RaITIn: Radar-Based Identification for Tangible Interactions

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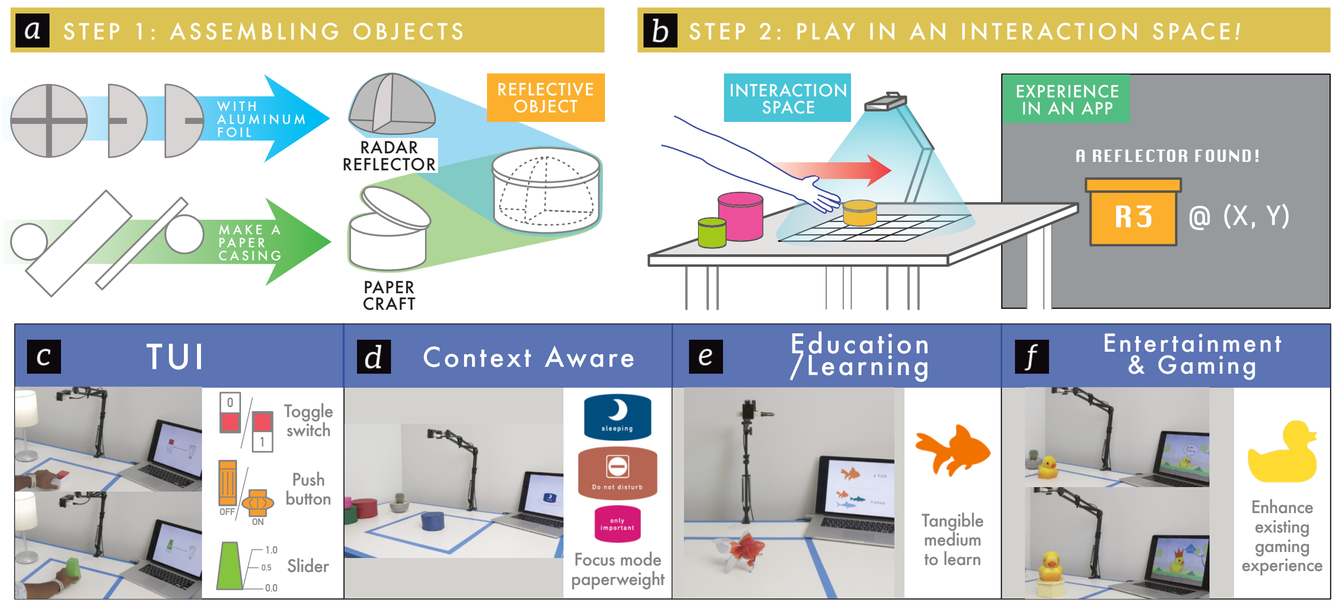

Figure 1: RaITIn provides radar based identification for tangible tabletop interaction. It uses a miniaturized radar to identify unique, low-cost embedded reflectors. (a) Assembling of radar reflector ID's, (b) The tangible tabletop interaction space, (c) Tangible User Interface application, (d) Context aware application, (e) Education application, (f) Game application.

ABSTRACT

Radar is primarily used for applications like tracking and large-scale ranging, and its use for object identification has been rarely explored. This paper introduces RaITIn, a radar-based identification (ID) method for tangible interactions. Unlike conventional radar solutions, RaITIn can track and identify objects on a tabletop scale. We use frequency modulated continuous wave (FMCW) radar sensors to classify different objects embedded with low-cost radar reflectors of varying sizes on a tabletop setup. We also introduce Stackable IDs, where different objects can be stacked and combined to produce unique IDs. The result allows RaITIn to accurately identify visually identical objects embedded with different low-cost reflector configurations. When combined with a radar's ability for tracking, it creates novel tabletop interaction modalities. We discuss possible applications and areas for future work.

CCS CONCEPTS

• **Human-centered computing → Ubiquitous and mobile computing**; *Interaction devices.*

KEYWORDS

radar sensing, tabletop system, radar identification, tangible interaction

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1 INTRODUCTION

Traditionally radar has been used to detect and track large moving objects. However, the miniaturisation of radar for consumer devices, such as smartphones and smart displays has enabled it to be used for gesture control [7]. Previous research has explored how radar can be used for ubiquitous human computer interaction, such as breathing rate sensing [16], gesture input [7, 13], material identification [27] and object tracking [31]. However, to the best of our knowledge, there has been little research that explored radar-based object identification and tracking using custom radar reflectors.

