RF-ISee: Identify and Distinguish Multiple RFID Tagged Objects in Augmented Reality Systems

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***Abstract*—In this paper, we leverage RFID technology to label different objects with RFID tags, so as to realize the vision of "show me what I see from the augmented reality system". We deploy additional RFID antennas to the COTS depth camera and propose a continuous scanning-based scheme to scan the objects, i.e., the system continuously rotates and samples the depth of field and RF-signals from these tagged objects. In this way, we can accurately identify and distinguish multiple tagged objects, by pairing the tags with the objects according to the correlations between the depth of field and RF-signals. Our solution achieves an average match ratio of 91% in distinguishing up to dozens of tagged objects with a high deployment density.**

I. Introduction

People nowadays start to leverage augmented reality (AR) systems to obtain an augmented view in a real-world environment. Specifically, users can effectively distinguish multiple objects of different categories, e.g., a specified object in the camera can be recognized as a vase, a laptop, or a pillow based on its natural features. However, these techniques can only offer a limited degree of distinctions among different objects, since multiple objects of the same type may have very similar features. Moreover, they cannot provide more inherent information about these objects, e.g., the manufacturers and production date. Therefore, it is rather difficult to provide these functions by purely leveraging the AR technology.

The rise of RFID provides us with an opportunity to effectively distinguish these objects, even if they belong to the same brand and have the same features of appearance. Fig. 1 shows a typical application scenario of the above vision. From the view of the camera, the depth camera can recognize several objects like the TV and pillow, as well as the depth information from its embedded depth sensor. The RFID reader can identify multiple tags within the scanning range, moreover, it is able to extract the signal features like the RSSI and phase value, as well as the detailed description of objects from the RFID tags. By effectively pairing these information together, the system can finally realize the vision of "show me what I see from the augmented reality system", and the detailed description can be directly associated with the corresponding objects in the camera's view.

In this paper, we leverage the RFID technology to further label different objects with RFID tags. We deploy additional RFID antennas to the COTS depth camera and propose a continuous scanning-based scheme to scan the objects, i.e., the system continuously rotates and samples the depth of field and RF-signals from these tagged objects. In this way, we can accurately identify and distinguish multiple tagged objects, by sufficiently exploring the inherent correlations between the depth of field and the received RF-signal. Specifically, we respectively extract the RSSI and phase value from RF-signal, and pair the tags with the objects according to the correlation between the depth value and RSSI/phase value.

Figure 1. Show me what I see from the augmented reality system

II. System Design

A. Design Goals

In order to realize the vision of "show me what I see from the augmented system", we need to collect the responses from multiple tags and objects, and then pair the RFID tags to the corresponding objects, according to the correlations between the depth of field and RF-signals. Therefore, we need to consider the following performance metrics: 1) *Accuracy:* Since the objects are usually placed in very close proximity, there is a high accuracy requirement in distinguishing multiple objects. 2) *Time-efficiency:* Since the AR applications are usually executed in a real-time approach, it is essential to reduce the time delay in identifying and distinguishing the multiple objects.

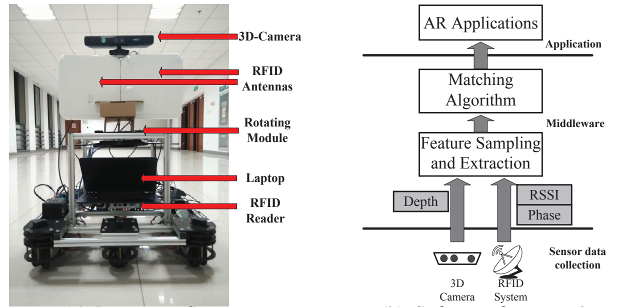
B. Hardware Framework

We design a prototype system as shown in Fig. 2(a). We deploy one or two additional RFID antennas to the COTS depth camera. The RFID antenna(s) and the depth camera are fixed to a rotating shaft so that they can rotate simultaneously. For the RFID system, we use the COTS ImpinJ R420 reader, one or two Laird S9028 antennas, and multiple Alien 9640 general purpose tags; for the depth camera, we use the Microsoft Kinect for windows. They are both connected to a laptop placed on the mobile robot. The mobile robot can do a 360 degree rotation with the rotating shaft. By attaching the RFID tags to the specified objects, we propose a continuous scanning-based scheme to scan the objects, i.e., the system continuously rotates and samples the depth of field and RF-signals from these tagged objects. In this way, we can obtain the depth of specified objects from the depth sensor inside the depth camera, we can also extract the signal features such as the RSSI and phase values from the RF-signals of the RFID tags. By accurately pairing these information, the tags and the objects can be effectively bound together.

