Md. Farhan Tasnim Oshim and Julian Killingback *Manning College of Information and Computer Sciences, University of Massachusetts Amherst, MA*
Dave Follette *Institute for Applied Life Sciences, University of Massachusetts Amherst, MA*
Huaishu Peng *Department of Computer Science, University of Maryland, College Park, MD*
Tauhidur Rahman *Halıcıoğlu Data Science Institute, University of California San Diego, CA*

Editor: Nirupam Roy

BUILDING MechanoBeat: Instrumenting Mechanical "Heartbeats" on Everyday Objects for User Interaction

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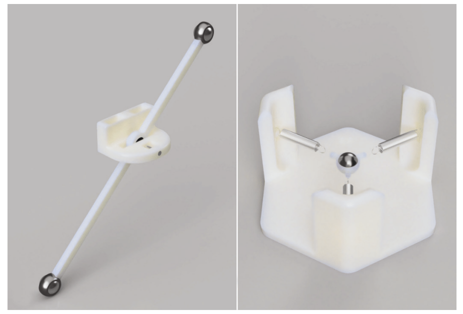
Knowing how and when people interact with their surroundings is crucial for constructing dynamic and intelligent environments. Despite the importance of this problem, an attainable and simple solution is still lacking. Current solutions often require powered sensors on monitored objects or users themselves. Many such systems use batteries [1-3], which are costly and time consuming to replace. Some powered systems connect to the grid, which may save swapping batteries, but at the price of restricted placement options. Other solutions use passive tags on monitored objects or require no tags at all, but many of these systems have prohibitive characteristics. For instance, camera-based systems [4,5] generally will not work if their view is occluded. Many other systems that rely on passive tags or do not use tags require direct line-of-sight or close proximity to work. As such, our goal was to design and develop small, cheap, easy-to-install tags that do not require any batteries, silicon chips or discrete electronic components, which can be monitored without direct line-of-sight.

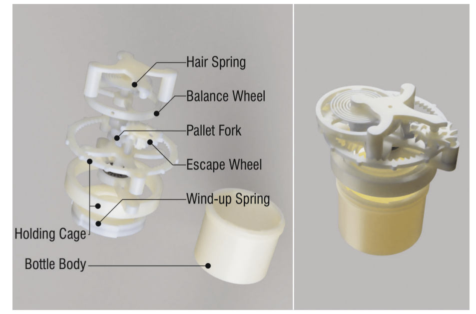
We propose *MechanoBeat*, which provides a solution that leverages the sensing capabilities of ultra-wideband (UWB) radar to detect unique harmonic oscillations or "heartbeats" produced by ultra-low-cost tags. These tags can be mounted on various stationary or movable objects and are monitored remotely by UWB radar boxes, which sense when a tag is activated. We explore various oscillation-based tag designs that allow for both stationary and mobile use cases. All of our tags can be printed on hobbyist grade 3D printers using various plastic filaments and can be adapted easily for injection molding. Our proposed tag designs can be manufactured for well below a dollar and require no power and minimal maintenance.

The proposed tags can be classified into two categories: stationary tags and mobile tags. Stationary tags can be used to detect interactions with stationary objects, for instance, kitchen appliances (freezers, microwaves, cabinets, drawers, etc.), washing machines, water faucets, and so on. These interactions are important for creating life logs, smarter homes, smarter workplaces, and potentially facilitate ambient assisted living. On the other hand, mobile tags can be attached to pill bottles, sugar jars, water bottles, etc., to track individuals' medication routines, sugar intake, and hydration status, respectively. To learn when and where tags are activated, we develop a deep learning classification pipeline, which takes radar data as input and outputs the tags that are currently active. We show empirically that our pipeline is robust to environmental noise and capable of inferring tag activity even when the radar is obscured. Furthermore, we demonstrate the versatility of our deep learning pipeline to detect a variety of tags in many potential use cases.



(a) (b)

FIGURE 1. Stationary tag design: (a) Pendulum-based tag and (b) linear spring-mass tag.



(a) (b)

FIGURE 2. Mobile tag design: (a) Tourbillon bottle tag explosion view and (b) assembly view.

TABLE 1. Different combinations of arm lengths to generate different frequencies for the pendulum-based tag.

$T = 2\pi\sqrt{\frac{l}{g\gamma}}$	*Single Ball*					*Double Ball*				
Version	*A*	*B*	*C*	*D*	*E*	*F*	*G*	*H*	*I*	*J*
Long Arm (mm)	40	60	80	28	42	40	60	80	100	100
Short Arm (mm)	0	0	0	0	0	28	42	56	70	80
Gravity Ratio (γ)	1	1	1	1	1	0.3	0.3	0.3	0.3	0.2
Frequency (Hz)	2.5	2.0	1.8	3.0	2.4	1.4	1.1	1.0	0.9	0.7

