Low-Cost Millimeter-Wave Interactive Sensing through Origami Reflectors

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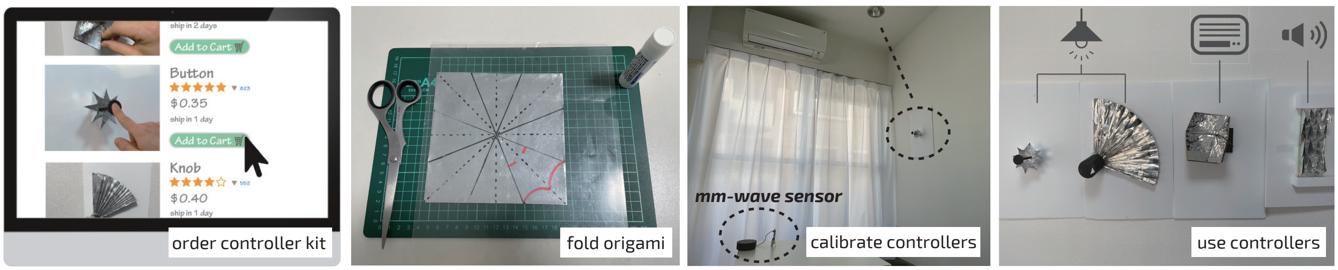


Figure 1: We envision a future scenario where users can (a) buy cheap materials (e.g., origami), (b) assemble to make controllers by themselves, (c) calibrate the controllers in their own environment guided by a dedicated app, and (d) deploy them as low-cost controllers for achieving ubiquitous interactivity. Please also see our Video Figure[1] for more details.

ABSTRACT

Millimeter-Wave (mm-wave) sensing provides an increasingly viable sensing solution for smart environments for its compact and solid-state form factor, non-intrusiveness, and low cost. While prior work in this domain has mostly focused on sensing humans – e.g., location, motion, and posture, we propose a new approach that leverage mm-wave sensing to enable tangible ubiquitous controllers such as buttons and switches. By encoding the controller state with the Radar Cross Section (RCS) of origami structures, our component-free controllers cost less than 40 cents per unit and require virtually zero maintenance effort, while achieving long-range wireless sensing with sufficient accuracies.

CCS CONCEPTS

• **Human-centered computing → Ubiquitous and mobile computing systems and tools**.

KEYWORDS

Millimeter Wave, Ubiquitous Computing, Battery-free, DIY

1 INTRODUCTION

Millimeter-Wave (mm-wave) sensing poses an inviting opportunity for ubiquitous sensing for being low-cost, compact, and privacy-sensitive – key properties that make commercial integrations possible. Recent years have seen an increasing trend of mm-wave sensing techniques featured on consumer products such as smartwatches, phones, autonomous vehicles, as well as home devices such as occupancy sensors, smart lightbulbs, and thermometers. In these systems, mm-wave sensors emit structured RF waves into user environments and decode the reflectance signals to infer user information such as presence, proximity, hand gestures, body postures, and beyond.

Meanwhile, conventional sensing techniques for ubiquitous interactivity have several constraints that have prevented smart environments from being widely adopted across society. Existing controllers such as switches and buttons are often wired, eliminating flexible deployments. Though, it is possible to enable flexible deployments with batteries and wireless transceivers, these components inevitably increase the maintenance and monetary costs. In response, prior work proposed interactive sensing techniques around computer vision [27], capacitive sensing [32], and RF backscatter [14]. Researchers have also leveraged user interactions as sources of power to eliminate the need for batteries [3, 24].

In this work, we leverage the increasingly popular mm-wave sensing technique to build wireless interactive controllers that are designed around origami-inspired structures. While most prior work on mm-wave sensing focused on sensing direct signals from users, our system senses objects – controllers that encode user interactions into their radar cross section (RCS), which we can detect to infer user interactions wirelessly at a room-scale. Moreover, our controllers consist of only common everyday materials

[1]https://youtu.be/BaLlQNVRVrI

(e.g., cardboard papers, aluminum foil), which are low-cost and component-free, enabling users to deploy them across their environments with negligible cost or maintenance effort.

