A machine learning approach to improve UHF RFID gate operation

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***Abstract*—The aim of this work is to improve the operation of a UHF RFID gate using a supervised learning approach based on Artificial Neural Networks (ANNs). In our setup, we assume that boxes containing items are inventoried using an RFID gate with random perturbations in the box positions as well as random items inside boxes. The gate has two bistatic dislocated antenna pairs and, for each box, it is possible to choose a particular pair or mix both (the antenna selection policy). Based on the interrogation statistics (tags read and average received signal strength) from initial reference frames it is possible to obtain a signature of the interrogation process to predict the probability of identifying the whole batch of items contained in the box. Predictions are carried out using the ANN, which is trained with data generated using a simulator. This system can be used online to select the best policy during operation, in order to minimize the time penalties caused by inventory faults.**

***Index Terms*—RFID gate, machine learning, supervised learning, online operation.**

I. INTRODUCTION

RFID technology has achieved maturity and its use is spreading as a common tool for supply chain managing and other uses [1], [2]. Some works like [3], [4] have highlighted that it is fundamental to improve the knowledge in the practical use of this technology, to understand and overcome the current technological limitations. In some cases a proper choice of the reader parameters (e.g., power, channel) may solve these problems. However, each setup has to be tailored to a particular installation, and even worse, if conditions change dynamically, the parameters have to be adaptively tuned, becoming a challenging problem.

Moreover, some works have analyzed particular scenarios using white-box approaches like simulators or *in-situ* measurements for constructing detailed models, which can be latter used to select suitable operation parameters. In many cases these systems rely on machine learning approaches to adapt to previously unseen situations.

For example, Windmann *et al.* [5] discuss a self-optimizing RFID system which adapts the transmission frequency and the transmission power of the RFID reader to the system environment. Authors use an unsupervised learning method based on clustering for this task and show that it reduces energy consumption while achieving a suitable communication link. In another work, Ma *et al.* [6] focus on the use of machine learning to identify false RFID positive readings (tags that are detected accidentally by the reader but not the ones of interest). They consider several statistical features extracted from received signal strength (RSS) and phase rotations derived from the raw RFID data, used as input for several types of classifier. Their results indicate that support-vector-machines (SVM) provide an accuracy up to 95.3%, fostering potential for fully automatic identification and tracking RFID systems. In [7] authors present a solution to discriminate the direction of goods crossing an RFID gate in a warehouse scenario using a recurrent neural network (RNN). Buffi *et al.* [8] introduce Artificial Neural Networks (ANNs) to discriminate tag actions in UHF RFID gates. They use real traces to build a multi-layer perceptron neural network to distinguish among tags incoming, outgoing or passing the RFID gate, obtaining a 99% accuracy. Zanetti *et al.* [9] study the individual physical-layer identification signature of passive UHF RFID tags using machine learning methods and analyze the implications of these results on tag holder privacy.

Beyond these applications, machine learning has proven useful in the RFID field in other applications such as RFID Network Planning (RPN) [10]–[13], position estimation enhancement [14] or data stream enhancement [15]

In this work we aim at developing a smart gate controller, based also on a white-box supervised learning approach, with the goal of selecting among several possible antenna transmission/reception policies the one maximizing the chances of a successful inventory process. That is, to guarantee that all tags in the reading zone are successfully detected. For that, a scenario layout is simulated and traces of the interrogation of about 120000 batches of tags are obtained. These batches are then used to train an ANN, which takes as inputs the policy selected and statistical features obtained in fixed reference frames at the beginning of the interrogation process. These features work as a signature of the batch configuration (e.g., actual position, tags distribution, etc.) which is unknown for the reader.