MechanoBeat: SYSTEM OVERVIEW

Design Considerations

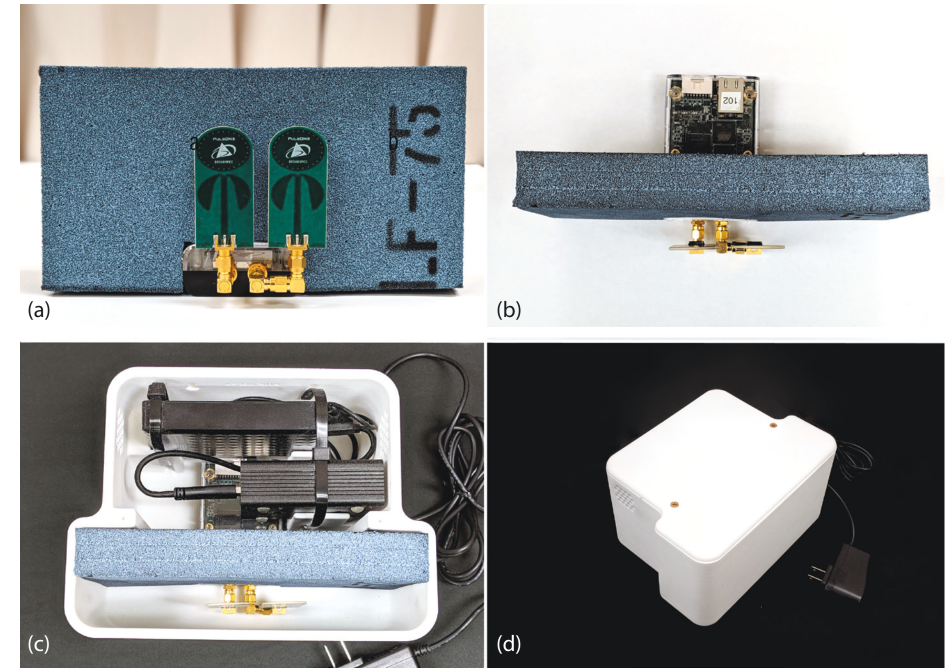
Before explaining our technical approach, let us discuss a few specific design considerations that went into the development of the MechanoBeat tag and sensor system.

1. We aimed to design and develop a low burden mechanism for recognizing interactions between humans and everyday objects with simple, low-cost tags and contactless sensors.
2. We required the tags to trigger a specific oscillation pattern with unique spectral characteristics at the moment of human-object interaction for a short period. Moreover, a reset mechanism can mark the end of the interaction and allow differentiation between two consecutive interactions with the same object.
3. Our goal was to make low-cost tags with small form factors that are scalable. Commodity desktop 3D printers offer readily scalable solutions for printing mechanical tags with cheap materials. The tags should be compatible and easily attachable to different everyday objects of interest. Lastly, the tags should be durable and reusable, which can provide us with a sustainable and a long-lasting human-object interaction tracking solution.
4. The sensing system should not require additional instrumentation of the user's body. The system should be able to detect active tags during human-object interaction in noisy and real-world conditions. Most importantly, in a real-world setting, there is no guarantee that a direct line-of-sight can be established between the sensor and the tags. Thus, our system should be able to have high accuracy even when the tags are obscured (non-line-of-sight scenario).

Based on these design considerations, we aimed to design, develop, and validate an approach that uses electronics-free 3D printable simple mechanical oscillators along with a UWB radar-based contactless sensor array. MechanoBeat leverages the P440 UWB radar operating at 3.1-4.8 GHz frequency that can see through different objects and detect human-object interactions happening behind a wooden or cardboard partition and even behind walls. We leverage multiple UWB radar units placed at different locations to observe human-object interactions from multiple points of view. The complementary signals are then fused to achieve better detection accuracy.

MechanoBeat Tag: Harmonic Oscillator

The simple harmonic oscillator designs that we explored in this work as MechanoBeat tags can broadly be classified into two types: stationary and mobile tags. The stationary tags are appropriate for tagging stationary objects, such as a drawer, door, or cabinet.



(a) (b) (c) (d)

FIGURE 3. (a) P440 MRM radar module with an absorber behind the antenna. (b) Top view of the radar with an absorber. (c) Radar Box with Raspberry Pi and a hard disk drive. (d) Enclosed radar box.

MECHANOBEAT LAYS THE FOUNDATION FOR DEVELOPING PHYSICS-INFORMED DESIGNS OF ELECTRONICS-FREE TAGS

On the other hand, the mobile tags can be used to tag objects that move with the user, such as a pill bottle, water bottle, or a sugar jar.

Stationary Tags: Since the user-object interaction mechanism for stationary objects (e.g., a drawer is opened and closed by applying outward or inward horizontal force) does not change over time, simple oscillators including a pendulum and a spring-mass can be used with an easy mounting technique. Another advantage is that once these simple tags are mounted to a fixed location, the direction of gravity does not change over time. As a result, simple tags that are comprised of a pendulum or spring mass oscillator maintain their periodic cycles. Figure 1a shows a pendulum-type tag design which includes two arms with length *l*. To tag multiple objects with this pendulum design, we need a scalable approach to design unique oscillation frequencies. To this end, we can either use a single ball option by attaching a weight to the lower arm and keeping the other arm free, or we can have a double ball option with weights at both arms. Both options offer unique oscillation frequencies. Table 1 illustrates examples of different pendulum-based tags and associated design parameters to produce unique frequencies in the range of 0.7 Hz to 3 Hz. The oscillation frequency is calculated as the inverse of the time-period found in $T = 2\pi\sqrt{\frac{l}{g\gamma}}$. The gravity ratio γ comes into play when we create a double ball tag with different arm lengths and can be calculated as $(long - short)/long$. This factor reduces the effect of gravity and increases the length of the period causing lower oscillation frequencies for tags with weights in two arms compared to the single ball option. Pendulum-based tags with both a single ball and double balls provide us with the opportunity to create distinguishable tags in a variety of oscillation frequencies.

