Artificial Intelligence enhances Smart RFID Portal for retail

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***Abstract*—This paper investigates a low-cost implementation of a UHF-RFID portal enhanced by artificial intelligence to assess whether a tag is crossing the portal or it is static in the surrounding. The reference scenario concerns anti-theft systems in fashion stores, where the use of shielded RFID portals is not feasible and spurious tag readings must be filtered by alternative methods. The portal consists of a commercial RFID reader connected to an array antenna placed at the store entrance to monitor the tag crossing. Data processing involves Received Signal Strength Indicator sequences and a comparison among Support Vector Machine (SVM) and several LSTM (Long Short-Term Memory) neural networks are investigated to perform classification. System and algorithm validation are conducted through an experimental analysis.**

***Index Terms*—RFID portal, UHF-RFID, RFID gate, machine learning, artificial intelligence, array antenna;**

I. INTRODUCTION

In recent years, there has been a growing interest in the use of new technologies for the Internet of Things (IoT) world, in areas such as logistics, supply chain management, manufacturing, and retail [1]. Particularly, the fashion industry has contemplated the integration of passive UHF (Ultra-High Frequency) band RFID (Radio Frequency IDentification) tags into paper clothing labels, mainly to manage inventories much more accurately than through traditional barcodes [2], [3]. The problems of self-checkout and anti-theft are relevant, especially in large stores. Both of these objectives can be handled with RFID portals [4]–[10], [10]–[14], which are identification points installed at key locations of the store to identify the crossing tags. They are composed by an RFID reader and one or more antennas.

Typically it is of interest to recognize the direction of movement of the tag, and this can be done through multi-antenna solutions [8] or with particular single-antenna configurations for which the phase of the signal response of the tag is different depending on whether it is entering or leaving the area [9], [10]. However, not all COTS (Commercial-off-the-shelf) readers provide the possibility to supply phase data as usable output, and therefore solutions based on the signal received power, measured through the Received Signal Strength Indicator (RSSI) parameter are sometimes preferred.

Since the commercial antennas of UHF-RFID systems have rather wide beams, the problem of stray readings, i.e., detected tags not passing under the portal, is prominent [11]. The signal coming from the static tags in the antenna reading volume, following the motion of the people nearby, respond to the reader queries with a perturbed signal, which can be mistakenly interpreted as a movement indicator. To curb this phenomenon, the literature first proposed shield-based solutions, e.g., RFID tunnels [12], which, however, are expensive and bulky. Alternatively, it is possible to discriminate crossing tags from those that do not through the analysis of RSSI data sequences [8].

This classification problems can be complex if the working environment is characterized by a strong multipath, or the speed of the tags is high. For this reason, the aid of artificial intelligence [10], [13], [14] can be resorted. Faced with an energy expense for the installation stage and training of the network, this solution allows to solve the problem with a relatively simple hardware architecture.

This article presents a solution based on an RFID reader connected to an array antenna for an anti-theft system in retails. The array antenna is exploited for its intrinsic ability to concentrate the reading zone in a given area of the space, e.g., the store entrance. However, the total absence of stray reads cannot be avoided and mis-classified tags can occur. For this reason, a Support Vector Machine (SVM) [15] and an LSTM (Long Short-Term Memory) [16] neural network are used to process the RSSI data and to discriminate among two classes: *crossing* and *static* tags. The article is divided as follows: Section II briefly presents the artificial intelligence-based processing methods that we investigated in order to analyze the performance of the portal, describes the measurement setup, the antenna, and the tests performed. Section III presents the results and, finally, Conclusions are drawn together with future work perspectives.

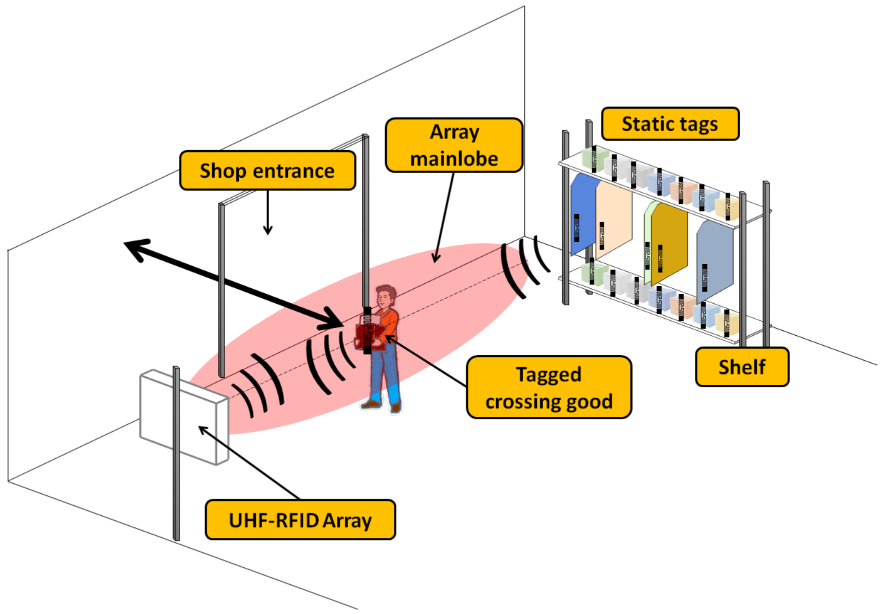


Fig. 1. Depiction of a fashion store with an RFID portal installed for anti-theft purposes.

