A Machine Learning Approach-based Chipless RFID System for Robust Detection in Real-world Implementations

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***Abstract* — This work describes a novel method based on a machine learning (ML) approach for highly accurate and robust identification of chipless RFID applications in realistic environments. For this purpose, effective transponder reading is achieved not only for a wide variety of ranges and contexts but also for different commercial objects attached to the chipless RFID tag, while providing tag-ID detection accuracy of up to 98.5%. A UWB transmitting tag antenna, four tags encoding the four 2-bit IDs, and a UWB receiving tag antenna were inkjet-printed onto flexible low-cost substrates and interrogated without cross-talk or clutter interference de-embedding at ranges from 2 to 50 cm, with different objects attached to the tag (non-conductive, aluminum can, and plastic bottle filled with water), for both configurations with and without the presence of scattering objects in the vicinity of the tags and reader. Finally, a Support Vector Machine (SVM) using the information of the measured transmission coefficients (S_{21}) outperforms the other methods displaying reading accuracies 98.5%.**

***Keywords* — chipless RFID, classification, inkjet printed tags, Internet of things, machine learning, support vector machine.**

I. Introduction

RFID is an emerging wireless technology for capturing data from tagged objects using HF, VHF, and RF waves automatically, unlike barcodes that require a human operator for interrogation [1]. The design and fabrication of ASICs needed for RFID are the major component of their cost, which is the main challenge to their adoption. To address this challenge, a printable chipless RFID tag [2], which uses materials and configurations that reflect a portion of the reader's signal back, and featuring a unique return signal that can be used as an identifier, was developed by using low-cost conductive inks. However, these types of tags have short reading ranges and are sensitive to interference, such as material contents of the tagged objects. Especially, cross-talk between reader antennas and environmental clutter interference can generically be de-embedded but this approach cannot account for large contextual changes in the vicinity of the tag and reader. A depolarizing chipless RFID tag [3] and a cross-polar orientation insensitive chipless RFID tag [4] were proposed to ease the detection of items in realistic environments such as tagging objects which contain high reflective and high absorptive materials. However, these need specialized tag designs and additional calibrations due to the limited reading range. In this paper, the first ML application for the enhanced accuracy with robust detection of chipless RFIDs regardless of the wide variety of the ranges and contexts, the tag's types and the materials attached to the tag, is proposed.

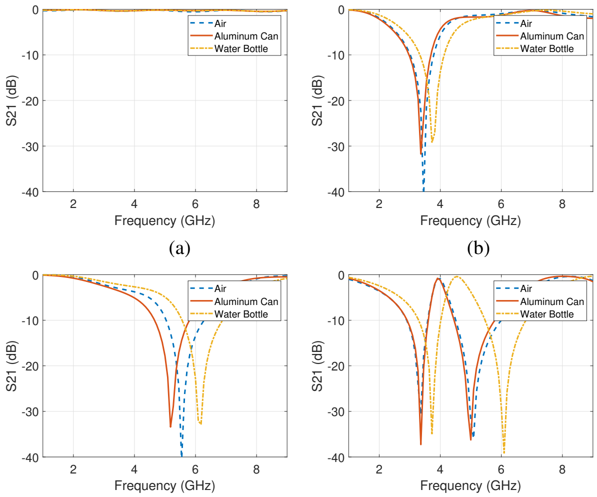
II. Chipless RFID System Characterization

A. Chipless RFID Tag design

Four proof-of-concept chipless RFID topologies with two T-shaped resonant elements encoding all possible 2-bit combinations were used, and the overall geometrical design for a T-shaped resonator is same used in [5]. Each vertical microstrip line represents a different stop-band resonance at 3.45 and 5.7 GHz, which can be used as IDs acting for logic '00', '01', '10' and '11'. To verify the detuning of the tag's resonator when changing the material to be attached, S_{21} values of all four tags were first simulated with a non-reflective object and highly reflective objects (aluminum can, plastic bottle filled with water). HFSS simulation shows that the tags get detuned when they are attached to highly reflective objects as shown in Fig. 1. Without manual analysis of the effect of the microwave propagation on different material on the tag response, the superiority of the ML approach making detection of tag ID placed on conductive objects is quantitatively demonstrated. For practical implementations, a UWB receiving tag antenna, a T-shaped resonator, and a UWB transmitting tag antenna are integrated, fully printed on PET substrate and connector-free as shown in Fig. 2 compared to authors' prior work [5] where the tag and antenna have been used separately.