Figure 1b shows another stationary tag, a linear spring-mass design (upside down). We attach a magnet to the bottom of the object we want to interact with (pill bottle, sugar jar, water bottle, etc.) and place it on top of the tag. The metallic ball at the center of three springs will be attracted to the top. The tag activates when the object is taken off the surface of the tag, causing the metal ball to oscillate at a unique frequency determined by the spring constant (k) and mass (m) of the ball $T = 2\pi\sqrt{\frac{m}{k}}$. Using different springs with varying spring constants, we can design more tags for large scale use.

MOBILE TAG EXPERIMENTS

Although pendulum and spring-mass tags are reliable for stationary setups, they are not robust to mechanical disturbances, such as a sudden change of position or orientation. Thus, they are not suitable for mobile settings where the tagged object may shift its 3D location in the environment.

Our mobile tag draws great inspiration from a tourbillon design, which has been used in mechanical watches for centuries to maintain accuracy against drag due to gravity. A basic tourbillon design (Figure 2a) has a holding cage, a wind-up spring, and a core revolving structure including a balance wheel, a pallet fork, an escape wheel, and a hairspring. The balance wheel is the "beating heart" of the tourbillon, which is analogous to the pendulum or spring-mass in the stationary tag design. It oscillates around its axis and is regulated by the connected hairspring. The key to the tourbillon design is to make the balance wheel revolve around the central axis of the entire holding cage, canceling the applied gravity effect. This is achieved by connecting the balance wheel to an escape wheel via a pallet fork. While the balance wheel oscillates on its own axis, the rotational motion is transmitted to the escape wheel, which drives the entire core structure to revolve around the holding cage, one tick at a time. The energy of the constant ticking motion is from the wind-up spring. Figure 2b shows our design, which integrates a printed tourbillon tag (based on Thingiverse Thing ID: 2751917) to a threaded pill bottle lid. The tourbillon's holding cage serves as the bottle lid and the wind-up spring can be fixed to the inner wall of the bottle body when the bottle lid is put on. When the lid is opened or closed, the twisting motion of the lid will wind the spring, driving the tourbillon to revolve. Note that different unique oscillation frequencies can be ensured by adjusting the balance wheel, the hairsprings, and the ticking steps of the escape wheel.

MechanoBeat Sensor: UWB Radar

MechanoBeat uses PulsON 440 (P440) ultra-wideband radar [6] in monostatic mode. The operating frequency of the radar ranges from 3.1 to 4.8 GHz with the center frequency at 4.3 GHz. Due to wide bandwidth and therefore extremely short pulse duration (nanosecond level), UWB radars have very high range resolutions, which make them appropriate for fine-grain sensing applications like monitoring vital signs and sensing harmonic oscillations.

As shown in Figure 3a, the P440 unit has a transmitter and a receiver antenna. To scan a target living space, the transmitter antenna repeatedly transmits a low energy, short-duration impulse signal, which gets reflected by different stationary objects (e.g., furniture and other static clutter), moving objects (e.g., MechanoBeat tags, fan), and the human body. The backscattered impulse signal is received by the receiver antenna and the time-of-flight (ToF) of these received pulses is estimated from the round-trip propagation delay, which is then used to calculate the target's distance by multiplying with the speed of light. The backscattered impulse signal from multiple scans is stacked together to form a two-dimensional radargram, which is used to detect the oscillation of different active MechanoBeat tags. Figure 4 illustrates a sample radargram signal in the form of an image. The oscillating pendulum based MechanoBeat tag was placed at roughly one meter from the radar, which corresponds to the 55^{th} range bin. Here, the horizontal axis indicates the distance or range bin number, also known as the fast time. Along the vertical axis from top to bottom, the scan number increases. This axis is also known as slow time (in seconds). The raw radargram signal captures reflections from all the objects (both moving and stationary)

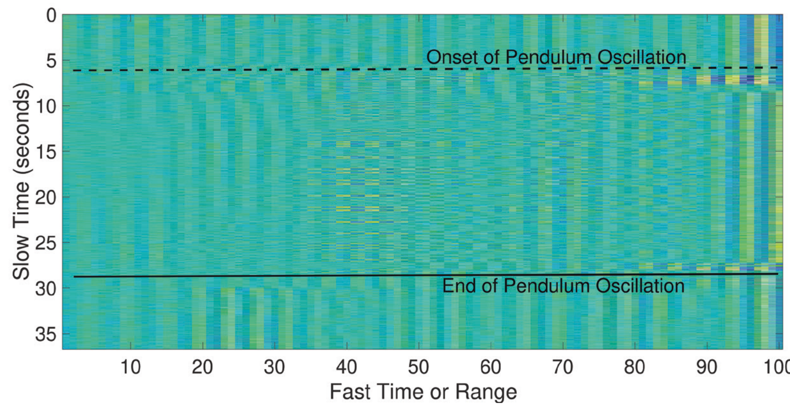


FIGURE 4. Radargram of a pendulum based MechanoBeat tag oscillation.