To that end, we present RaITIn, a tangible tabletop system that uses a miniaturized radar to identify unique, low-cost embedded reflectors. Unlike conventional tabletop interactions, a radar enables unique modalities; it is robust, able to penetrate certain material, and can track objects very accurately. With RaITIn, it can also identify low-cost reflectors that are embedded within outer casings within a trackable space with an accuracy of up to 98.96%. This paper makes the following novel contributions; 1) We introduce low-cost DIY radar reflectors with unique identification for tangible input and interactions, 2) We present system design, identification techniques and software algorithms for identifying different radar reflectors, and 3) We provide examples of desktop-based interaction based on radar enabled tangible interactions and applications.

2 RELATED WORKS

RaITIn extends two areas of prior work; radar-based interactive sensing and identification, and sensing for tabletop interactivity. We review related work in each of these areas, and explain the novelty of our approach.

2.1 Radar-based Interactive Sensing

The recent development of miniature radar sensors like Soli [13] have enabled radar-based precise motion sensing to be explored for human computer interaction. For example, Ens et al. [3] showed how mico-gestures detected by Soli could be combined with large scale gestures for intuitive input in a gesture based Augmented Reality interface. Similarly, Wang et al. [22] reviewed a range of possible micro gestures that can be detected with Soli. These sensors support micro gestural interaction with a small footprint, low power consumption and fewer privacy concerns compared to other gesture sensing techniques. This makes them suitable for integration into everyday consumer devices such as Google's Pixel 4 smartphone[1] or the Nest Hub smart display [2].

Research has also been conducted on using radar for material and object identification. For example, FG LiquID [12] uses radar to distinguish different liquids at a distance of 40cm, although it requires the objects to remain at a fixed distance. Cubesense [26] supports radar interactions based on corner reflectors but is not able to identify different corner reflectors and objects. Yeo et al. [27, 28] demonstrated the ability to detect and classify different objects placed on the radar sensor for context-aware and tangible applications. However, this system can distinguish these materials only at a constant distance from the sensor and by changes in the material properties. The closest related work is by McIntosh et al. [14] that used an array of microwave Doppler sensors beneath the table. However, this requires a large setup space and multiple antennas which is not practical for everyday use. Arakawa et al. [1] proposed low cost origami based tangible controllers using mm wave radar sensor. However, they did not identify the various controllers. In RaITIn, we use a single 60 GHz radar sensor to identify custom low-cost radar reflectors on desktop setup for tangible interaction. Zhao at al. demonstrated identification and tracking of human participants using point cloud data on millimetre wave radar[31] . Hsu at al. demonstrated identification using RF reflections from human participants with high accuracy using 5.46-7.25 GHz FMCW radio[8]. The research detailed in these papers shows that radar can be used to support human-computer interaction and object/material identification at a fixed distance[29]. However, there has been little to no prior research work that uses custom radar reflectors to identify objects on a tabletop surface where the object distance with respect to radar sensor changes. Our research is based on the properties of radar reflectors. Passive radar reflectors are octahedral corner reflectors that reflect radar signals at any angle towards the source radar. These reflectors are used on boats to make then identifiable to other boats [30].

In a radar system, the ability to detect a target is dependent upon its radar cross-section (RCS). The radar cross-section measures the reflection ability of targets in the radar system. The magnitude of the RCS is not related to the physical area of corner reflectors. A specific region, called the effective aperture area, is responsible for three reflections within three corner reflectors. The amount of reflected RF energy, or RCS, is proportional to the size of the effective aperture area. When a trihedral corner reflector of radar is illuminated at boresight (the symmetry axis), its effective aperture area is largest, which results in the highest RCS peak. Further details can be found in these previous works[3] [2, 4].