B. Measurements and Data Collection

Overall, the measurement setup is similar to that used in [5]. The proposed chipless RFID system consists of the transmitter reader/tag antennas, receiver reader/tag antennas and resonator tag attached to different material objects (plastic box, aluminum can, and plastic bottle filled with water) its height of 8 cm from the ground, in a realistic environment as shown in Fig. 3. The Rx/Tx antennas were cross-polarized to enhance cross-talk isolation and placed on the sponge, the thickness of 4 cm. The S-parameters were measured using a vector network analyzer (VNA), with a total of 612 measurements varying in the range of interrogation distances 2 to 50 cm (in step of 3 cm), with different objects where tag placed with consideration of radiation pattern between reader and tag, and in the presence of clutter in between the tag and



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

Fig. 1. Simulated S_{21} values of (a) the tag '00', (b) the tag '10', (c) the tag '01', and (d) the tag '11' with respect to attached materials.

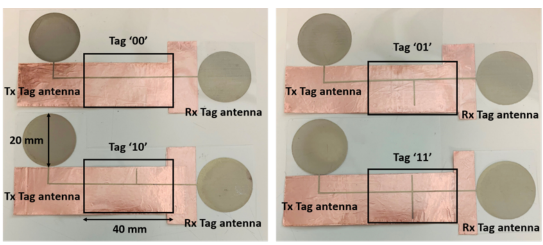


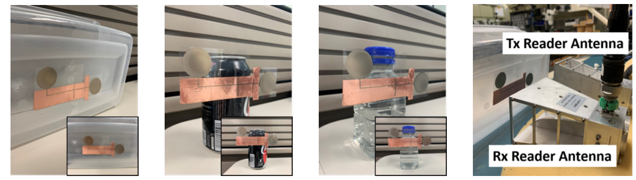
Fig. 2. Inkjet printed chipless RFID tags and antennas.

reader. To emulate the clutter, a paper sheet or a copper sheet (18 cm x 20 cm) was always placed in the middle of the tag and the reader antennas as shown in Fig. 4-(b),(c).

In other words, each tag underwent a total of 153 measurements varying the: 1) range of distances, 2) object materials, and 3) presence of clutter. S-parameters of the measurement data were saved from 1 to 10 GHz in total 500 points per measurement. Only the information of the S_{21}, which serves as the channel transfer function between the reader antennas involves discrete frequencies, were interested and used in the training. To acquire the 612 measurement dataset faster, MATLAB Instrument Control Toolbox is used to communicate with a VNA directly for collecting and analyzing data, visualizing the results, and automating test without having to save and import it into MATLAB at a later time.

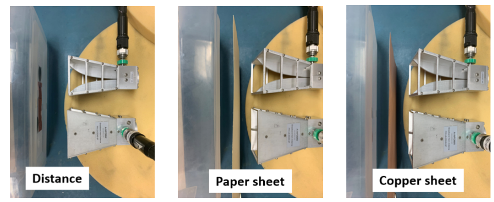
III. Machine Learning Approach and Performance Evaluation

From the literature, four potential ML approaches were identified: Decision Trees, k-Nearest Neighbor (k-NN), Linear Discriminant Analysis (LDA), and Support Vector Machine (SVM). We have explored these approaches and the effect of combining different RF features to see how this does affect the performance. As mentioned in Sec. 2-(B), the measured S_{21} parameters from 1 to 10 GHz with 0.018 GHz interval (in total 500 points per measurement) were used as input data for the training process. The output of the algorithm was set as the parameter, the IDs of the tags.