Specifically, we designed a series of origami-inspired controllers to implement conventional controls, including ones with discrete states such as buttons and switches, as well as ones with continuous states such as knobs and sliders. We built a signal processing and detection pipeline around a Frequency-Modulated Continuous Wave (FMCW) radar and conducted a series of evaluations to demonstrate our system's feasibility. Overall, we believe our system proposes a promising approach to achieving ubiquitous interactivity.

2 INSPIRATIONS

This work took much inspiration from prior literature, including recent effort in HCI that leveraged paper as interaction medium, where researchers empowered paper with sensing [14, 30] and power generation [2, 11]. We were also inspired by a vast amount of online resources on origami structures in the design of our controllers. Finally, our project chose to follow the same low-cost and do-it-yourself spirit as Nintendo Labo [17], a phenomenal interaction design concept for console games. For these reasons, we chose paper, one of the most accessible and tangible materials to build our controllers. We envision a future where these paper-based controllers can be easily accessed and assembled by average homeowners to facilitate smart environment interactivity (Figure 1).

3 RELATED WORK

To situate our work, we first review previous approaches proposed for room-scale interactions. We also review how RF sensing has been utilized to power interactions in HCI.

3.1 Room-Scale Interactions

Many previous works have aimed to achieve room-scale interactivity by deploying ubiquitous sensing modules based on various principles. Vision-based sensing approaches have been widely proposed [13, 27]. For example, WorldKit [27] is a system that uses a depth camera and a projector to make ordinary surfaces (e.g., walls) interactive. SurfaceSight [13] is a LiDAR-based sensing system that enriches IoT experiences by enabling sensing context on table surfaces. On the other hand, sensing approaches without relying on vision sensors have also been investigated. Wall++ [32] is a capacitive sensing approach for allowing walls to become a smart infrastructure that senses users' touch and gestures. Moreover, lasers have been utilized for sensing room-scale interactions from a distance [19, 31].

Meanwhile, there are also wireless sensors which allow flexible installation and portable use (e.g., TV remotes). Still, these controllers are often battery-powered, which requires user maintenance (e.g., battery replacement). In response, there have been developed battery-free wireless controllers. For example, The Peppermill [24] utilizes human operation as a source of power, and PaperID [14] uses RF backscatter to sense how a user is manipulating RFID-instrumented paper. In addition, Iyer et al. [9] embedded backscatter structures into 3d-printed objects to make wireless sensors such as buttons, knobs, and sliders. Finally, there have been several commercial products such as QIACHIP switches [21] and EnOcean switches [4].

In this paper, we propose an approach for achieving battery-free wireless controllers that consist of only ultra-low-cost everyday materials in origami forms, working in conjunction with mm-wave sensing. The proposed approach enables users to deploy controllers with negligible cost and effort to maintain. Furthermore, in the future, we expect our work to facilitate users making and replicating these paper-based controllers easily on their own, enabling DIY smart environment experience.

3.2 RF Sensing in HCI

On the technology front, our approach is closely related to systems that leverage RF sensing. RF sensing has been actively integrated into applications in our lives. One of its representative uses is in autonomous vehicles where mm-wave radar is used primarily for detecting objects around the vehicle (e.g., other vehicles and pedestrians) [8, 26, 35]. Recently, Prabhakara et al. [20] showed that a wireless approach to sensing tire wearing is also possible by using mm-wave.

Closer to our work are prior systems that focus on interactivity in HCI. For example, Soli [15] is a ubiquitous gesture sensing technology based on FMCW mm-wave sensing, which allows precise finger tracking at close range [25]. The same mm-wave sensing has also been applied for classifying proximate material and object [28, 29]. Moreover, similar FMCW-based sensing using RF signals are proposed for capturing human pose and motion even when they are occluded from the device or in a different room [1, 33, 34]. These approaches have been expanded to be capable of identifying users by analyzing the signal reflections and been utilized for collecting behavioral data in homes [6].

Ultra-wideband (UWB) radar has been another common RF sensing technique used for various purposes such as localizing surrounding IoT devices and enhancing interactions with them [7, 10]. MechanoBeat [18] is a low-cost mechanical tag that can work with UWB radar arrays for unobtrusively monitoring user interactions. Additionally, the RF Doppler effect can also be utilized for detecting movements of targets. For example, Goel et al. [5] leveraged the effect to detect facial gestures by monitoring user's tongue, cheeks, and jaw movements.