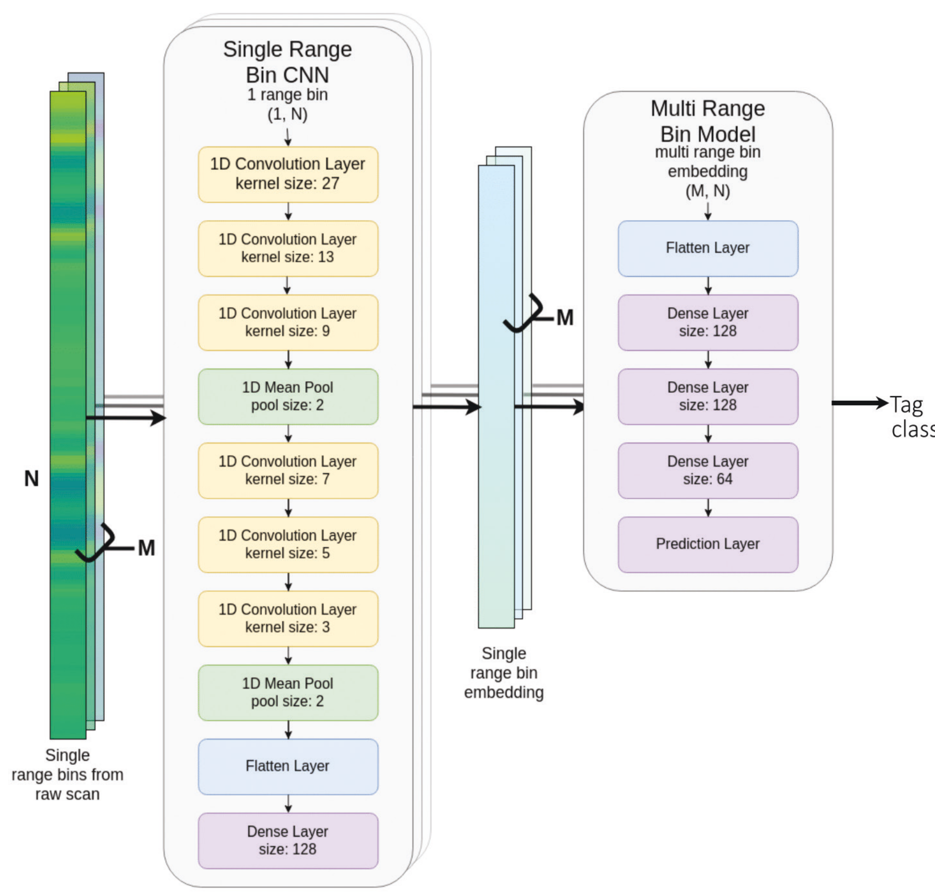


FIGURE 5. Deep learning classification pipeline.

at different distances or ranges. If we observe closely (between the onset and the end of oscillation in Figure 3), we can see periodic changes due to the active MechanoBeat tag.

The radar antennas are omnidirectional, so a microwave absorbing material of dimension 8.5″ x 4.5″ x 1.13″ is placed at the back of the antennas to attenuate the signals from behind the radar. The absorber material we used is a commercially available *LF75* absorber, which provides attenuation of -20 dB for a frequency range of 2.5 GHz to 40 GHz. The PulsON 440 UWB radar unit, the absorber material, a Raspberry Pi unit, and a hard disk drive to store the data locally are placed in a 3D printed T

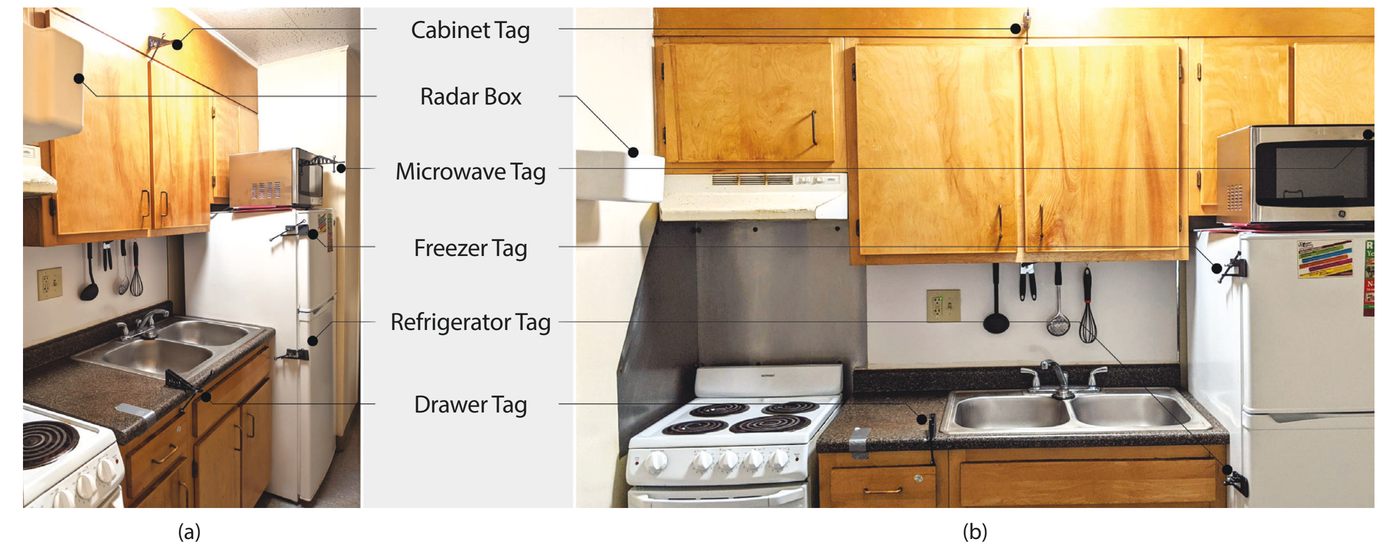


FIGURE 6. (a) Side view and (b) front view of the kitchen with instrumented pendulum-based tags.

shaped box as shown in Figure 3b-d. The radar data collection program written in C is run on the Raspberry Pi in the background and stores each minute of data locally with corresponding timestamps.

