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A Novel Robot Based Data Acquisition Methodology for Chipless RFID Systems

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***Abstract*—In this paper, a novel automated data acquisition methodology is presented for chipless RFID systems. The proposed method utilises a Raspberry Pi to act as an interface between a vector network analyser and a universal arm robot to perform automated measurements. A 98% improvement in data acquisition time is achieved when compared to standard manual data collection methodology. The system is validated by collecting 9,600 radar cross section electromagnetic signatures from a 3-bit chipless RFID capacitive sensor tag for five different cases at four positions. By enabling large, efficient, and accurate data collection, this methodology can support the development of machine learning models that can improve the performance and functionality of chipless RFID technology.**

***Index Terms*—Automation, chipless RFID, Data acquisition, Electromagnetics, Machine Learning, RFID, Robots.**

I. Introduction

In a Radar Cross Section (RCS) based Chipless Radio Frequency Identification (CRFID) system, when a reader sends an Electromagnetic (EM) signal to the tag, the tag reflects the signal back with a unique reflective pattern that encodes the data. The reader then analyses the reflected EM signal to decode the information stored in the tag (See Fig.1). The reflective pattern can be encoded by varying the shape, size, or material properties of the tag antenna. However, detecting the encoded data from reflected signals is challenging due to distortion from interferences like noise, reflections, and interferences from other tags [1]. This makes it necessary to employ sophisticated signal processing techniques to improve the accuracy of data detection. Some techniques utilised in the literature have applied supervised machine learning (ML) and deep learning algorithms to overcome the abovementioned challenges [2]–[4].

These techniques have pattern classification capabilities that can mitigate the challenges, resulting in a robust system. For example, in [2], the authors use an RCS-based tag for gesture recognition. The tag is developed using three split-ring resonators to create specific 3-bit EM signatures in the backscattered EM wave. A Feed-forward Artificial Neural Network (ANN) is utilised for training the models and classifying the eight possible combinations. Further, in [3], the authors utilize a deep learning-based security model to provide a high accuracy above 93%, when classifying a cloned tag from a genuine CRFID tag, even in the presence of additive RF interference in real-time.

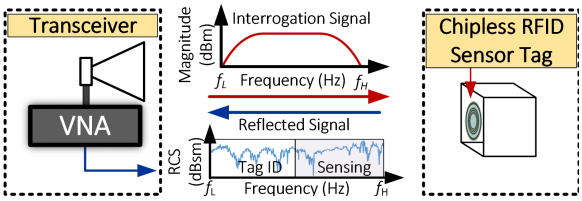


Fig. 1. Overview of a chipless RFID System.

In [4], the authors use RCS-based tags to develop a segregation system for a plastic recycling application. Using a dataset of 300 data points, the authors achieved an accuracy of 90% and 65% when classifying the two plastic types from homogenous bales and non-homogeneous bales, respectively. These papers, however, are limited to the number of IDs used for training. These papers also lack an efficient ML model evaluation for a CRFID sensor tag with both Identification and sensing information encoded within an EM signature. However, to develop high data storage capacity CRFID sensor tags for various IoT (Internet of Things) applications, it is essential to evaluate cases with a relatively higher number of IDs and sensing capability. One of the challenges to using ML is to have a large dataset of all possible bit combinations for training the models. It is also essential to have actual measurements, including noise and other interferences, in the dataset for model training to have robust detection in real-world scenarios [3].

As the bit capacity of a tag increases, collecting data for all bit combinations becomes impractical and time-consuming. For instance, an 8-bit tag requires data from all 255 combinations for measuring each possible bit string. In practical scenarios, multiple signatures are necessary to develop a robust ML model that accounts for interferences, noises, different read ranges, and orientations. This process is time-consuming and prone to errors; hence, an automated data acquisition methodology is preferred. One approach to this problem is to use automated robots, which could acquire large and efficient datasets with real-world measurements for robust data processing. This paper proposes a novel automated data acquisition methodology using a standard universal robot for CRFID systems. To the best of the authors' knowledge, this is the first time a similar approach has been used for CRFID systems. An automated system is presented in this manuscript programmed to carry out all the measurements and RCS calculations.