2.2 Sensing approaches for tabletop interactivity

Our work is informed by prior research related to interactive tabletops. An interactive tabletop system requires two major technical elements: (a) identification, and (b) tracking. The Digital Desk is an early example of an interactive table, using physical metaphors to interact with digital objects such as documents [24]. A variety of approaches can be used for unique object identification on a table top surface. Previous research has used sensors such as cameras [17, 23, 25] which use computer vision techniques to identify[9], RFID system using tags [11, 20], NFC [21], capacitive sensing with tangible markers [18] and even a pressure sensing mat [5, 6]. For object tracking prior work has explored using cameras [17, 25],

[1] https://store.google.com/us/product/pixel_4
[2] https://store.google.com/us/product/nest_hub_2nd_gen
[3] https://www.radartutorial.eu/17.bauteile/bt47.en.html

optical tracking [19], capactive sensing [15, 21], and magnetic sensing [10, 15]. However, these methods have some drawbacks, such as suffering from occlusion, illumination requirements, relatively large setup and requiring active tangible objects. In RaITIn, we use low-cost DIY passive radar reflectors which are easy to make and do not suffer from any of the above limitations. We use 60 GHz mmWave radar, which provides accurate tracking and is robust to environmental changes, making our overall system reliable and secure.

3 IMPLEMENTATION

In RaITIn, we have developed a low-cost tabletop system using radar reflectors for input and interaction. This section covers the system design details, radar reflector design, data collection method, and machine learning model architecture.

3.1 System Design

We built the prototype of RaITIn using a Soli sensor. Soli is a Frequency-Modulated Continuous-Wave (FMCW) 5 millimeter wavelength radar that utilizes radio wave at the frequency range from 57 GHz to 63 GHz [13]. The range-bin resolution of the senor is 2.5 cm. The range bin resolution of radar measures the ability to distinguish between targets in either range or bearing. We placed a Soli sensor on top of a table surface at a distance of 40 cm. As marked in Figure 2 (b), the blue space denotes the user interaction space. The corners of the interaction space are 50 cm from the sensor. Choosing this distance allows us to detect the majority of radar reflectors, including smaller ones with a radius of 1 cm in the interaction space. The sensor configuration determined the interaction space we used, although the interaction space can be expanded based on the sensor's operating frequency and bandwidth. For the current prototype, we used the C++ - based Soli software development kit to interface with the sensor and extract Complex range Doppler (CRD) map data.

3.2 Radar Reflector Design

Radar Reflectors are conventional corner reflectors i.e. those that tend to reflect majority of the incident waves back towards the emitter. We designed our custom radar reflectors based on the traditional passive octahedral radar reflectors used in boats[4]. However we modified it into a tetrahedral design because the bottom space of the octahedral reflectors is hidden from radar view when placing it on the table. The radar reflectors consist of two main components; the reflector itself and an outer case. Using conductive metal reflectors of various sizes results in a unique, identifiable pattern from the radar signal. Each reflector is placed in an outer case, allowing for various external tangible shapes and sizes while still being identifiable by the radar.

Radar reflectors are made from conductive metals. We 3D print and assemble each reflector component for our radar reflector design, covering them with aluminium tape (Figure 3 - a, b). The thickness of the reflectors is 2 mm, which is less than the wavelength of the signal. These reflectors are enclosed inside a case made from 180 grams per square meter (GSM) craft paper to make it tangible for user interactions (3 (c)). Based on prior experimental trials and research, we found that the paper has excellent transmittance with the highest signal to noise ratio. We tested the 3D printed outer case with various thicknesses; its material property adds more noise to the reflected signal from the radar reflectors. Therefore, we opted for 180 GSM craft paper thick enough to make it reliable, transparent to the radar and durable.

In the RaITIn prototype, we created 6 custom radar reflectors with radii of 2 cm, 3 cm, 4 cm, 5 cm, 6 cm, and 7 cm, and enclosed with cylinders made from 180 GSM paper. To create different IDs, we utilised different cylinder lengths to create new stacking IDs. The sensor range-bin resolution is 2.5 cm, hence stacking two different radar reflectors with multiple range-bin lengths creates different reflected energy and RCS.

In order to detect, track, and identify radar reflectors, we considered the following reflector design factors: (a) Radar Cross-Section (RCS), including size and shape, (b) surface smoothness, (c) material, (d) orientation, (e) distance from the radar, and (f) incident angle of radio frequency waves. In our system, we create ID's based on two factors: (a) varying the RCS of the radar reflectors and (b) stacking two radar reflectors with varying range bin distances between them.