MechanoBeat Sensing Pipeline

The sensing pipeline starts from the radargram data (as shown in Figure 4), which contains reflections from both stationary (e.g., walls, furniture) and moving objects (e.g, Mechano-Beat tags, fan, human movements) in the living space. Each column of the radargram matrix can be considered as a time series signal corresponding to a single range bin. This time domain signal contains reflection information from different stationary and moving objects at that particular range bin. To get rid of the stationary components as well as the unwanted higher frequency oscillation from different machines or appliances (e.g., fan or air-conditioner), we apply a bandpass IIR filter on the time domain signals of each range bin across different scan numbers or slow time. Thus, the filtered radargram only preserves the operating frequency range of the tags and removes all undesirable frequencies.

To train a user-object interaction classifier based on the tag frequency, first we window the radargram signal across the slow time or scans. Instead of using all the range bins, we focus on a specific window of range bins (i.e., focus range region). Since each tag is located in a small portion of the range covered by the radar and the tag's oscillation signal is subtle in nature, focusing on a window of range bins allows the subtle tag frequency to be preserved. Moreover, similar to the windowing across slow time, which allows the classifier to detect an active tag over time, the windowing across fast time or range allows the classifier to automatically locate the position of the tag.

Modeling with Deep Learning Approach

As single range bin inputs have only one dimension, time, we adopted a one-dimensional convolution neural network (1D CNN) architecture. Our 1D CNN model has a total of six 1D convolutional layers. Each layer contains 64 kernels, uses a ReLU activation function, and has a stride length of 1. The convolutional layers are split into two sections that are separated by a mean pool layer. The first section has kernels of length 3, 5, and 7. The mean pool layer has a pool size of 2 and a stride length of 2. The second section has kernels of length 9, 13, and 27. After the second convolutional section, there is a second mean pool with a size of 2 and stride of 2, then a flatten layer followed by a fully connected layer with a ReLU activation function and size 128. A final fully connected prediction layer consists of a softmax or sigmoid activation function and a size equal to the number of classes. We use softmax for all experiments except the multiple tag classification experiment, in which we use sigmoid. The loss is categorical cross entropy for all experiments except for multi-tag classification, in which the loss is binary cross entropy. For all experiments, the optimizer is Adam using the default parameters in TensorFlow.

A minimal stride length is used to preserve as much information as possible in each layer. We found that 64 kernels gave us minimal overfitting while still providing low validation and test loss. In order to reduce further over-fitting, we introduced spatial dropout with a dropout rate of 0.1 between the first and second convolutional layers, as well as a spatial dropout with a dropout rate of 0.05 between the second and third convolutional layers in both convolutional sections.

Input is a single range bin for a given time window of length N. The small time-window allows the model to detect short lived oscillations enabling greater freedom in tag design and future applications. After the single range bin model is trained, the prediction layer is removed and all layers are frozen. At this point the model outputs an embedding of length 128 for each range bin inputted. The embedding for each range bin in each time window is then combined to get a 128 x M embedding for the entire time window.

The second step of our deep learning pipeline takes a 128 x M embedding as input and outputs the final tag class. For this step a simple fully connected neural network model is used, which we will refer to as the mutli-range bin model. The first layer in the model is a flatten layer, followed by three dense layers of size 128, 128, and 64 each with a ReLU activation function. Between each of these layers is a dropout layer with a dropout rate of 0.1. The final layer is a prediction layer with a softmax activation function and a size equal to the number of classes. The loss for the multi-range bin model is categorical cross entropy and the optimizer is Adam using the default parameters in TensorFlow.

REAL WORLD DEPLOYMENT WITH STATIONARY TAGS

To test MechanoBeat in a real-world scenario, we deployed MechanoBeat tags in a kitchen environment. We outfitted a drawer, cabinet, freezer, refrigerator, microwave, and counter-top with pendulum and spring-mass based tags. Each tag has a unique oscillation frequency, which was achieved by varying the arm length (i.e., 40, 60, 70, 80, and 100 mm) and spring-mass weight.

One UWB radar box was placed on the stove-side wall and a second radar box was placed on the wall opposite to the kitchen hallway. Both radars were placed a distance of at least one meter away from the closest tag. The location of each tag and UWB radar boxes can be seen in Figure 6. Figure 7a-c shows how each pendulum-based tag was attached to a given appliance, cabinet or drawer. Figure 7d shows a condiment storage rack instrumented with a spring-mass-based tag and a magnetic reset mechanism.

All tags were attached to a stationary part of their corresponding appliance. Each tag was activated when its application door was opened, or in the drawer's case when the drawer was pulled out. Opening an application's door releases the oscillator arm, thus activating the tag. After the interaction is over, we have a reset mechanism to stop the oscillation. When the cabinet/drawer is closed the oscillator arm is held in place by the door/drawer. The freezer and refrigerator use a secondary part called a reset arm which attaches to the freezer/refrigerator door. When the door is closed, the piece holds the pendulum up so it cannot swing. When the condiment is taken away from the rack, the spring-mass oscillation is activated for a period of time until it dies out. As soon as

FIGURE 7. The (a) cabinet, (b) microwave, and (c) refrigerator are instrumented with pendulum-based tags. (d) A condiment bottle is instrumented with a linear spring-mass tag.