In the next section, the operation of the proposed system is

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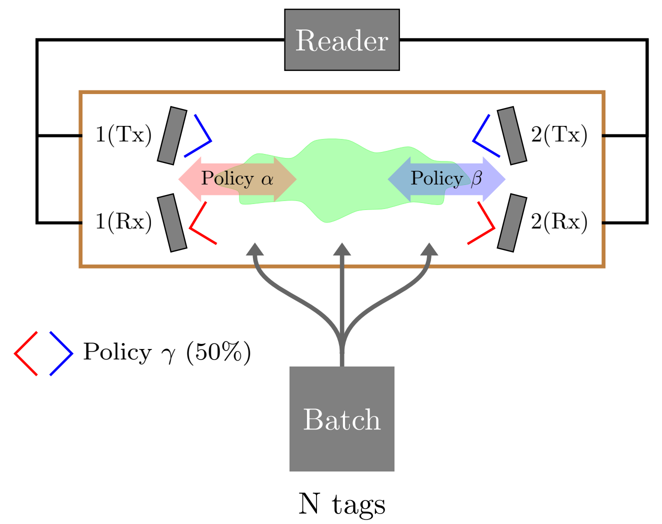

Fig. 1. Scenario setup. The gate is composed by two bistatic dislocated antenna pairs. Boxes containing tags arrive to the reading area and their location is random. The position is unknown to the reader. The reader can apply three different policies to adjust the Tx/Rx operation: (α) Use always the antenna 1 pair, (β) Use always the antenna 2 pair, (γ) Alternate between both. Depending on the position, the box contents, and the policy, the batch can be readable or not.

thoroughly described. Section III summarizes the main characteristics of the simulation used to obtain interrogation samples. Section IV discusses the development of the predictive system, and section V provides evidence of the ANN accuracy and the saving achievable by selecting online the best predicted policy. Finally, the main conclusions are provided in section VI.

II. System Description

Our scenario consists of a single reader which manages two pairs of bistatic dislocate antennas, as shown in the figure 1. Tags arrive to the reading area attached to objects which are packed inside boxes. The position where the boxes are left has a random component. The box contents (tags number and position) is also random.

To interrogate a box the reader can select one among three different antenna use policies:

- The α policy, which always uses the first antenna pair.
- The β policy, which always uses the second antenna pair.
- The γ policy, which alternates the role of both antennas.

The principal operative goal is to **identify all tags in the batch**, that is, avoiding inventory faults which will require human intervention. Other questions, such as the minimization of the reading time are not considered as a goal, as they will only lead to marginal improvements. The critical factors which determine the success in the batch identification are the position and the internal geometry of the box containing the tags. Other factors, such as interferences in the surroundings can also affect the outcome from the reading process. However, all this data is unknown for the reader. To overcome this issue we propose to use, at the beginning of the interrogation process, several fixed-configuration interrogation frames whose statistics will serve as a signature for the performance of the whole interrogation process.

In particular, let us denote as R the number of reference frames used. Three options have been considered, from R=1 to R=3. For each of them, the following statistics are captured:

- For R=1, in the first reading frame the antenna 1 pair is used for transmission (Tx) and reception (Rx). Three statistics are obtained: (i) the number of tags read in the frame, (ii) the average RSS in slots with successful tag identification, and (iii) the average RSS in slots with collision.
- For R=2, a second reference frame is used, in this case using antenna 2 pair. Similar statistics are obtained for this frame.
- For R=3, statistics of an additional reference frame are captured, in this case, antenna 1 is used for TX and antenna 2 for RX.

After the R reference frames the policy selected is used for the rest of the interrogation process. The final outcome is either a successful batch interrogation (all tags are read) or an inventory fault (some missing tag). The main technical goal of this work is developing a predictive structure for this outcome, using the signature information from the reference frames as well as the policy selection. This way, the best policy can be selected to read the batch or an alarm can be triggered reporting the problem in advance.

III. Scenario Simulation

Our learning agent will be focused on predicting the batch interrogation probability (BIP). To that end, a dataset with samples containing statistic data from the reference frames and the actual interrogation outcome is required. To construct this dataset the model described in the previous section has been simulated in a fully-detailed UHF RFID gate layout. Table I summarizes the main parameters of this simulated gate.

In the simulator, for each box (batch), the following process is repeated:

1) Position, tags' distributions and orientations are selected.
2) Interrogation begins using three fixed FSA frames with frame-length 128 slots. First frame uses α policy, second one the β policy, and the remaining one the γ policy, as described in the previous section.
3) The statistics described in the previous section are extracted from the reference frames to obtain a signature from the interrogation process.
4) The interrogation policy is chosen at random between α, β, and γ.
5) Then, the interrogation process continues using this policy and dynamic-FSA as the anti-collision protocol until either all tags are identified or the reader is unable to recover the identity of some tags (e.g., due to the lack of power reaching the tags).
6) The final outcome (batch read or inventory fault) is registered together with the ratio of tags read and the total elapsed time in the interrogation process.