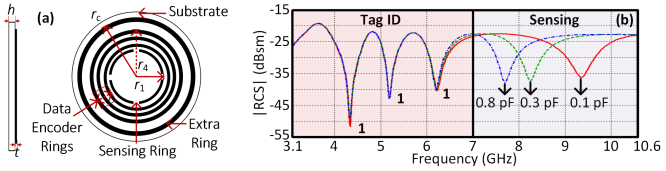


Fig. 2. A 3-bit CRFID sensor tag: (a) Topology (r_c = 14 mm), (b) Simulated EM RCS response of tag ID 111 with 0.1, 0.3, and 0.8 pF sensing points.

Further, the data is stored in appropriate folders for ML training. This methodology can reduce measurement time significantly from days to hours, acquire larger amounts of data efficiently, and lead to larger and better-constructed datasets.

II. 3-BIT CHIPLESS RFID SENSOR TAG

A. Design and Fabrication

For this study, a 3-bit polarization insensitive capacitive sensing RCS-based CRFID tag design is developed based on the design methodology discussed in [5]. The tag is developed using nested ring resonators. As shown in Fig. 2(a), the tag consists of an extra ring at the outermost edge, a sensing ring at the innermost edge, and three rings in between for 3-bit data encoding. The ultra-wide frequency band (UWB) of 3.1 to 10.6 GHz encodes the identification and sensing information. The tag is printed on a flexible 0.125-mm thick Polyethylene terephthalate (PET) substrate (ϵ_r = 2.9), and silver ink with a thickness of 0.01 mm is used to realize the conductive part using screen-printing technology. The data from the tag is retrieved by observing its RCS. As introduced in [5], the presence of the ring and its associated trough is utilised to represent bit '1', and their absence is used to represent bit '0'.

B. Data Encoding

The tag ID (from 0 to 7) is encoded within the frequency range of 3.1 – 7 GHz, while the rest of the UWB band is utilised for the sensing information. In this study, each tag ID is associated with three sensing points related to the capacitance values of 0.1, 0.3 and 0.8 pF. One example of the tag RCS response is shown in Fig. 2(b) for a tag carrying encoded information 'ID 111' with three sensing states. Therefore, the amplitude variation is utilised to detect the different IDs and the shift in frequency for sensing.

III. DATA ACQUISITION METHODOLOGY

For data acquisition, all 24 combinations of the tag were first characterised. Further, a data acquisition plan to collect data at four different positions and on five different surface shapes were considered, as shown in Fig. 3. A simplified polystyrene foam structure was devised to accommodate the five test cases outlined for the data acquisition. The flat side of the structure was utilized to hold the tag, which emulated a planar surface (Case I). The top edge of the same side was then utilised to replicate two corner bends by flexing the tag at 50/50 (Case II) and 25/75 (Case III) percent, as depicted in Fig. 3. Additionally, the structure consisted of two cylinders positioned on two sides, with radii of 40 mm (Case IV) and 10 mm (Case V), to replicate normal and severe cylindrical bends, respectively.

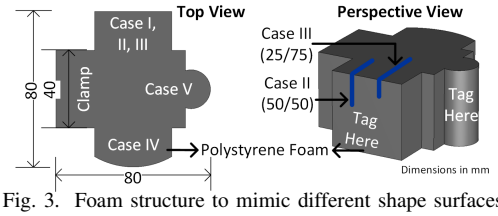


Fig. 3. Foam structure to mimic different shape surfaces.

The foam structure was developed to streamline the experimental procedure by enabling the robot to be programmed to position one of the sides of the structure towards the front of the transmitting/receiving antenna through the rotation of the clamping arm, thus minimizing the need for manual intervention. The five cases were considered along with four positions for 24 tags. For each combination, 20 measurements were performed to include varying noise levels and interferences leading to a total dataset of 9,600 signatures (e.g., 24 tags x 5 cases x 4 positions x 20 measurements).