The equation below denotes received power(P_{rx}) which is linearly proportional to the RCS of the target(σ) at a fixed distance(R) with a constant scale factor of transmitted power level (P_{tx}), transmitter gain (G_{tx}), receiver gain(G_{rx}), and signal wavelength (λ):

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

In the line of sight from the radar sensor, the reflector acts as a circular plate. Other points in the interaction space behave as a corner reflector. As a general rule, the reflected energy corresponds to larger RCS as size increases. We use this factor to create different ID's. However, a reflector of a particular radius (a) does not have a constant RCS throughout the interaction space due to distance and incident angle changes. In our prototype, we used tetrahedral corner reflectors at any point of the space; this meant that at least one part of the corner reflector will be visible to the radar. The tetrahedral corner reflectors' RCS and reflected energy vary drastically with distance and incident angle. However, the reflected energy will be unique across reflectors of different sizes at particular distances and incident angles. We use this phenomenon to ID reflectors of different sizes across the interaction space. Hence it is possible to create a machine learning algorithm that filters reflected energy based on spatial position data and results in identification of reflectors with different size.

3.3 Signal Processing and Feature Extraction

The main signal obtained from the sensor is the range-Doppler which allows us to observe three key ID characteristics: (a) energy intensity of the reflected signal, (b) radial distance and (c) velocity of the target. We utilised the clutter removal function of the Soli SDK to remove the noise from the stationary objects on the table. For machine learning we convert the received range-Doppler data to range profile data by summing all the Doppler signals across the range data. The range profile data has the target range information and reflected energy from the target. The stacked radar reflector's

[4] https://www.ussailing.org/wp-content/uploads/2018/03/2007-Radar-Reflector-Test.pdf