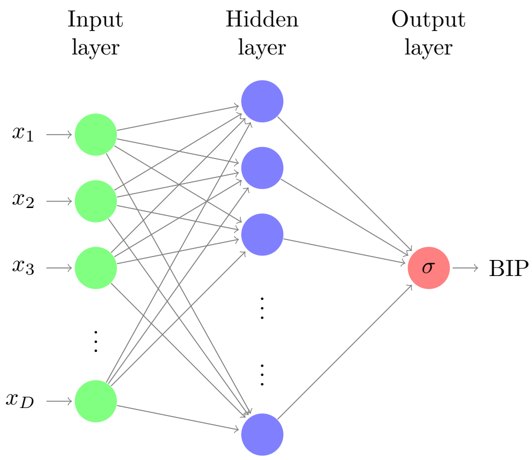

Fig. 2. ANN layout. Input layer consists of the normalized data obtained from the initial reference frames and input variables indicating the policy. Output indicates the probability that the batch is read if the given policy is applied.

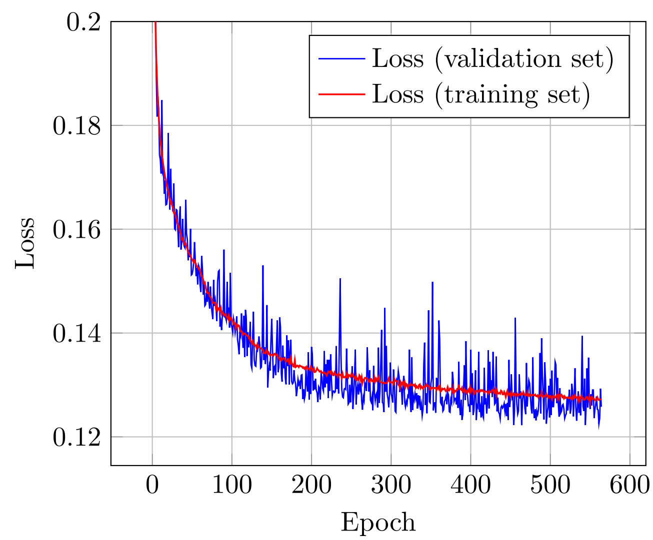

Fig. 3. Loss (binary-cross-entropy) evolution for both the training and the validation set for the R=2 configuration. ANN training continues while loss decreases in both datasets to avoid overfitting (early-stopping mechanism with patience of 100 epochs).

This experiment has been repeated 120000 times to construct a rich dataset that allows to train the predictive system to classify whether new, unseen, boxes will be read or not according to the registered records. Next section describes the predictive technique used.

IV. Predictive system

Our predictive problem is of supervised classification type. Several structures can be used for this purpose. In this work, an Artificial Neural Network has been chosen since it simplifies the prediction problem by automatically finding proper non-linear input data transformations. Figure 2 shows the layout selected. The input has $3(R+1)$ variables. $3R$ correspond to the normalized (in the range $[0, 1]$) reference frame statistics. The remaining three variables represent the policy selection (with one-hot-encoding). The ANN has a hidden layer composed of 20 nodes with tanh activation function. The output layer is formed by a single node, with sigmoid activation (since the output represents the batch identification probability). The loss function is the binary cross-entropy.

From the dataset, 20% of the records have been left out as validation data. Training overfitting have been controlled with an early stopping mechanism (with 100 epochs patience). The back-propagation optimizer used was Adam with a batch size of 32. For all values of R the training stopped in about 600 epochs. As an example, figure 3 shows the loss evolution for both the training and validation datasets.

Network training and design has been implemented using Keras https://keras.io/. The training datasets and the Jupyter notebook implementing this process is publicly available at the authors' github site https://github.com/javiervales/smartgate.