A. Interface

In Fig. 4, the experimental setup to realise the automated data acquisition system is shown. An Anritsu MS2038C Vector Network Analyser (VNA) was interfaced with the Raspberry Pi (RPi) module [6] using Secure Shell (SSH) interface and using the Python programming language. The PyVISA, NumPy, and Pandas libraries were used for establishing communications and performing the required computations [7]. The VNA's port one was connected to a horn antenna (Schwarzbeck BBHA9120D), which is used for transmitting and receiving EM waves. Once secure communication was established with the VNA, the S-parameter (.S2P) files were acquired from the VNA. To compute the monostatic RCS, an open-source Python package Scikit-RF was utilised [8]. The monostatic radar measurement approach is used to reduce the measurement complexity. To calculate the RCS (Eq.1), first, the reflection coefficient of the horn antenna without the tag (S_{11Iso}) is measured, and then a flat copper plate as a calibration object is measured on the VNA (S_{11Ref}). Finally, we place the tag under test and take a measurement (S_{11tag}) [5], [9]. The first two calibration steps are only needed once and are used to compute the RCS of tags (from #1 to #24), as long as the test bench and environment near the bench remain unchanged.

$$\mathrm{RCS}(\sigma) = \left| \frac{(S_{11_{\mathrm{Tag}}} - S_{11_{\mathrm{Iso}}})}{(S_{11_{\mathrm{Ref}}} - S_{11_{\mathrm{Iso}}})} \right|^2 \times \left(\frac{4\pi A^2}{\lambda^2} \right) \mathrm{m}^2 \qquad (1)$$

where A is the area of the calibration plate, and λ is the wavelength. Further, the universal robot (UR16e) [10] is used to automate the movement process. The robot has six rotating joints with ± 360 degrees of working range and a maximum move speed of 120 - 180 degrees per second. The robot has a repeatability tolerance of ± 0.05 mm. The robot has a typical Tool Center Point speed of 1 m/s (39.4 in/s), which is suitable for a range of industrial applications, such as pick and place operations, assembly, packaging, and material handling. The UR16e robot is programmed using a programming language called Universal Robot Script (URScript). A flowchart process of the program is shown in Fig. 5.

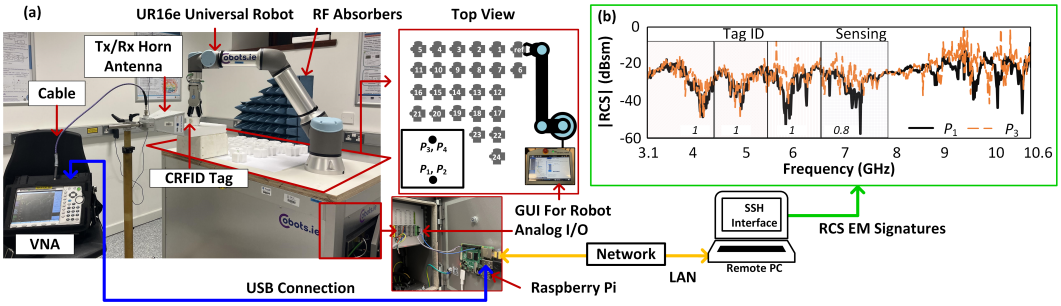


Fig. 4. (a) Automated RCS data collection setup using Ur16e Robot (b) Measured RCS of tag ID '111' with 0.8 pF sensing value at P_1 and P_3.

This language is specific to Universal Robots and is similar to other programming languages, such as Python. It allows the robot's movements, sensors, and external devices to be controlled and coordinated, enabling it to perform a wide range of tasks. As seen in Fig. 4, the robot's GUI was used to create waypoints for the operation's pick, drop, and place moments.

The foam structures are placed so the robot can pick and drop them one by one after each measurement. The robot is flexible and requires less time to place the tags in the correct position accurately. The RPi module is then loaded with the URScript with predetermined waypoints. The analog I/O pins are connected from RPi to the robot control system to control the movements. There is no manual work required after this step for each case. The robot can autonomously collect as much data as needed. For our case, we started with 9,600 signatures, but some cases may require much larger dataset for ML training. Moreover, in this paper, we had to manually place the tag on different surfaces to replicate the five cases after completing each case.