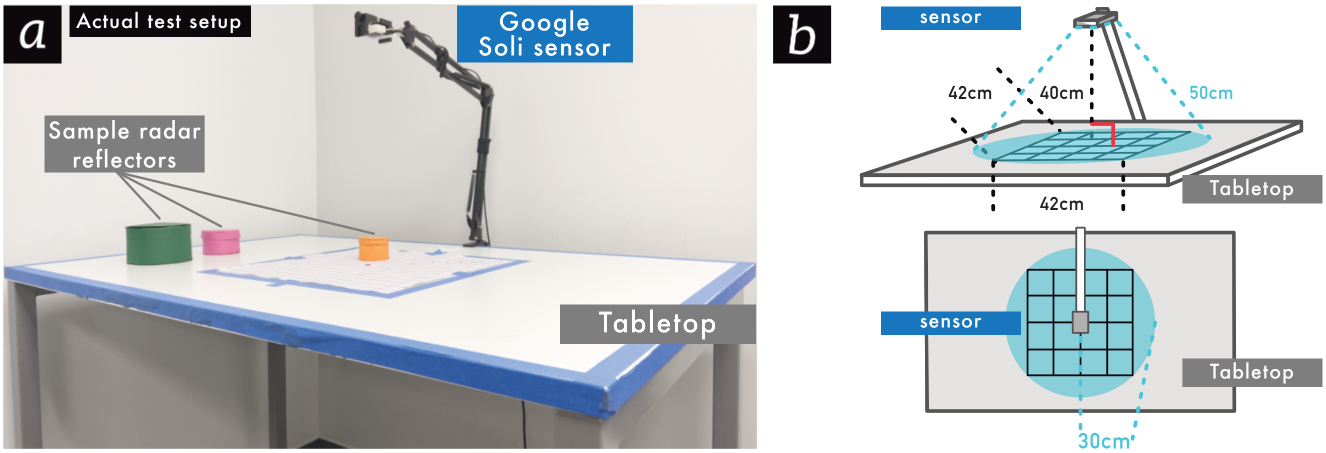

Figure 2: System design

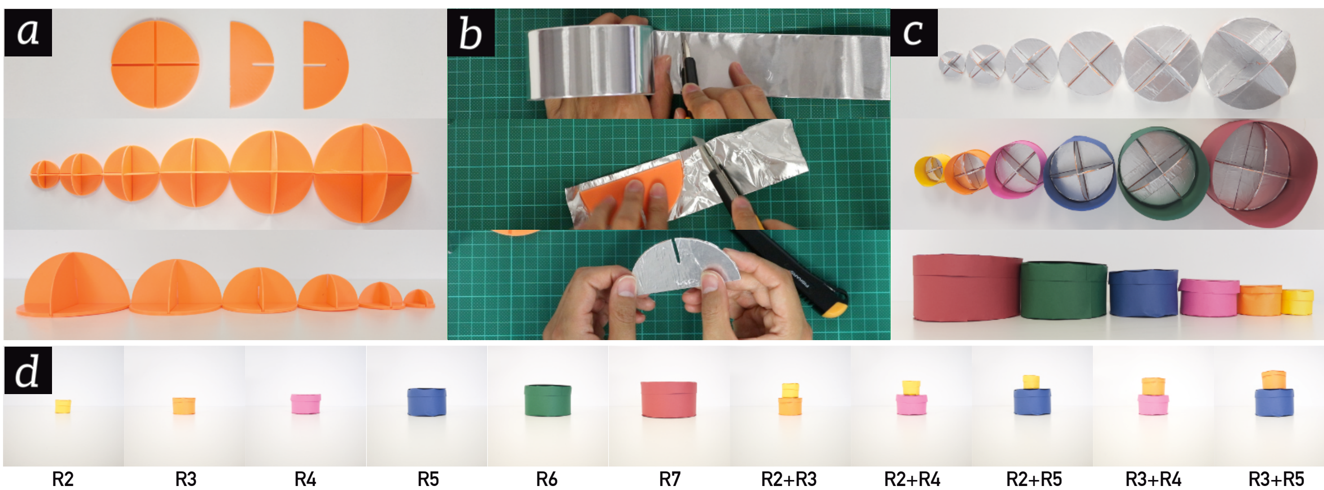

Figure 3: (a) Custom 3D printed parts of radar reflectors (b) Aluminium coating over radar reflectors (c)Encasing the reflector with paper (d) Radar Reflectors of radii 2 cm, 3 cm , 4 cm, 5 cm, 6 cm, 7 cm and stacked radar reflectors radii of 2 cm and 3 cm, 2 cm and 4 cm, 2 cm and 5 cm, 3 cm and 4 cm, 3 cm and 5 cm.

range profile data will have two peaks separated by the range-bin length compared to the single radar reflector.

The received radar intensity is influenced by the reflection and transmission properties of the material. Reflected signals from many points both within and on the object surface are overlapping and hence contribute to the received signal. The radar signals are stable and highly discriminative, so we currently use all three channels from the Soli chip as input range profile data features; each channel consists of 32 data points, yielding 96 features. We also extracted global maxima, global minima, standard deviation, root mean square and mean for each channel, and the location information of the reflectors such as range, azimuthal angle and elevation angle as suggested by Liang et al. [12]. This yields 5 (statistical features) * 3 (channel) + 3 (Location information) = 18 features. In total, we extracted 114 features for training the model.

3.4 Data Collection

Following the procedure proposed by Yeo et al. [27], we collected data based on sessions. We restarted the Soli sensor for each session and waited for three seconds for calibration and clutter removal. For data collection purposes, we divided the interaction space into 256 small squares with a length of 2.5 cm each. We placed the radar reflectors on the table at a orientation within the interaction space in each session and collected the data samples. During each session, this process was repeated ten times. To avoid repetition, we did not repeat the same position across sessions. We also collected background data samples which included no reflectors present and movement of the hand mimicking an interaction on the tabletop.

To evaluate stacking ID's, we placed a reflector with radius of 2 cm on top of reflectors with radii of 3 cm, 4 cm and 5 cm with the difference between the base of the reflectors as 5 cm, i.e. two range bins. Additionally, we placed the reflectors with a radius of 3 cm on top of 4 cm and 5 cm reflectors, with the difference between the bases of the reflectors being 5cm. This decision was made to evaluate the classifier to differentiate between stacking reflectors of the same range bin.

In this research, we limited the possibility of stacked ID's as we can develop many possible configurations by changing the radius and multiples of range bin difference between the stacked reflectors, which we are planning to do in future. In total, we collected data samples using six unique single reflectors, five stacked reflectors and background data. Overall, we conducted 290 sessions yielding $290x10x12$ (no. of reflectors/class) = 34800 data points for training set. We collected data from 150 separate sessions (18000 data points) covering most of the interaction space for both the testing and development set individually.

