKGROUND

A. Propagation of Wireless Signals

When wireless signals are emitted by a transmitter, they spread in all directions, with some fraction arriving directly at a nearby receiver, while most bouncing off various obstacles and reflectors

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in the vicinity, before subsequently arriving at the receiver. If the wireless signal was an impulse, the time-domain representation of the delayed arrival of these signals would describe the response of the wireless *channel* to the transmitted impulses. This power-delay profile is called the channel impulse response (CIR). We use ultra-wideband (UWB) radios that transmit raised cosine pulses specified by the IEEE 802.15.4z [3] standard and compute the CIR from the received signal. The wireless reflections experienced by the UWB signals is subject to the placement or location of various materials in the vicinity and the signal's physical interactions with the material. During solid-liquid state-transition, the physical properties of the material undergo changes, that affect the reflection and absorption of signals. As a result, the obtained CIR also changes; detecting these changes forms the basis of our wireless sensor.

B. Primer on Complex Permittivity

The complex permittivity of a material $\epsilon^* = \epsilon' - j\epsilon''$ describes the interaction of electromagnetic signals with materials. The real part ϵ', representing the material's ability to store electrical energy, and the imaginary part ϵ'', indicating energy dissipation, are both crucial in understanding how electromagnetic waves are affected by materials [1], [4]. During the thawing process, the ice-water transition results in notable changes to ϵ', significantly affecting signal propagation.

C. Interaction of Wireless Signals with Materials

When a traveling wave encounters a material, only a fraction of its energy penetrates into the material, called the transmittance of the substance. This fraction, t_E relates to the intrinsic impedance of the abutting materials as follows: $t_E = \frac{2Z_2}{Z_1+Z_2}$, where Z_1 and Z_2 are the intrinsic impedances of the leaving and entering in materials respectively. The intrinsic impedance is dependent on the material's complex permittivity (ϵ^*), given by: $Z^* = \frac{Z_0}{\sqrt{\epsilon^*}}$, where Z_0 is the impedance of free space.

If the complex permittivity of a substance changes, so does the signal's ability to penetrate into and reflect from the substance. Solid-liquid state transition of water causes a substantial change in its complex permittivity which also affects water-based beverages, and substances that contain substantial amounts of water, covering a vast majority of food items. This causes wireless signals to reflect differently providing us with a novel ability to detect thawing and freezing and the transition in-between.

III. RELATED WORK

Identification of materials using wireless sensing has recently gained significant attention, leading to several innovative solutions in this area. Perhaps closest to our work is the work by [5] which uses chipless RFID time-temperature sensors to perform cold-chain integrity monitoring for cooking oils. Their technique relies on phase shifts due to melting of cooking oils. Similarly, RF-EATS [6] is a system capable of sensing food and liquids in closed containers without direct contact, using passive backscatter tags to non-invasively identify container contents in diverse indoor environments. In a completely different context, [7] explores use of millimeter wave radiometry for characterizing water freezing and ice melting dynamics for environmental monitoring, especially pertinent in the context of global warming. In contrast, we have developed an IoT sensor system, which employs ultra-wideband (UWB) wireless signals to non-invasively detect the solid-liquid state transitions of food items by leveraging the large shift in complex permittivity during ice-water phase transition.

Further contributions to this domain include leveraging wireless signals for material identification [8]. In a similar vein, TagTag [9] employs RFID signals for fine-grained material identification, based on material-specific RF-phase changes. Further, TagScan [10] explores simultaneous target imaging and material identification using RFID. Similarly, LiquID [4] uses UWB signals for liquid identification. IntruSense [11] relies on CIR stability, in a manner similar to ours, however, it does so in the context of physical intrusions. However, none of these prior arts have explored solid-liquid transition which uThaw specializes in.

Our paper extends these innovations by harnessing ultra-wideband (UWB) wireless signals for detecting solid-liquid transitions in food, addressing the limitations of scalability and direct applicability in diverse conditions. By leveraging significant permittivity changes during state-transitions, our system offers a non-invasive, cost-effective, and broadly applicable solution for monitoring thaw processes, even through packaging, contributing to food safety within cold chains.

IV. SYSTEM DESIGN AND CHALLENGES

Our system, called uThaw, comprises a UWB transmitter and receiver placed within a small enclosed space. Figure 1 shows the overview of the uThaw algorithm. The transmitter sends UWB packets which are received by the receiver and analyzed in terms of the obtained signal reflections (as obtained from the CIR). The receiver builds a history of the obtained CIRs computing a long-term average. If the enclosed space remains undisturbed and the materials continue to remain in their original state, either frozen or thawed, every newly obtained CIR closely matches the long-term average. We have developed a simple similarity metric that first aligns the newly obtained CIR with the long-term average CIR using the first direct path between the transmitter and the receiver, represented by the first peak in the CIR. We then compute the L1 norm of the difference in the two CIRs. A low L1 norm is indicative of high similarity, while a high L1 norm is indicative of low similarity between the current CIR and the long-term average.