C. Software Framework

Fig. 2(b) shows the software framework. The system is mainly composed of three layers: the sensor data collection layer, the middleware layer, and the application layer. For the sensor data collection layer, the depth camera recognizes multiple objects and collects the corresponding depth distribution, while the RFID system collects multiple tag IDs and extracts the corresponding RSSIs or phases from the RF-signals of RFID tags. For the middleware layer, we sample and extract some features from the raw sensor data, and conduct an accurate matching among the objects and RFID tags. For the application layer, the AR applications can use the matching results directly to realize various objectives. We respectively implement the following schemes:

1) *Static Scanning via Depth-RSSI Pairing (SS-RSSI)*: The system scans the tagged objects once at a fixed position, and pairs the tags with the objects according to their partial orders respectively in collected depth and RSSI.
2) *Hybrid Scanning via Depth-Phase Pairing (HS-Phase)*: The depth camera continuously rotates and scans the tagged objects, while the RFID antennas scan the tagged objects once at a fixed position, and pairs the tags with the objects according to the extracted depth and phase.
3) *Continuous Scanning via Depth-RSSI Pairing (CS-RSSI)*: The system continuously scans the tagged objects while it is rotating, and pairs the tags with the objects according to the extracted series of depth and RSSI.
4) *Continuous Scanning via Depth-Phase Pairing (CS-Phase)*: The system continuously scans the tagged objects while it is rotating, and pairs the tags with objects according to the extracted series of depth and phase.

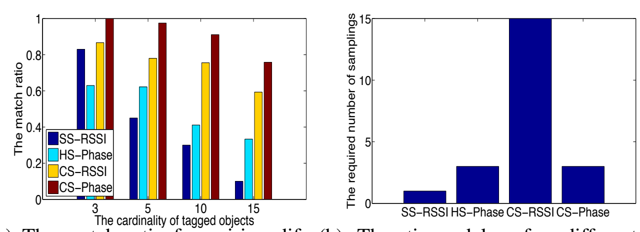


(a) Prototype System (b) Software framework

Figure 2. System Framework

III. Performance Evaluation

We evaluated our system using one Microsoft Kinect for windows, one ImpinJ R420 reader, two Laird S9028 RFID antennas, and multiple ImpinJ E41-B general purpose tags. We deploy multiple objects in an area of about 3m$\times$ 3m, and attach each tag to an object. We use the Kinect as the depth-camera and use the RFID reader to scan the tags. We run experiments to evaluate the accuracy in pairing the tags with the objects. We evaluate the match ratio for pairing different cardinalities of tagged objects. As shown in Figure 3(a), as the cardinality of tagged objects increases from 3 to 15, the match ratios of SS-RSSI and HS-Phase decrease in a rapid approach, whereas the match ratios of CS-RSSI and CS-Phase decrease slowly. We further evaluate the time-efficiency via the number of samplings. As shown in Figure 3(b), SS-RSSI achieves the least time delay, as it only requires to scan once, whereas CS-RSSI achieves the most time delay, as it requires to scan multiple times to find the peak point via continuous scanning, HS-Phase and CS-Phase achieve the medium time delay, as basically 3$\sim$4 samplings are enough for them to estimate the position of tagged objects.



(a) The match ratio for pairing different cardinalities of tagged objects (b) The time delay for different schemes

Figure 3. The experiment results

Acknowledgments

This work is supported in part by National Natural Science Foundation of China under Grant Nos. 61472185, 61373129, 61321491, 91218302; JiangSu Natural Science Foundation, No. BK20151390; EU FP7 IRSES MobileCloud Project under Grant No. 612212; CCF-Tencent Open Fund. This work is partially supported by Collaborative Innovation Center of Novel Software Technology and Industrialization. Lei Xie is the corresponding author.