As shown in these works, while most previous works have been focusing on sensing direct signals from users, we aim to sense the states of objects as controllers that encode user interaction. In detail, we propose an approach to utilizing origami-inspired structures as ultra-low-cost reflectors that can change their shapes upon user interaction. We expect that this shape change can result in unique RCS values which can be sensed remotely with a mm-wave radar. In Section 5, we explain how our origami-based controllers were designed.

4 SENSING HARDWARE

We used the Infineon Position2Go [2], a 24GHz radar sensor development kit utilizing BGT24MTR12 RF transceiver and XMC4700 32-bit ARM® Cortex®-M4 MCU series, which costs approximately $300. The sensor has one transmitter (Tx) and two receivers (Rxs)

[2]https://www.infineon.com/cms/en/product/evaluation-boards/demo-position2go/

and its board size is 50 mm × 45 mm. The horizontal and vertical field of view are 76° and 19°, and the minimum and maximum distance for sensing are 1 m and 25 m. The sensor streams raw data to a PC via USB, with 2.5 W power consumption. We utilized the officially provided Matlab APIs to receive the streamed data and developed our detection algorithm, which will be described later in Section 7. Note in the equation below that the received power (P_{rx}), which is calculated through FFT computation on raw radar measurements, is linearly proportional to RCS of a target object (σ) at a fixed distance to the radar (R), with a constant scale factor of transmitted power level (P_{tx}), transmitter gain (G_{tx}), receiver gain (G_{rx}), and signal wavelength (λ):

$$P_{rx} = \frac{P_{tx} G_{tx} G_{rx} \sigma \lambda^2}{(4\pi)^2 R^4}$$

As a result, we treated the received power as an indicator of RCS in the rest of this paper.

5 REFLECTOR DESIGN

Our design rationale is to create shape-changing reflector structures that can 1) be actuated by force at a single point, and 2) result in distinctive RCS at different shapes. To explore potential origami models suitable for our purpose, we first looked into a variety of existing works available on the Internet. We anticipated that structures consisting of mutually perpendicular surfaces would have high RCS values. This is inspired by the fact that corner reflectors, which have three mutually perpendicular intersecting flat surfaces, reflect waves directly towards the source, resulting in high RCS values [12, 22].

We found four designs that could be used for our controllers. In general, all form-changing origami designs change their RCS when morphing. However, as we anticipated, the four selected origami designs feature mutually perpendicular surfaces, which get distorted during the folding and unfolding process, resulting in significant RCS changes. For example, we incorporated Miura-fold [16] into one controller that forms such perpendicular surfaces when its structure is gradually expanded. Herein, we show the current controller designs: Button, Toggle Switch, Knob, and Slider (see Figure 2 and Figure 3). We used conventional silver origami, paper with aluminum films coated on the surface, to further improve the RF reflectance of surfaces. Our total material cost is less than 40 cents per controller unit.

- Button (umbrella-fold): This controller works as a push-and-pull button and has discrete states (i.e., on and off). It consists of an umbrella-fold and a 3d-printed handle attached to the origami. The umbrella part opens when the handle is pushed and closes when it is pulled.
- Toggle Switch (corner reflector): This controller works as a toggle switch and has discrete states (i.e., on and off). It is a corner reflector structure made of cardboard papers coated with silver origami. The three surfaces get mutually perpendicular in the on state. This structure is disrupted when the switch is turned off. Users interact with the attached 3d-printed handle to switch between the two states.

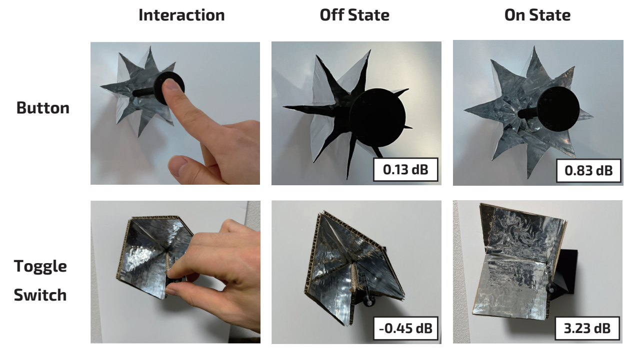


Figure 2: Two types of discrete controllers (top: button, bottom: toggle switch). These controllers have two discrete states (i.e., on and off).