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

Fig. 3. (a) Tag attached to the plastic. (b) Tag attached to the aluminum can. (c) Tag attached to the plastic bottle filled with water. (d) Measurement setup from reader side.



(a) (b) (c)

Fig. 4. (a) No object between the tag and the reader antennas. (b) Paper sheet between the tag and the reader antennas. (c) Copper sheet between the tag and the reader antennas.

A. Detection Results in Different Context

One of the fundamental motivations for this research was to create a practical chipless RFID tag reading system, which can enable the easier detection of items in realistic environments such as not only tagging the objects which have high reflective and high absorptive materials but also feature an accurate detection/interrogation in the presence of scattering objects in the vicinity of the tags and reader. To verify the effect of the underlying material as well as of the presence of nearby objects, an extract set of datasets at specific composition (17*4=68) from the whole dataset was not used for the training. In other words, 68 datasets were not included for training, but were then used as testset to demonstrate the effect of this specific dataset on the RFID system performance under a certain condition.

As Table 1 clearly shows how the accuracy changes for different materials under the tag and for different objects nearby, the accuracy improvement through the presented technique is very significant especially in challenging contexts lacking detailed data, such as the presence of a copper sheet between the reader and tag antennas. After training with 544 measured data points while leaving 68 others with the proposed SVM and LDA classification, the trained model displayed the lowest error rate of around 23.93%, as shown in Table 1, for measurement data sets with a copper sheet that were not included in the training. It can be easily observed that the dataset composed of measurements with a copper sheet have a more prominent impact of the classification capability than other factors. Although, the tag ID detection accuracy decreased up to 12% with the highly reflective object between the reader and tag antennas, an accuracy above 97% was achieved utilizing combined features will be discussed in this

Table 1. Accuracy without specified composition of the dataset

	No object		Paper Sheet		Copper Sheet	
	SVM	LDA	SVM	LDA	SVM	LDA
Plastic box	67.1	69.5	67.6	68.9	74.8	79.4
Aluminum can	69.1	68.4	70.6	68.6	75.2	76.1
Bottle filled with water	67.6	69.9	68.9	67.8	75.7	75.2
Average Error rate	31.4		31.27		**23.93**	

Table 2. Comparison accuracy of the different trained models

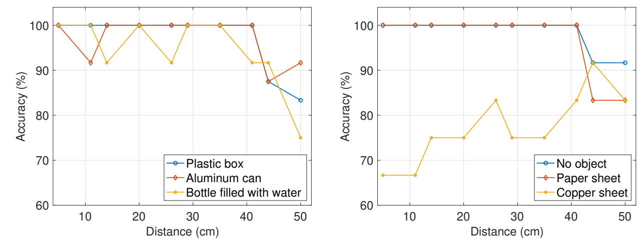
	Decision Trees	k-NN	LDA	SVM
Magnitude	43.5	52.3	70.3	70.6
Real	28.9	38.9	58.8	42.2
Magnitude & Phase	86.9	97.2	**98.2**	**98.5**
Real & Imaginary	79.9	96.6	97.2	90.3

section part B, suppressing the effect of the environment and nearby highly reflective objects.

B. *Performance Characterization of tag detection*

In order to detect tag IDs, several classification algorithms were trained with multidimensional information generated from various possible combinations of all or subsets of magnitude, phase, real, and imaginary information of S_{21} which form the hybrid features. Results, presented in Table 2, based on these combined features show indeed a substantial improvement in the algorithm prediction resulting in significant enhancement in tag ID detection. Table 2 shows that the LDA classifier achieved an accuracy of 98.2% when magnitude and phase information of the measured S_{21} were used for training process. Moreover, k-NN classifier also features high accuracy of reading success rates above 96% for raw data, without any cross-talk or environmental-clutter removal calibrations. Especially for SVM classification, several kernel functions of SVM techniques were explored including linear, quadratic, cubic and Gaussian functions. Results obtained show that a cubic kernel method outperforms the other methods for detecting tag's IDs with an accuracy of 98.5% as also shown in Table 2. In this context, the algorithm demonstrates a remarkable performance for detecting tag's IDs comparable with those obtained by other classification methods.