V. Results

In this section the predictive capacity of the ANN is analyzed. The accuracy, the precision, the recall (true-positive-rate), and the fall-out (false-positive-rate) are summarized in Table II for different R configurations. Precision determines the ratio of batches which are tagged as readable and are actually readable to the total number batches tagged as readable (actually readable or not). Recall evaluates the ratio between the batches tagged as readable and actually readable to the total number of actually readable batches. Finally, the fall-out evaluates the ratio of batches which can't be read but are tagged as readable to the total number of unreadable batches. Although related, the main goal for the operation of the smart gate system should be minimizing the fall-out, to reduce human supervision on the gate system.

As expected, results from table II demonstrate that adding more reference frames improves the signature of the reading process and leads to better estimations. Even with the simple features selected the results are promising, with about 5% of fall-out for R = 3.

As additional insight, it is also possible to determine the per-policy metrics. That is, the prediction statistics when a particular policy is selected. Table III shows those statistics for the R=3 configuration. Results reveal a slight better reliability of the γ policy predictions, although close to the operation of the other policies.

In addition to the ANN reliability analysis it is worth to study how this predictive system can save time compared to a conventional gate system. For that, an experimental simulation has been performance with the following assumptions made for this comparison:

- A predictive system with R=3 is assumed to be available at the gate.
- For each new box the reference frames are obtained and then the BIP prediction is obtained for each of the policies (α, β, γ).
- The one with the highest predicted BIP is selected.

TABLE I
SIMULATED SCENARIO CONFIGURATION

Parameter	Value
Box position	Random $\pm$ 1.5 m in X direction and $\pm$ 0.5 m in Y direction
Tags per batch (N)	Random between 100 and 1000
Box dimensions	Cube with 1.2 m size
Tags distribution and orientation inside boxes	Random uniformly distributed with random orientation
Frame interrogation protocol	DFSA [16] for regular frames, FSA with framelenght 128 for signature (reference) frames
Collision resolution	Signal-to-interference-noise is computed per slot to determine the preamble decoding probability of the main signal at the reader
Distance between antenna pairs	4 m
Distance between Tx-Rx antennas	1 m
Reader antenna	Panel antenna (4.9 dB gain)
Antenna height	2.5 m
Antenna tilt	35^o aimed to the center of the box placement area
Antenna azimuth	$\sim 15^o$ aimed to the center of the box placement area
Tag antenna	Half-wave dipole (2 dB gain)
Tag power threshold	-13 dBm
Reader sensitivity	-80 dBm
Frequency	865.7 MHz
Transmission power	25.8 dBm
Noise level	-108 dBm
Channel model	2-way line-of-sight with Rician fading
Polarization mismatch	0.5
Tag modulation factor	0.25
Material to which tags are attached to	Cardboard
Power transmission coefficient	1

TABLE II
ANN PERFORMANCE STATISTICS: ACCURACY, RECALL AND FALL-OUT FOR EACH R CONFIGURATION

Configuration	Accuracy	Precision	Recall	Fall-out
R **= 1**	89.74%	89.98%	89.27%	9.80%
R **= 2**	94.55%	94.30%	94.61%	5.50%
R **= 3**	94.86%	94.75%	94.81%	5.10%

TABLE III
ANN PERFORMANCE STATISTICS: PER-POLICY ACCURACY, PRECISION, RECALL, AND FALL-OUT FOR R=3 CONFIGURATION

Policy	Accuracy	Precision	Recall	Fall-out
α	94.59%	92.92%	94.03%	5.02%
β	94.73%	92.44%	94.92%	5.40%
γ	95.26%	97.51%	95.24%	4.70%

- The actual outcome (batch read/inventory fault) depends on the predicted BIP and on the per-policy precision. First, the outcome (readable/unreadable) is determined by sampling a Bernoulli random variable with probability given by the BIP obtained by the ANN. If the output is positive (batch read), another random sample is compared against the per-policy precision since this statistic accounts for batches incorrectly tagged as readable. If the random sample is higher than the per-policy precision, the batch is considered incorrectly tagged as readable.
- The time required by the selected policy to interrogate the batch has been determined using an auxiliary ANN. This second ANN is configured as a regressor and has been trained with the same data gathered from the simulations. The mean-squared-error achieved on the validation dataset (outside the training records) has been 0.325, which yields a 27% of error compared to the mean batch interrogation time.
- Unreadable batches are relocated, a process performed by a human operator which takes a random time between 10 and 30 s to perform this operation. We assume that after relocation the batch can always be read.
- This (best) policy is compared against static α, β and γ policies. The same procedure to determine the interroga-