- Knob (zigzag-fold): This controller works as a knob and has continuous states. It consists of a zigzag-fold and a 3d-printed handle attached to the origami. The zigzag-fold part gradually opens as the handle is rotated in one direction and closes as it is rotated in the opposite direction.
- Slider (Miura-fold): This controller works as a slider and has continuous states. It consists of a Miura-fold [16] origami and a 3d-printed handle. The Miura-fold part gradually expands and shrinks as the handle is manipulated by a user.

We measured RCS changes of each controller when they morphed. To do this, we first recorded signals without a controller as a base signal. Then, we placed a controller perpendicularly, 1 m away from the sensor. We recorded the signals with a controller in each state and calculated the ratio of their amplitude to that of the base signal, measured in dB. Overall, We found significant RCS changes between different states of the controllers. We elaborate an algorithm as to how these values are utilized for detection later in Section 7 and document the evaluation of our system in Section 8.

6 USER INTERACTION

Before explaining the sensing algorithm, we describe our envisioned future scenario of how users will set up and use our proposed origami controllers (Figure 1). First, a user purchases controller tool kits of interest from a distributor. These tool kits allow the user to easily make controllers from pieces on their own. Then, the user opens a dedicated smartphone or smart speaker app to initiate the setup. The app will prompt the user to identify mm-wave sensors in their room and origami controllers within the sensing range, and start the calibration process. For calibration, he user collects a small amount of sample data corresponding to each state of the controller, and the our system is ready to use.

7 SENSING ALGORITHM

Our detection approach is based on FMCW sensing [23]. At each frame, the Tx transmits N_{chirp} chirps and there are N_{sample} samples in each chirp, resulting in a reflected signal matrix: $X_{raw} \in \mathbb{C}^{N_{sample} \times N_{chirp}}$. When we apply fast Fourier transform (FFT) with the size of N_{fft}, we get $X_{fft} \in \mathbb{C}^{N_{fft} \times N_{chirp}} = FFT(X_{raw})$. Then,

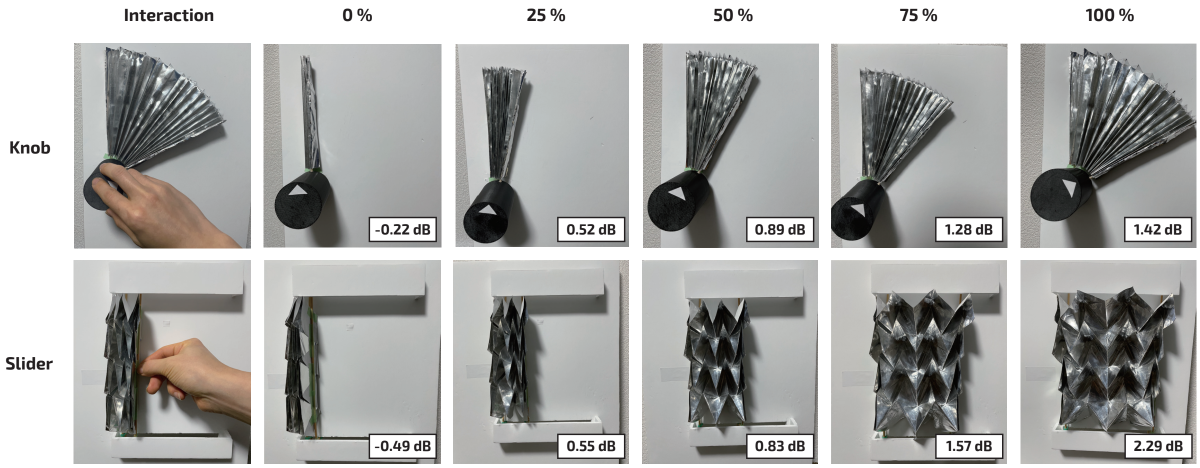


Figure 3: Two types of continuous controllers (top: knob, bottom: slider). We expanded each controller from 0% to 100% with 25% interval.