To further understand the ability of the trained model to successfully read chipless RFID tag IDs for distances ranging between 5-50 cm, the detected and the actual ID values of each different testset were analyzed. Every testset composed of 12 measurement configurations at constant ranges with values between 5-50 cm in steps of 3 cm, for different attached materials and nearby objects that had not been included in the training sets. Since the amount of original data used for the training was relatively independent between each measurement sets, extract testset from the measured data are essential to verify the prediction capability. Another reason to create the testset from measured data that has not been used for the training before in this application is to demonstrate the robustness of the chipless RFID measurement approach,



(a) (b)

Fig. 5. (a) Detection accuracy for different materials attached to the tag at different interrogation distances. (b) Detection accuracy for different nearby clutter objects placed between the reader and the tag antennas for different interrogation distances.

especially in challenging contexts such as these used here with large antenna crosstalk and significant nearby clutter and, thereby, difficult to extract tag IDs. After training with 1200 (600 of magnitude data and 600 of phase data) measured data points while leaving 24 (12 of magnitude data and 12 of phase data) others at each distance for testing with the proposed SVM classification, the trained model displayed an accuracy above 90% during self-testing for distances up to 40 cm with the exception of the case of dataset with the copper sheet “clutter" object causing a high reflection close-by, as shown in Fig. 5, for dataset that were not included in the training. For example, 100% of accuracy in Fig. 5 is calculated where the trained model correctly detects 24 tag's IDs among 24 cases of the test dataset.

This work reveals the very significant read range and successful interrogation enhancement that can be achieved with this technique, without any required knowledge of the specific operating environment, and in practical conditions featuring variable interrogation distances and dynamically changing clutter without the need for additional calibration.

IV. Conclusion

In this study, the feasibility of a ML classification approach for highly accurate and robust identification of chipless RFID applications in realistic environments is discussed. First, four tags encoding the four 2-bit tags with two UWB monopole transmitting and receiving antennas were inkjet-printed onto flexible low-cost PET substrates. The implementation of several ML classification techniques for the effective transponder reading not only for a wide variety of ranges and contexts but also for different commercial objects attached to the chipless RFID tags, while providing tag-ID detection accuracy of up to 98.5% was provided. This is the first application of such concepts for enhanced-accuracy detection of chipless RFIDs along with a robust reading capability in realistic environments. This approach could potentially enable not only the successful tagging of objects consisting of highly reflective/highly absorptive materials but also feature an accurate detection/interrogation in the presence of arbitrary scattering objects in the vicinity of the tags and reader eliminating the need for any additional processes such as background subtraction technique and calibration for specific materials.

REFERENCES

[1] K. Finkenzeller, *RFID Handbook: Fundamentals and Applications in Contactless Smart Cards and Identification*, 2003. [Online]. Available: https://books.google.com/books?id=KQLqjwEACAAJ

[2] S. Preradovic, I. Balbin, N. C. Karmakar, and G. Swiegers, "A novel chipless rfid system based on planar multiresonators for barcode replacement," in *Proc. IEEE Int. Conf. RFID*, Las Vegas, NV, April 2008, pp. 289–296.

[3] A. Vena, E. Perret, and S. Tedjni, "A depolarizing chipless rfid tag for robust detection and its fcc compliant uwb reading system," *IEEE transactions on microwave theory and techniques*, vol. 61, no. 8, pp. 2982–2994, 2013.

[4] F. Babaeian and N. Karmakar, "A cross-polar orientation insensitive chipless rfid tag," in *2019 IEEE International Conference on RFID Technology and Applications (RFID-TA)*. IEEE, 2019, pp. 116–119.

[5] S. Jeong, J. G. Hester, W. Su, and M. M. Tentzeris, "Read/interrogation enhancement of chipless rfids using machine learning techniques," *IEEE Antennas and Wireless Propagation Letters*, vol. 18, no. 11, pp. 2272–2276, 2019.