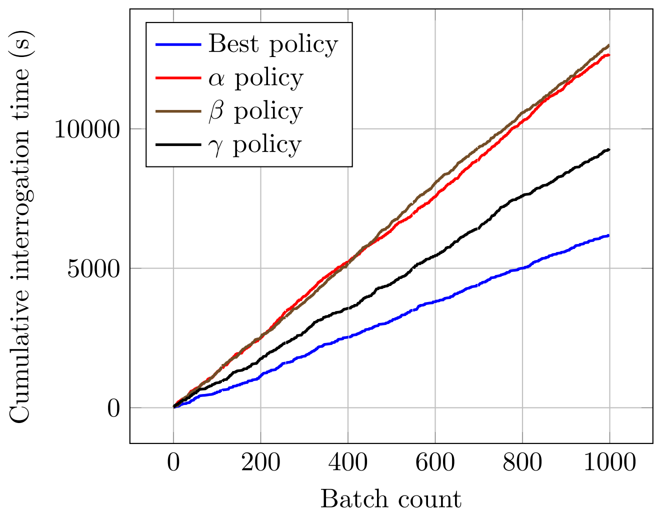

Fig. 4. Cumulative interrogation time versus batch count. Total time required to interrogate batches with the best adaptive policy versus the static α, β, and γ policies. If the batches can't be read with the selected policy they have to be relocated by a human operator. The timing also includes these relocation operations.

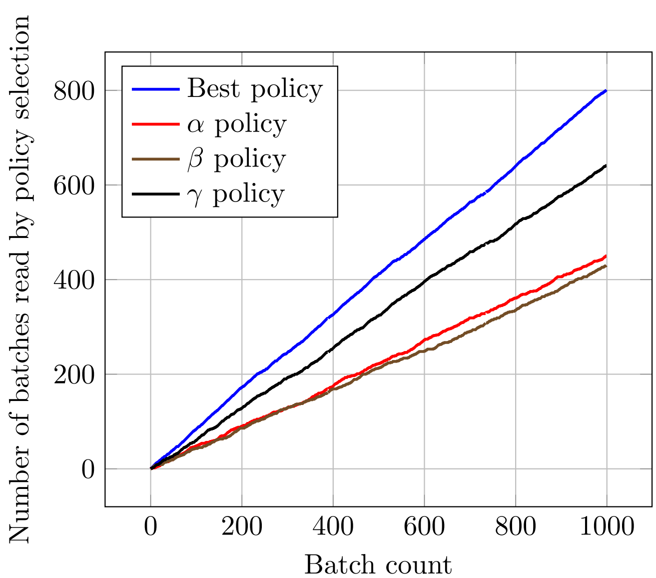

Fig. 5. Number of batches correctly read by the selected policy versus the batch count. This metric counts how many batches don't require relocation to complete their interrogation.

tion success probability and timings as the best policy have been used.

We have simulated this experiment for 1000 batches. Results are shown in figure 4 and figure 5. Clearly, the performance of the best policy, which is adaptive, outperforms the static ones by a non-marginally gap. The ratio of batches which don't require relocation to complete the interrogation is 80.2% with the adaptive policy, but it drops to 64% with the best static policy. Due to this effect, the time savings between the best adaptive policy and the best static policy is in the order of 30%.

VI. Conclusions

In this work we have proposed a new predictive capability for RFID gates. Based on the signature acquired from fixed-configured initial reading frames, the probability that the batch can be totally identified is predicted. Results show a fall-out statistic less than 5%, which indicates a good performance for this method, opening possibilities to be implemented during online gate operations. We have also shown the ability of this method to save operation time by selecting the best adaptive policy for each situation. In the future we aim at searching new features to add to the reading signature to improve the accuracy of this method.

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