the largest value in each row (i.e., over N_{chirps} chirps) was taken out after calculating the amplitude, resulting in a frame vector $x \in \mathbb{R}^{N_{fft} \times 1} = \max |X_{fft}|$. Each of the values in the N_{fft} bins corresponds to the power of the reflected signal within specific ranges from the sensor. The range resolution is given by $\frac{c}{2B}$, where c is the light speed and B represents the used bandwidth.

Our current implementation ignores frames that contain non-negligible human body movements that interfere with our RCS sensing. To do this, we applied a simple threshold-based algorithm. In detail, we calculated the difference of two consecutive frames, say x_t and x_{t+1}, and classified the frame x_{t+1} as containing human body movements if the norm of the difference (i.e., $|x_{t+1} - x_t|$) is larger than a predefined threshold. Note that the current detection algorithm requires users to exit the controller proximity after interaction. This means our system only works in an asynchronous manner, where there could be a lag between user interaction and its detection.

Once a frame is detected as not containing human body movements, the frame is processed for detecting the controller's state. Here, we assume that the system knows the bins of the feature vector x that correspond to the controller position in terms of its distance from the sensor. This information is provided during the user calibration process. By extracting the values in these bins of x, we can focus on the data relevant to the controller's state. Thus, we denote the values in these bins as a sub-vector y and use it for the subsequent processing.

For detecting discrete states of the controllers, users first collect data for on and off states of the controllers in the calibration, as we described in Section 6. Then, we calculated the mean values of data collected from these two states as the thresholds to classify new frames of data after calibration.

Similarly, for detecting continuous states of the controllers, users provide sample data in the calibration for some of the data points in the detection range. We trained regression models (i.e., linear) with the data collected during the user calibration process. Note that we found the RCS change as the controllers morph to be monotonous and linear, and thus our straightforward regression models worked sufficiently well in practice.

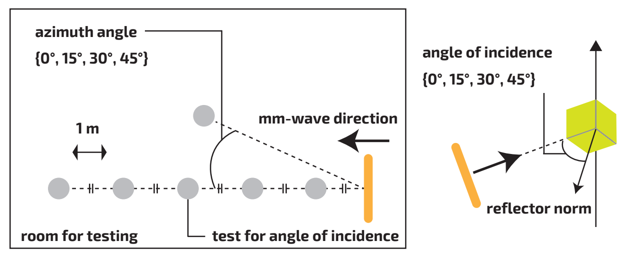


Figure 4: Setting of the pilot test for discrete detection. We placed a controller to the gray positions and tested the detection accuracy by changing its distance, azimuth angle, and angle of incidence.

8 PILOT TEST

We examined the accuracy of the proposed algorithm. In this pilot test, we set the sensor parameters as followings: N_{chirp} = 4 chirps per frame, N_{sample} = 256 samples per chirp, N_{fft} = 256, and B = 200 MHz bandwidth. We averaged the measurements across the two Rxs for calculating x and y in this pilot test. We conducted the test in an open indoor space of approximately 10 m^2.

8.1 Discrete Detection

We first tested the accuracy of detecting discrete states of the controllers – button and toggle switch.

8.1.1 Setting. We examined the sensing accuracy in a variety of settings in terms of the controllers' distance from the sensor, azimuth angle, and angle of incidence. Figure 4 (left) shows the locations we tested and Figure 4 (right) illustrates the angles of incidence we tested. For each controller, we first placed it in the mm-wave

RF beam direction with 1 m interval up to 5 m. Then, we fixed the distance to 3 m and changed the azimuth angle with 15 degrees interval up to 45 degrees. Lastly, we fixed the distance to 3 m and the azimuth angle to 0 degrees, and changed the angle of incidence with 15 degrees interval up to 45 degrees.

For each placement pattern, we first placed our controller and conducted calibration, as described in Section 7. After the calibration, we changed the state of the controller to be on and off repeatedly, five times each, while we recording the output of the algorithm each time.