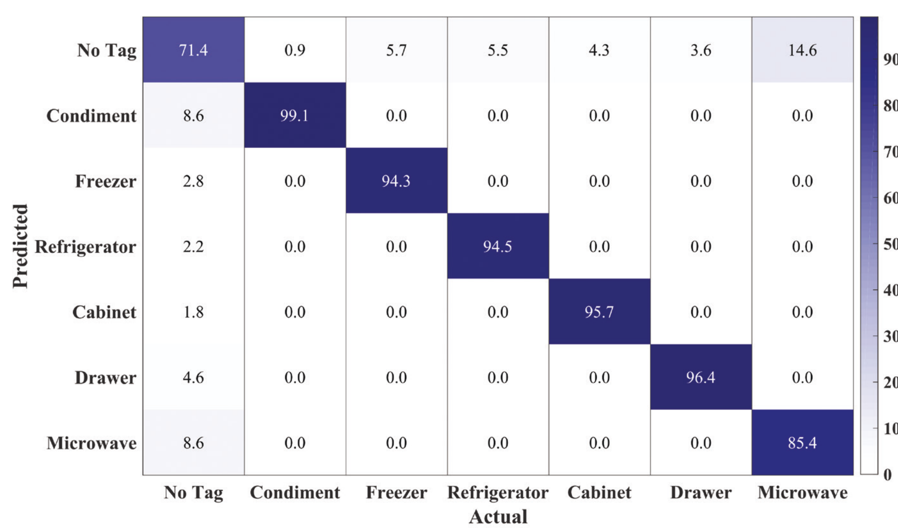


FIGURE 8. Confusion matrix for the stationary kitchen tags.

the condiment bottle is replaced in the rack, a magnet attached to the bottom of the bottle attracts the mass back to its initial position.

Each experiment started with 10 seconds in which no tag was active. Then the tagged appliances were interacted with for 10 rounds. Interaction with the appliances involves opening and closing the appliance door. On average, the interaction duration (time span between opening and closing) was approximately 10 seconds. We refer to each round of appliance interaction as a cycle, i.e., collecting 10 cycles of data means 10 independent interactions with that appliance. We recorded the start time, end time, tag location, and interaction time for each cycle so that we have ground truth data for use in evaluation and training of the tag activation detection and classification model.

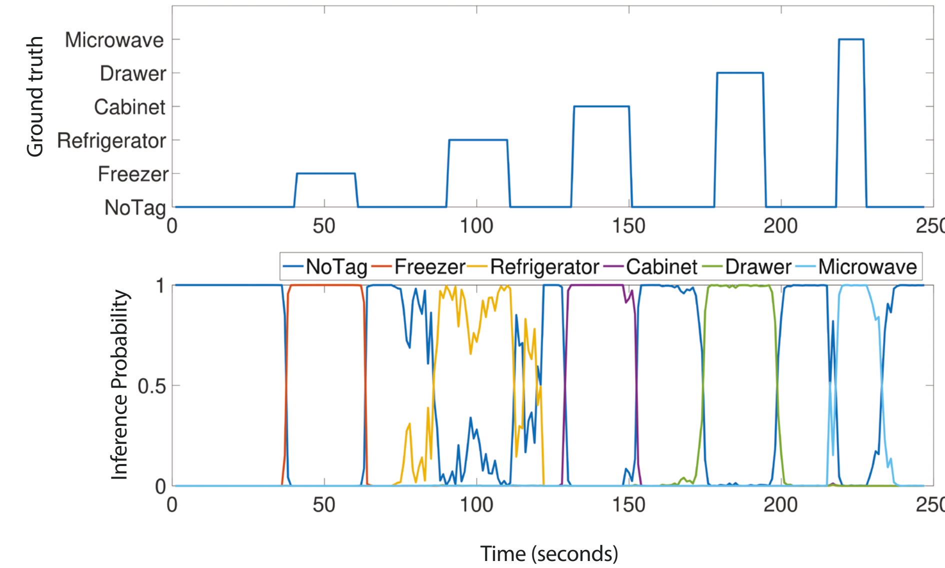


FIGURE 9. A sample recording.

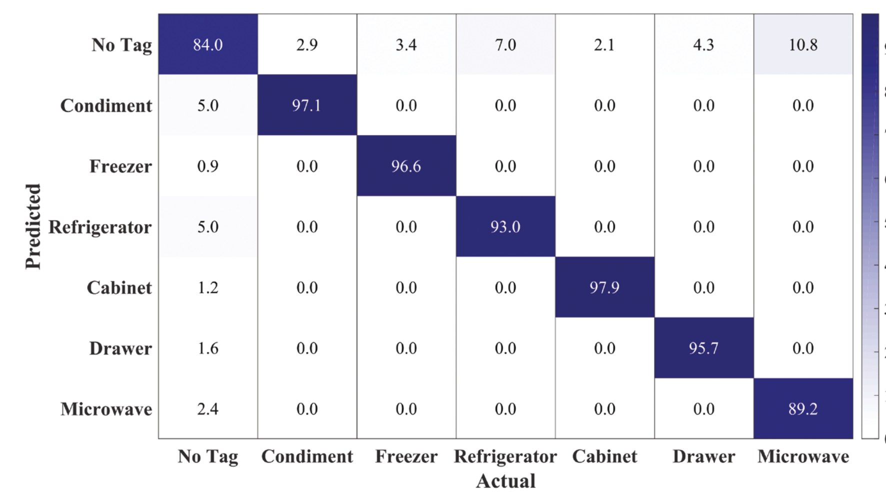


FIGURE 10. Confusion matrix for the stationary kitchen tags in a NLOS scenario.