A low similarity indicates something has changed from the previous average. We assume we have an independent switch that triggers whenever the enclosure was opened, which would indicate new food being added or removed from the enclosure. Such an event triggers elimination of the previous long-term average and re-computation of a new average CIR. If the similarity drops without a trigger from the door-open event, a state transition is identified. It is then expected that subsequent CIRs will also mismatch with the long term average, but will also mismatch with each other as state-transition progresses. Finally, when the entire material has transitioned into a new state, consecutive CIRs start to match with one another once again and form a new long-term average. The time over which the long-term history is calculated is a tunable parameter, depending on the exact application space.

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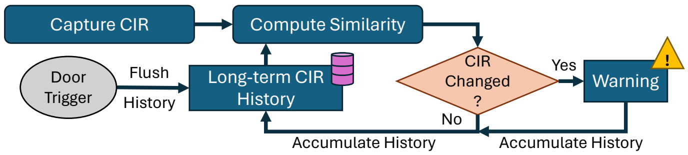

Fig. 1. Overview of uThaw algorithm: raises an alarm when thawing occurs.

A. *Adapting uThaw for Diverse Applications*

To generalize uThaw's applicability to different freezer enclosures and material configurations, the following considerations are key:

1) Variations in Freezer Volume and Internal Configuration: Larger enclosures may introduce additional signal reflections and multipath effects, requiring recalibration of the similarity metric to handle more complex CIR profiles. The placement of objects (e.g., shelves, containers) can also affect reflections. Adaptive filtering or dynamic modeling techniques could mitigate such challenges in future implementations.

2) Enclosure Material and Properties: The material of the freezer (e.g., metal, plastic, or cardboard) influences UWB signal propagation. Metal enhances signal confinement (and is therefore preferred), while plastic and cardboard may permit signal leakage and external influence. We expect future work to deal with external influence via careful truncation of the obtained CIR.

3) Distribution of Water/Ice Within Food: Foods with uneven water distribution (e.g., mixed vegetables) exhibit variable thawing patterns. While our results indicate detectability even for such cases, future work will refine the system for highly heterogeneous foods. Addressing these variations will further improve generalization.

V. EXPERIMENTAL SETUP AND IMPLEMENTATION

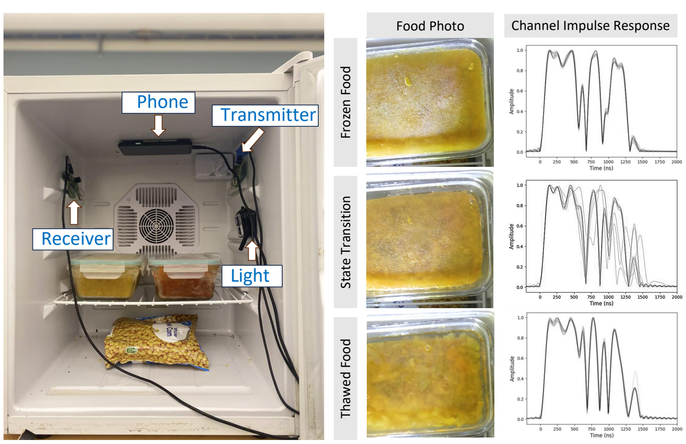

Fig. 2. uThaw data collection platform: a UWB transmitter, UWB receiver, a phone for capturing video, and an LED light, inside a small freezer.

Our data collection platform is low-cost (sensors cost less than $50) and requires minimal processing power. Figure 2 shows our uThaw platform placed inside a small fridge. Two UWB devices—each using a DWM1000 UWB module [12], [13] controlled by Cortex M0 processor [14]—are installed in the fridge, with the receiver's data sent via USB cable to a Dell Laptop for processing in Python (not shown in the figure). We are able to observe the thawing of the food placed inside the fridge using a phone camera and the food is lit-up by a dedicated, always-on light.

VI. EVALUATION

We evaluate uThaw by recording (i) the thawing of a block of ice, and (ii) the thawing of food in glass containers and a bag of corn all kept in the fridge simultaneously. First, we investigate the feasibility of detecting state transitions by checking the stability of the CIRs for fully frozen and fully liquid states, followed by the results from our similarity metric.

A. *Stability of CIR inside the enclosed space*

An important premise of this work is that the channel impulse response (CIR) as observed by UWB devices inside the closed container, say a refrigerator or a microwave oven, will be quite stable over time, so long as there are no changes to the contents of the enclosed space.

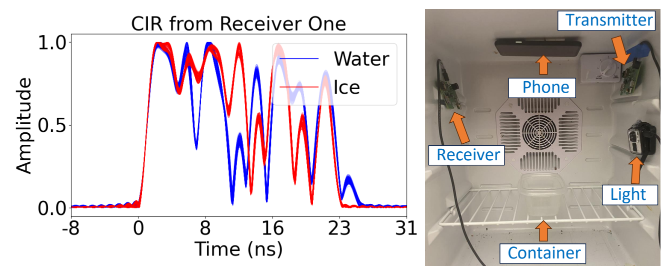

Fig. 3. CIR of water (blue) and ice (red) from receiver one.