3.5 Machine Learning Algorithm

Based on preliminary trials, we found the machine learning model that gave the best recognition results was the adaboost algorithm [32] with classifier as decision tree. We trained our adaboost algorithm using the training data and then evaluated the classification accuracy using data collected from the test session. We used grid search to obtain the best hyper parameters for the development set. The model was trained with a learning rate of 0.4 and n_estimators of 50. We implemented the model using the Scikit-learn[5] library for Python.

4 RESULTS AND DISCUSSION

The conventional 10-fold random holdout cross-validation method using all samples in the training set yielded an accuracy of 99.17%. The confusion matrix is shown in figure 4—a, the accuracy of the testing set yielded 98.96%. Figure 4 - b and c shows the difference between the energy reflected from the radar reflector of different sizes versus distance. Based on figure 4 - b, there is a clear distinction between each reflector's reflected energy signals across the distances. However, based on figure 4 - c, the energy reflected by stacked reflectors was similar. There is minimal difference between them because the graph shows the highest energy reflected by the target. The range-Doppler data in the figure 4 - e, f shows the energy distribution across a range of single and stacked radar reflectors. Range-Doppler data obtained from stacked radar reflectors show differences in range bins among the stacked radar reflectors. Each configuration of the stacked radar reflector produces a unique reflected energy distribution. The clear range-bin separation, the unique reflected energy distribution and spatial position data is the reason for the high accuracy obtained from the machine learning model results.

5 INTERACTION DESIGN AND APPLICATION

We implemented the following examples to showcase the application opportunities of RaITIn.They demonstrate the wide range of possible interactions with our tabletop system. Our system is low cost and has an easy setup, can be used to make any tabletop surface into an interactive surface. This allows many possible applications in remote collaboration, learning, creativity/prototyping tools and entertainment, and other domains. These application prototypes were implemented using Python. First, The soli sensor operates at 32 FPS. Second, The data from the soli sensor are converted to features as explained in section 3.3. Third, these incoming data is predicted using the trained machine learning model. Finally, the inferred class(Or the ID) is sent to the application program, which was implemented using PyGame[6].

Tangible User Interface We implemented a primary user interface such as a button, toggle switch and slider using our prototype (Figure 1-c). We designed the button, toggle switch and slider using origami craftwork. The button uses stacked reflectors. When the button is pressed, there is a change in the range bin difference between the two reflectors results in a new ID. The toggle switch and the slider work on the tracking feature of the radar, and it records changes in azimuthal and elevation angle to compute the sliding interaction. This enables many applications in an interactive desktop scenario, such as controlling the brightness and colour of LED desk lamps and turning on/off devices.

Context aware applications We implemented context-aware applications using radar reflector ID (Figure1-d). We assigned each ID to focus modes found in iOS and Android devices. These focus modes are Do not disturb, personal, work, reading and sleeping mode, and help increase task productivity. Placing any ID on the desktop will control all the other devices in the desk space to behave a particular mode. For example, When the user places a radar reflector corresponding to work mode on the desk, the devices such as laptops, phones and smart devices give notifications related to work, such as emails from coworker.

We also implemented another example where we assigned timer options to IDs. Each ID will have a different time setup. For example, radar reflectors with a radius of 2 cm will have a timer of 20 seconds. We can use stackable ID's to compute more timer options. Placing these IDs can act as a countdown clock which alerts the user once the timer is done. This allows tangible interaction of timing similar to weights in a weighing scale.

Education and Learning application In education and learning applications (Figure 1-e), we use single IDs and stacked IDs to teach singular and plural forms of words. We created different animals and everyday objects using origami, and embedding each with radar reflectors. We can also use the Stacked ID's and Single ID's combination to teach mathematics like basic addition and subtraction to children using the interactive tabletop setup.

Entertainment and Game application We implemented a generic 2D Pokemon[7] fighting game (Figure 1-f) for the deskop with RaITIn. We created the animal format of Pokemon using paper-craft. Each single radar reflector ID represents non evolved Pokemons. As the players gain experience, they can utilise stacked IDs to represent the evolution in Pokemon. As the player character evolves, the character's energy level declines; hence the player can switch between the evolution of Pokemon to fight appropriate opponents. This game was implemented to enhance the gaming experience by bringing Pokemon's evolution to tangible physical experience.