IV. Data Collection

The following process (Fig. 4) was used to collect data. A video showing the robot operating and collecting measurements is also available on [11]. In particular:

- The user gives a remote instruction to start the process to RPi. RPi sends a command to the VNA to obtain (S_{11Iso}) and then sends a command to the robot to pick the reference plate placed on a ref foam structure to measure (S_{11Ref}).
- The robot picks, places, and then comes to a rest position and sends a command to the VNA to take the reference measurement. The arm is then taken to the rest position to avoid any interferences in measurement due to the Robot arm.
- RPi records the (S_{11Ref}) and sends a command to drop the reference plate back into its position and pick tag 1.
- Robot picks the tag 1, places it at position 1, comes to rest, and sends command to take the measurement.
- The RPi then records a measurement at a rate of 1 measurement/second.
- Once the data is collected, the RPi in real-time computes the RCS based on (S_{11Iso}) and (S_{11Ref}).The RCS data is stored in appropriate folders as a .csv file ready for further data analysis or real-time measurement monitoring.
- The robot then moves the tag 1 to position 2 and repeats the measurement process. After the data from all four positions are collected the robot repeats the process for tag 2, and so on up to tag 24. All the movements and data collection process is autonomous and requires no manual work, which is essential when larger datasets needs to be collected efficiently.

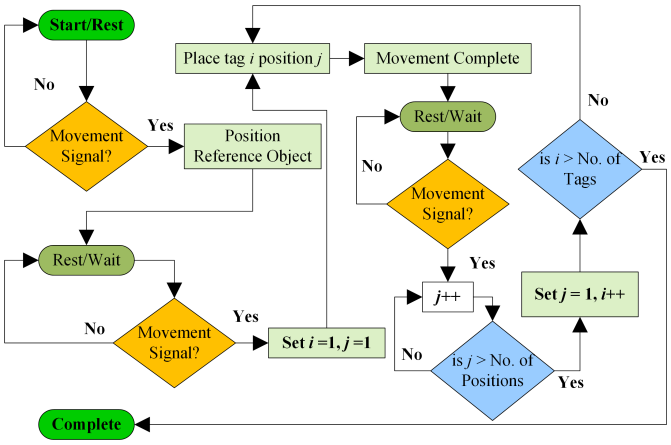


Fig. 5. Flow process for UR16e robot program.

V. Results and Discussion

After the two calibration measurements are taken, the total time taken by the robot to carry out a complete data collection for a single case (e.g., collecting 20 measurements for each position and computing their RCS and storing the files in appropriate folders) for each tag is approximately 115 seconds with no human requirements (Shown in Table I). At the same time, the manual procedure would approximately take 4950 seconds. Further, manually we will only be able to collect the .S2P files from the VNA and would still need to post-process the data to compute RCS. This procedure requires a human to be present in the loop at all times. The proposed automated data acquisition method is thus approximately 43 times faster compared to a manual intervention by a human operator. This also ensures repeatability and reduces the possibility for human operators to introduce measurement errors. For example, if the setup is disturbed by a human movement, the whole measurement must be repeated. In Fig. 4(b), an example from the collected measured signatures is shown for tag ID 7, with a sensing value of 0.8 pF at positions one and three.

TABLE I
AUTOMATED VS MANUAL MEASUREMENTS.

Movement	Automated (s) (± 0.05 mm)	∼ Manual intervention (s) (by a human operator)
Pick and Place to P_1	8	60
Take 20 Measurements	20	1200
Move to P_2	9	30
Take 20 Measurements	20	1200
Move to P_3	9	30
Take 20 Measurements	20	1200
Move to P_4	9	30
Take 20 Measurements	20	1200
Total Time	**115 (1.91 mins)**	**4950 (82.5 mins)**

As seen, the data is noisy and varies significantly at the two positions. Therefore, capturing these discrepancies can meaningfully help the ML models to detect the correct values. Further, the variation of positions and repetitive measurements can easily be increased as per the requirements, leading to a large dataset for efficient data processing. In addition to the significant time savings and reduction in measurement errors that the proposed automated data acquisition method offers, it also has important implications for the development of ML models. The collected data can be used to train ML algorithms to accurately detect and classify different CRFID tags based on their unique EM signatures. By capturing the discrepancies and variations in the collected data, ML models can learn to distinguish between similar tags that might otherwise be difficult to differentiate. Moreover, the automated data acquisition method has potential applications beyond ML. For example, it can be used to efficiently and accurately collect data for various types of EM measurements, including those for antenna design and testing. The method can also be applied to other contexts where repetitive data collection is required, such as in environmental monitoring. Overall, the proposed method has the potential to transform the way in which EM signatures are collected, with significant benefits in terms of speed, accuracy, and repeatability.