We show in Figure 3 the CIRs collected by our setup for ice and for water after the ice has completely thawed. Observe that all the CIRs obtained during any one state overlap well with each other, meaning that the UWB signals are experiencing very similar reflection and refraction patterns for both states. We observe similar stability when food is introduced in the refrigerator (experiment (ii)), but do not include the graph for brevity. The freezer being an enclosed metal box, various external movements, for example of the researcher moving around in the lab, has no influence on the observed CIR inside the enclosed container.

B. *Unpacking Similarity Indices: Insights and Requirements*

The Cumulative Distribution Function (CDF) quantifies the distribution of similarity scores across different experimental states—frozen, thawed, and transitioning. The similarity score is computed as the L1 norm of the difference between the newly observed CIR and the long-term average CIR, normalized and max-subtracted.

Each plot in Figure 4 is built from similarity scores calculated for multiple CIR samples collected during the experiments. Specifically:

- For the frozen state, we compute the similarity score of all frozen-state CIRs against their respective frozen-state long-term average.
- Similarly, for the thawed state, we compare all thawed-state CIRs against the thawed-state long-term average.
- For the transition state, we calculate similarity scores against both frozen and thawed long-term averages, leading to lower similarity values.

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To ensure accurate similarity analysis, sufficient data is required for computing stable long-term averages. In our experiments:

- **Frozen State:** A minimum of 100 CIR samples, collected over 10 minutes, were used to establish the frozen-state long-term average.
- **Thawed State:** An equivalent number of CIR samples were collected post-transition to compute the thawed-state average.
- **Transition State:** Continuous CIR sampling (over 20–30 minutes) was performed to detect deviations from the initial frozen-state average.

Providing these thresholds ensures accuracy in similarity analysis while minimizing false positives caused by environmental disturbances. However, the rate of CIR collection and the stable CIR collection duration can be tuned based on application needs.

C. Observing state transition as a similarity score

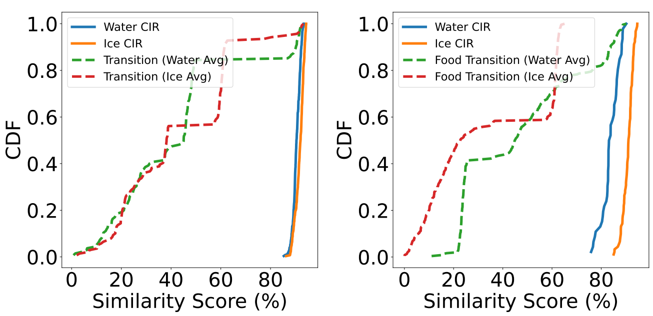

Fig. 4. CDF of similarity scores comparing CIRs to respective long-term averages. (Left) Ice-water transition. (Right) Frozen-thawed food transition. Each plot uses similarity scores from CIR samples normalized against their respective long-term averages.

We use an L1 norm of the difference of the CIR and the long term average to detect state transition. We overlap the long term average CIR with the current CIR and compute a per-tap difference. Summation of this difference is expected to be very small for CIRs that are similar to each other, while quite large when the CIRs have a significant mismatch. A normalized max-subtracted score is then computed. This work differs from our one-page poster [2] where the promise of this approach was showcased. In this work, we focus on state transition, and as such are most interested in determining when recently obtained CIR data starts to diverge from the long-term average observed previously. We have therefore, devised a simplistic similarity metric to aid this comparison. Figure 4 shows the CDF of the similarity scores. We observe in Figure 4 (left), that all CIRs during the ice-state produce a high similarity score with the ice long term average. Similar consistency is observed for water as well. During the transition, however, similarity score drops drastically differing from both the ice average as well as the water average. Depending on the kind of food and homogeneity, some temporal stability may be observed where the CIR remains similar during transition, most likely when only a small amount of ice remains stuck to the container as thawing occurs from the sides.

D. Observing state transition for food

Frozen food shows similar behavior to what we observed for pure ice-water transition. Figure 4 (right) shows the similarity CDF for the frozen and fully thawed food and also shows the lower similarity score when the thawing process is underway.

VII. CONCLUSION

The paper demonstrates the application of UWB wireless signals in detecting the ice-water transition in food items without direct contact. The experimental setup and implementation, employing low-cost off-the-shelf devices, validate the feasibility of the proposed system in real-world scenarios. The stability of the CIR and the distinct signal patterns associated with different states of water in the food show the effectiveness of this approach, though our settings are limited in size. Our findings hold significant promise for improving food safety protocols, optimizing cooking and thawing processes, and potentially transforming the monitoring practices within the frozen food and cold-chain logistics industries. Future work could focus on refining the system for commercial or household use and exploring its application in use-cases beyond the freezer, including microwave ovens, traditional oven, thawing trays, or even industrial conveyor belts where progressively food is cooled down to freeze it or warmed up to thaw it for further processing. Additionally, further refinements are required for broader applicability to diverse enclosures and packaging materials (e.g., metal, cardboard).

VIII. ACKNOWLEDGMENT

This work is partially supported by the NSF under grant 2145278 and NSF Graduate Research Fellowship.

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