Tag Detection and Classification

We fine-tuned a 1D CNN that had been pre-trained on data collected from pendulum and spring experiments. The multi-range bin model was trained from scratch. In order to incorporate data from both radars in our model, we average the concatenated single range bin embeddings before passing them to the multi-range bin model. We used a three-second time window with a one second shift to convert our continuous time series data to discrete instances, which we provide to our model. For each instance, we provided the model with range bins starting at the tag location minus 50 and ending at the tag location plus 50.

When training the entire pipeline, we used leave-one-cycle-out cross-validation, wherein one cycle from each tag was held out for testing and another cycle held out for validation. All other cycles were used for training. We calculated the confusion matrix for each held out test cycle and summed all confusion matrices to get the results in Figure 8.

Our results show that MechanoBeat is able to accurately differentiate the various tags despite their close proximity to one another. Additionally, MechanoBeat could distinguish between no tag and tags with good accuracy. It is important to keep in mind that there is some lag between when a participant is instructed to start and end an interaction with an appliance and when the interaction starts and stops. As such, some instances that we labeled as no tag may have contained an active tag and vice versa. Thus, what is more important than the absolute accuracy compared with our ground truth is that for each instance MechanoBeat is able to detect the correct tag and shows no tag before and after the instance. We demonstrate this characteristic for a single recording in Figure 9 in which our system is able to infer the correct tag at the right moment and has instances of no tag between each sequence attributed to a tag. As the figure shows, there is generally a slight decrease in the probability of the tag towards the end of the active period. We attribute this to the decreasing displacement of the oscillating tag arm over time.

Through Wall Sensing

In the real world, it is not always convenient or possible for a radar box to have a clear view of a given tag. Obstructions are common in indoor environments and can include walls, furniture, and people. In order to show that MechanoBeat is robust to such occlusions, we conducted the stationary tag experiment in an NLOS scenario. To simulate a non-line-of-sight situation, we placed the radar boxes behind 9 inches of material similar to that used in home walls. The NLOS scenario was conducted in an identical fashion to the line-of-sight scenario except for the added material. The confusion matrix for the non-line-of-sight scenario can be seen in Figure 10. The recall, precision, and F1 score for both the line-of-sight and non-line-of-sight scenarios can be seen in Table 2. We can see that in the NLOS scenario MechanoBeat performs similarly well to the line-of-sight scenario, which indicates our system is capable even when obstructed.

MOBILE TAG EXPERIMENTS

Stationary MechanoBeat tags have a wide range of potential uses, but they are limited to a static location, which may hinder some potential utilizations. In this section, we explore the design and results of a mobile MechanoBeat tag. We attach a mobile tag to a pill bottle to test one of the likely applications of such a tag. Tag oscillation is triggered when the lid of the pill bottle is twisted open. This oscillation can then be detected by the UWB radar and machine learning pipeline. Figure 2 shows the prototype mobile tag design.

In our experiment, a pill bottle tag is held in the participant's hand while walking to four different chairs located in various locations within a 3m x 3.5m space. Participants began by walking from a designated starting point to chair 1 while holding the pill bottle. While seated, the participant opened the pill bottle starting the tourbillon's oscillation, which continued for approximately 10 seconds. Next, an activity simulating drinking water from a cup (available near the chair) was performed to create a realistic medicine intake event. The same protocol was maintained for the rest of the chairs/locations sequentially from chair 2 through chair 4. The entire event was repeated 10 times.

The MechanoBeat sensor received strong reflections from the moving body of the participant as well as the subtle motions from the tag's oscillation. Leveraging two UWB radars placed at two adjacent walls in the room, we can track the movement of a user by applying a standard localization algorithm [7,8]. Figure 11 illustrates the motion trajectory of a person in the room superimposed with the locations where the pill bottle tag was activated. The MechanoBeat system is able to localize and track the user in the room from the starting position to each of the chair's location accurately. The inferred trajectory also matches the ground truth (green dash line) well. Moreover, the pill bottle interactions were correctly detected at locations near the chair locations. Figure 12 shows the model's probability that the mobile tag is active against the ground truth, which clearly shows the models capability to distinguish active tag instances from non-active instances in the presence of moderate level of external body motion. By fusing the tag activation and location information, the MechanoBeat system can not only find when a mobile tag has been activated, but also its location in space.

DISCUSSION AND FUTURE WORK

We present MechanoBeat, a system that employs electronics-free tags that can be used to instrument everyday objects, a UWB radar array, and a novel sensing technique that leverages a 1D CNN classification model. We have shown that MechanoBeat fills a void in existing activity recognition and object interaction systems. Unlike other systems, MechanoBeat is capable of detecting tag activation without line-of-sight and shows strong performance even with non-static tags. In addition, we have designed various oscillation tags that can be made with common and affordable materials. We have tested MechanoBeat in a kitchen environment with two radars and multiple tags. However, more experiments can be conducted to better understand how MechanoBeat performs in complex scenarios, such as environments with multiple people interacting with multiple tags. The tags were kept on their respective stationary appliances for a few months to simulate everyday use. In that period, the tags produced the same oscillation frequencies throughout. A long-term deployment of MechanoBeat could further validate our system against mechanical wear and tear and allow us to examine the durability of our system over an extended time frame. Such a deployment would also provide us with additional data, which could be used to train our detection model, further improving accuracy.