8.1.2 Result. Figure 5 shows the accuracy, each corresponding to when we changed distance (top), azimuth angle (center), and angle of incidence (bottom). The toggle switch showed a stable detection accuracy over the conditions. On the other hand, the accuracy for detecting the button's state gradually decreased as it was placed far from the sensor or its perpendicularity lost (i.e., as we changed the azimuth angle or angle of incidence). Overall, the high detection accuracy confirmed the validity of using our origami-based reflectors as discrete controllers.

8.2 Continuous Detection

Next, we tested the performance of detecting continuous states of the controllers – knob and slider.

8.2.1 Setting. We first recorded signals without a controller placed in the environment and obtained y_{base}. Then, we placed a controller 1 m away from the sensor board perpendicularly so that both the azimuth angle and angle of incidence were 0°. We then changed the expansion level of the controller from 0% to 100% with 25% interval, while we recording the corresponding signals y. We calculated and plotted the ratio of the amplitude of y to y_{base} in dB. We also trained a linear regression model and calculated the mean absolute percentage error (MAPE).

8.2.2 Result. Figure 6 shows the measured ratio of the amplitude of y to y_{base} in each of the controller's expansion level. As expected, the values gradually increased as the controllers were expanded. The MAPE for each of the controllers are 33.2% (knob) and 28.6% (slider), respectively. The results clearly showed the correlation between the expansion level and RCS, with which our regression models can be easily trained for using origami-based reflectors as continuous controllers. However, our proof-of-concept regressor implementation did not yield high accuracies due to large deviations when controllers were expanded to certain levels (e.g., 75%). We suspect this issue was caused by fabrication defects, which we plan to further investigate and make improvements in our future work.

9 EXAMPLE APPLICATIONS

As we discussed in Section 1, our low-cost controllers can be a promising approach for ubiquitous interactivity. For example, average homeowners can easily deploy the controllers into their environments and connect them with various IoT applications, such as light, music player, TV, air conditioner, etc. Moreover, the controllers can be installed in public places such as museums, hospitals, restaurants, and buses, replacing exiting controllers that are mostly wired and powered. Overall, we believe the advantages of our approach being ultra-low-cost, wireless, and battery-free facilitate