VI. CONCLUSIONS

In conclusion, RCS-based CRFID technology is an exciting development in the field of RFID, offering several advantages over conventional RFID tags, such as low-cost, maintenance-free operation, and flexibility in design. However, it also presents some challenges, including the difficulty of detecting the encoded data from the reflected signal in the presence of interferences. To address these challenges, ongoing research and development are being conducted to improve the performance of RCS-based CRFID technology and enable its wider use in various applications.

One of the solutions is to use ML models to detect the encoded information. However, one main challenge is collecting large datasets from tags with high bit capacity and different sensing ranges. The automated data acquisition methodology proposed in this paper can reduce the time required for acquiring larger datasets to develop robust ML models.

The cost-effectiveness of the proposed solution depends on several factors, such as the specific hardware and software used, as well as the scale of the project. The robot used in this paper is expensive; however, it can be easily replaced with lower-cost robots and open-source software, making it accessible to a wide range of users. Finally, the long-term benefits of increased efficiency, repeatability, and reduced errors make the automated data acquisition method a worthwhile investment for many applications.

In future, the aim is to use this data to train ML models and test the detection accuracy when the tag is bent on different surfaces, positions and tilt angles. The aim is to train the models to detect the tags regardless of their surface shape in a predetermined read range area and varying angles.

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REFERENCES

[1] A. Subrahmannian and S. K. Behera, "Chipless RFID: A unique technology for mankind," *IEEE Journal of Radio Frequency Identification*, 2022.

[2] M. Hajizadegan and P.-Y. Chen, "Gesture recognition using a portable and flexible meta-atom panel and machine learning," in *2019 IEEE International Symposium on Antennas and Propagation and USNC-URSI Radio Science Meeting*. IEEE, 2019, pp. 637–638.

[3] G. Khadka, B. Ray, N. C. Karmakar, and J. Choi, "Physical-layer detection and security of printed chipless RFID tag for internet of things applications," *IEEE Internet of Things Journal*, vol. 9, no. 17, pp. 15 714–15 724, 2022.

[4] F. Villa-Gonzalez, R. Bhattacharyya, and S. Sarma, "Single and bulk identification of plastics in the recycling chain using chipless RFID tags," in *2021 IEEE International Conference on RFID (RFID)*. IEEE, 2021, pp. 1–8.

[5] N. Rather, J. Buckley, B. O'Flynn, and M. Pigeon, "A novel RCS based CRFID tag design," in *2022 16th European Conference on Antennas and Propagation (EuCAP)*. IEEE, 2022, pp. 1–5.

[6] G. Halfacree and E. Upton, *Raspberry Pi user guide*. John Wiley & Sons, 2012.

[7] A. Patel, S. Sisodia, and S. K. Pandey, "Interfacing of high temperature z-meter setup using python," in *AIP Conference Proceedings*, vol. 1832, no. 1. AIP Publishing LLC, 2017, p. 060002.

[8] A. Arsenovic, J. Hillairet, J. Anderson, H. Forsten, V. Rieß, M. Eller, N. Sauber, R. Weikle, W. Barnhart, and F. Forstmayr, "scikit-rf: An open source python package for microwave network creation, analysis, and calibration [speaker's corner]," *IEEE Microwave Magazine*, vol. 23, no. 1, pp. 98–105, 2021.

[9] N. Rather, R. B. Simorangkir, J. Buckley, and B. O'Flynn, "Flexible and semi-transparent chipless RFID tag based on PDMS-conductive fabric composite," in *2022 International Workshop on Antenna Technology (iWAT)*. IEEE, 2022, pp. 33–36.

[10] U. Robots, "The UR16e," https://www.universal-robots.com/products/ur16-robot/, 2022, [Online; accessed 26-April-2023].

[11] N. Rather, "Automated data acquisition using an ur16e robot, https://drive.google.com/file/d/19k-LHsGM7j9XVsXU9na0QYW1hGzVXGBS/view," 2023.