[5]https://scikit-learn.org/stable/

[6]http://www.pygame.org/

[7]https://www.pokemon.com/us/

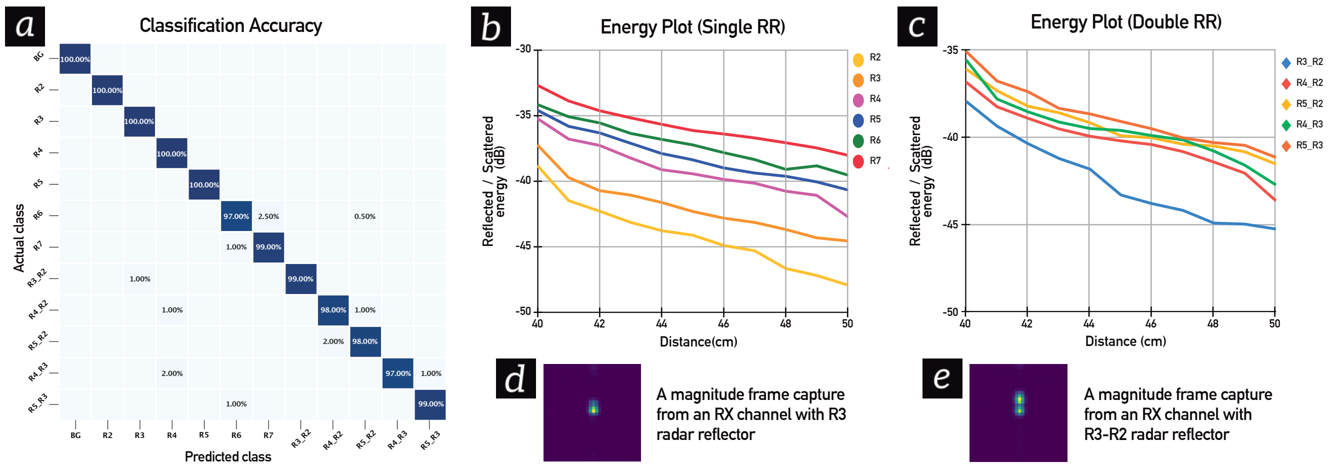

Figure 4: (a) Confusion matrix - 12 reflectors classes, (b) Reflected energy versus distance of single radar reflectors, (c) Reflected energy versus distance of stacked radar reflectors, (d) Absolute range Doppler map of single reflector of radius 3 cm, (e) Absolute range Doppler map of stacked reflector of radii 2 cm and 3 cm.

6 LIMITATION AND FUTURE WORK

Our system has a number of limitations. Firstly, our system ID's only one radar reflector ID at a time in the interaction space. We want to support multi-object identification and position tracking in the future. Additionally, our system's data collection process is time consuming because we must calibrate the radar reflector ID across the interaction space. We plan to improve this by developing a non-linear interpolation for the feature extraction method to ease the data collection process. We have also not tested all possible configurations of radar reflectors for Identification. With the improved data collection method, we will provide a comprehensive testing result for this. In addition to this, like other prior works, our system has limited interaction space and is sensitive to outer casing materials. Furthermore, the prototype cannot identify radar reflector when covered with hand or if the hand is present within the interaction space. we plan to overcome this limitation by placing another soli sensor horizontal to the table and train the machine learning algorithm with the hand's reflection. Lastly, only the size of the reflectors were used to differentiate them. Future iterations can look into other possibilities like material, shape, and so on.

Although our system uses soli radar sensor to built the prototype, the method to identify custom radar reflectors can be expanded to all 60 GHz FMCW radar sensor. We envision this system can be developed using commercially available devices such as Pixel 4 or Google Nest as a plug-and-play tangible interaction.

7 CONCLUSION

In this paper, we introduce RaITIn, a radar-based identification method that allows for novel tangible interactions. RaITIn uses custom DIY radar reflectors embedded into outer cases of any shape. Each ID is also stacked to create new configurations, allowing various tabletop modalities. Our results show an identification accuracy of 98.96%. The main novel contribution of the system is the use of 60 GHz FMCW radar sensors to classify different objects embedded with low-cost do-it-yourself (DIY) radar reflectors of varying sizes on a tabletop setup.As miniaturized radars are becoming more consumer-friendly in the future, we envision RaITIn to be used to enable new forms of tabletop interaction that are easy to access, setup and interact with. In order to create this future, our next steps are developing multi-object identification and position tracking within the interaction space.

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