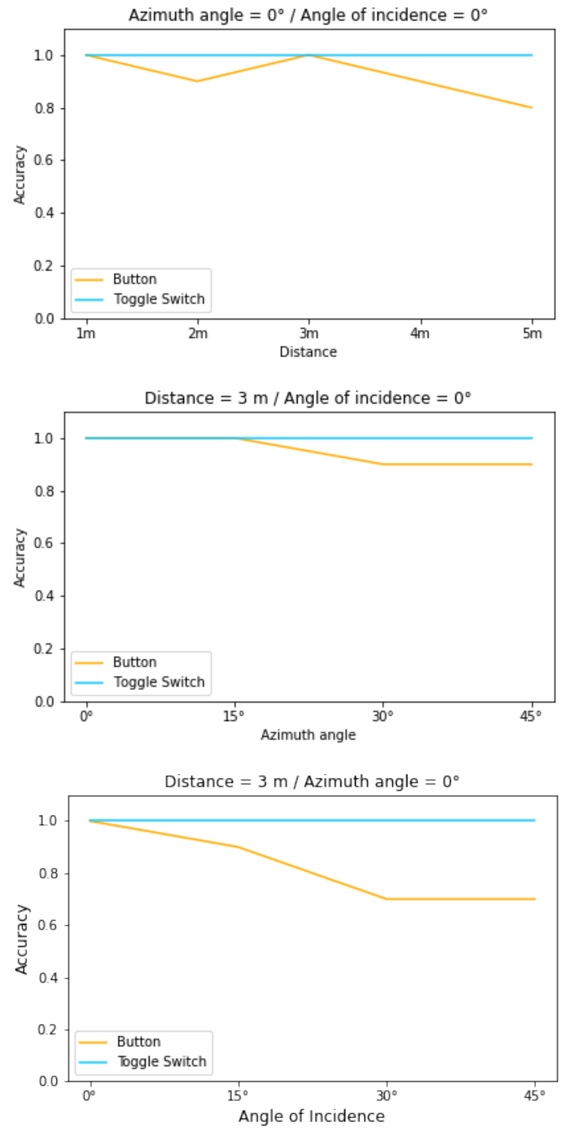


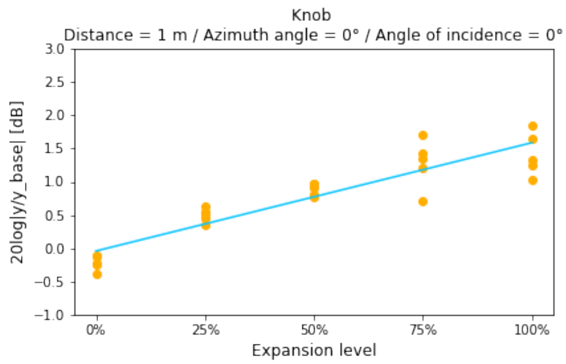
Figure 5: Accuracy of button and toggle switch when we changed their distance (top), azimuth angle (center), and angle of incidence (bottom) from the mm-wave sensor board.

DIY smart environment experience across a wide spectrum of applications.

10 DISCUSSION AND FUTURE WORK

There are some directions to further refine our approach. First, the accuracy and robustness can be improved by adopting better fabrication process. For example, adding linings on top of basic origami structures could yield more programmable shape changing of the continuous controllers. We could also add protective coatings to mitigate degradation of origami structures over time.

Secondly, we will expand the origami design set. In this paper, we demonstrated four designs, but considering the abundant



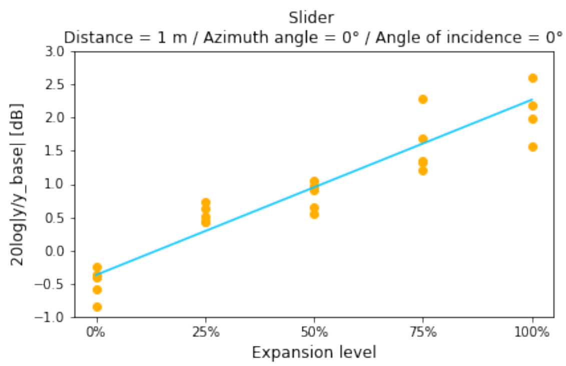


Figure 6: The measured ratio of the amplitude of the reflected signal to that of the base signal when controllers were expanded from 0% to 100% with 25% interval (top: knob, bottom: slider). Blue lines represent the fitted linear regression model while orange dots correspond to the measured data points.

origami structures found, we believe there are many other possible designs. We would like to run simulations to estimate RCS changes of origami structures for comprehensive exploration and optimization.

Third, for achieving the ubiquitous interactivity through our controllers, it is demanded to enable the system to detect spatial information of controllers. We would like to utilize beamforming and Angle of Arrival estimation with radars that have multiple transmitter and receiver antennas to increase spatial resolution. This improvement on spatial resolution will allow a user to deploy multiple controllers in the environment. Additionally, improved spatial resolution will help locate users more precisely, which could mitigate the current limitation that the users must be out of the controller proximity for detection.

Lastly, current controllers are relatively large in comparison to conventional ones. In future work, we will miniaturize the controllers with better fabrication techniques based on human-machine ergonomics. Specifically, we will apply automated fabrication techniques such as laser cutting combined with vacuum forming, which will enable us to develop more complicated origami structures. At the same time, we would like to further investigate the interaction space where users can easily assemble controllers from basic material primitives, as we discussed in Section 2 and Section 6.

11 CONCLUSION

In this paper, we proposed a novel approach to achieving ubiquitous interactivity: ultra-low-cost (less than 40 cents), wireless, battery-free controllers made of origami in concert with mm-wave sensing. We demonstrated four controller designs (i.e., button, toggle switch, knob, and slider). These controllers change their RCS significantly upon user interaction, which can be detected remotely by mm-wave sensing (e.g., FMCW). Our pilot test demonstrated the feasibility of the proposed approach. We believe that our work demonstrates a novel technique for ubiquitous interactivity, and will greatly facilitate users' DIY of future smart environments.

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