MechanoBeat lays the foundation for developing physics-informed designs of electronics-free tags. In future iterations, we plan to design tags by leveraging the material's shape, size, and electromagnetic scattering properties. We aim to build a novel computational design framework that uses an electromagnetic simulator and evolutionary algorithm to determine the shape and position of 3D printed tags within the target object. More specifically, by utilizing radar-cross-sections of different omnidirectional corner reflectors and their arrangements within the target object's body, optimized by genetic search, we can encode unique identifiers in the form of scattering patterns. These optimized physics-informed designs with the help of sophisticated machine learning algorithms can fuse dynamic back-scattered signals captured by multiple ultra-wideband radars to contactlessly identify and track user interactions with the electronics free tags. These tags can support contactless and unobtrusive identification, tracking, and user interaction detection of mobile objects to further facilitate assisted living. ■

N.B: This article is based on the original article of MechanoBeat [9] by the same authors.

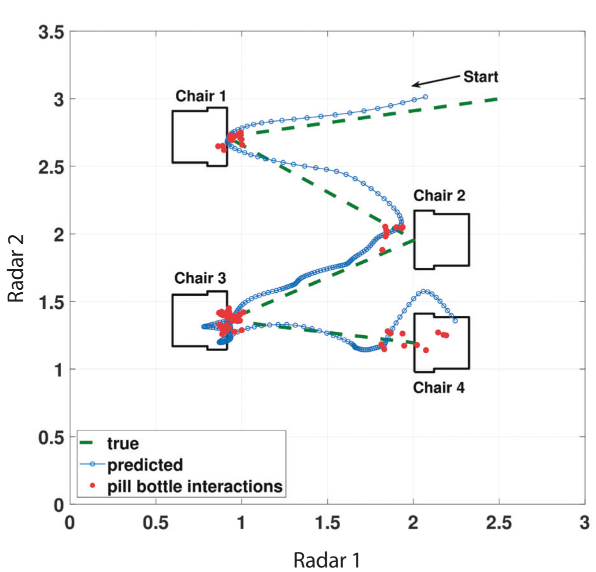


FIGURE 11. Movement trajectory predicted with the MechanoBeat system.

TABLE 2. The model performance in line-of-sight and non-line-of-sight (i.e., through wall) settings. The model performance was measured in terms of recall, precision, and F1 score.

Setting	Recall	Precision	F1 Score
Line-of-sight	0.89	0.91	0.9
Through Wall	0.87	0.93	0.9

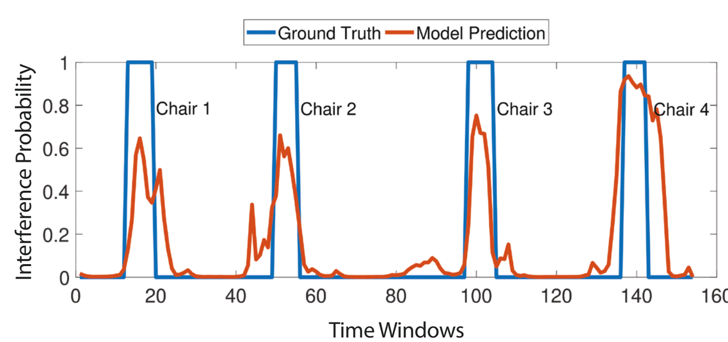


FIGURE 12. Probability that the mobile tag is active over time.

Md. Farhan Tasnim Oshim is a PhD candidate in Computer Science at the University of Massachusetts Amherst. His research focuses on contactless sensing of mobile health and human-computer interaction. His current research involves using radar signals to perform contactless vital sign monitoring, human-object interaction detection, and indoor localization by developing efficient signal processing and machine learning algorithms. farhanoshim@cs.umass.edu

Julian Killingback is a first-year PhD student at the University of Massachusetts Amherst. He is interested in self-supervised learning, contrastive learning, and representation learning. Currently, his focus is on applying the aforementioned techniques to information retrieval and natural language processing in low data regimes. jkillingback@cs.umass.edu

Dave Follette is the director of Advanced Digital Design and Fabrication (ADDFab) and Device Characterization at the Institute for Applied Life Sciences (IALS) at the University of Massachusetts Amherst. He joined the ADDFab and Device Characterization cores at IALS after working with Carbon3D in Silicon Valley developing a new kind of 3D printing for manufacturing. He holds an undergraduate degree in Mechanical Engineering from Princeton University, a master's in mechanical engineering from MIT, and an MBA from MIT's Sloan School of Management. follette@umass.edu

Huaishu Peng is an assistant professor in the Computer Science department at the University of Maryland, College Park. His research interests range from human-computer interaction to mixed reality and robotic fabrication. He builds software and machine prototypes that make the design and fabrication of 3D models interactive. His work has been published in CHI, UIST, and SIGGRAPH and won Best Paper Nominee. huaishu@cs.umd.edu

Tauhidur Rahman is an assistant professor in the Halıcıoğlu Data Science Institute at the University of California San Diego, where he directs the Mobile Sensing and Ubiquitous Computing Laboratory (MOSAIC Lab). His current research focuses on building novel ubiquitous and mobile health sensing technologies that capture observable low-level physical signals in the form of an acoustic and electromagnetic wave from our bodies and surrounding environments and map them to relevant biological and behavioral measurements. His work has been featured in several American and international media outlets. His laboratory has been funded by NSF, NIH, DARPA and industry grants. trahman@ucsd.edu

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