II. Classification algorithms

Suppose we are in a store where the items are tagged as depicted in Fig. 1. An RFID reader is connected to an array antenna positioned to the side of the entrance to monitor passing tags, orthogonal to the floor. A person picks up an item without purchasing it and is about to exit the store. As this person moves through the portal, the reader measures the change in power of the tag response. In the meantime, due to multipath caused by the moving person himself, a tag on a shelf, that was normally undetectable by the antenna, is detected. So, the power measurements of the tag on the shelf are also collected by the reader and a discrimination becomes mandatory. So, the goal is to discriminate the two classes, i.e., *crossing* and *static* tags. As first hypothesis, once data over time has been collected, they can be aggregated to build a single feature useful to classification algorithms. This is the case of the employment of a Support Vector Machine (SVM). Alternatively, the data sequence can be processed by a neural network specifically created to elaborate variables changing over the time, the so called Long Short-Term Memory (LSTM). After a preliminary stage, we evaluated the following types of processing with different input features:

- SVM applied to the single variance value calculated over all RSSI samples;
- LSTM neural network with the whole RSSI sequence as input;
- LSTM neural network with multiple average RSSI values gathered with a moving window approach, named as *moving RSSI average*;
- LSTM neural network with multiple variance RSSI values gathered with a moving window approach, named as *moving RSSI variance*
- LSTM neural network which processes both the *moving average* and the *moving variance*.

The SVM aims at finding a hyperplane or set of hyperplanes in a high- or infinite-dimensional space to separate two data groups. In the case where a single feature, i.e., the variance of the RSSI, is processed, the SVM searches for the optimal threshold to separate *crossing* and *static* tags.

Indeed, the LSTM neural network is a network capable of analyzing sequences of data, and has several advantages over other convolutional neural networks to which it belongs. In particular, the training process to obtain the optimal parameters of the network is very robust.

III. Experimental Analysis

A. The array antenna

As already mentioned, we employed an antenna array to build the RFID portal, depicted in Fig. 2. It is a custom 3×3 array of circularly polarized (LHCP) patch antennas printed on a 3.2 mm-thick FR4 substrate ($\varepsilon_r = 4.3$ and $tan(\delta) = 0.025$), designed to work in the UHF-RFID ETSI band (865-868 MHz). The array element is a truncated–corner patch antenna, with a side of 78 mm (Fig. 3). The patch exhibits a half-power beamwidth (HPBW) of about 120°, in both principal planes. A single-port feed has been implemented through a 50 Ω coaxial cable. The spacing between the elements is $\lambda/2$. The array beam is fixed and cannot be steered.

B. Experimental trials

To validate the robustness of the proposed solution, an experimental setup was built at the facilities of the University of Oviedo as depicted in Fig. 3. The right-handed coordinate reference frame is chosen such as the motion of the people is along the x-direction (Fig. 3).

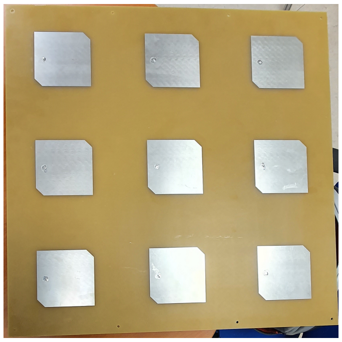


Fig. 2. 3×3 array of circularly polarized (LHCP) patch antennas used for the measurements.

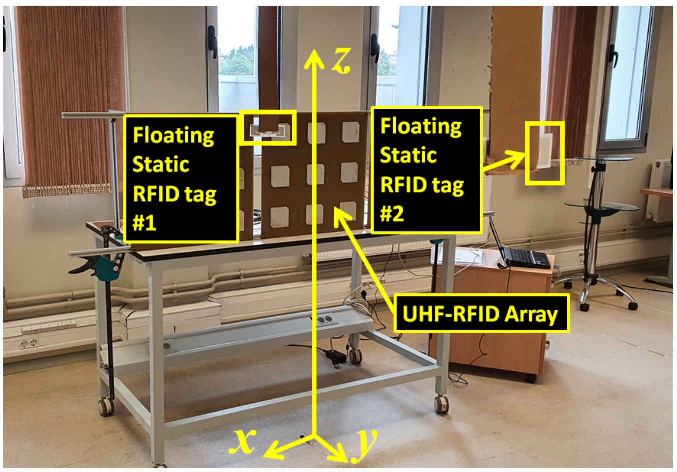


Fig. 3. Measurement setup at the University of Oviedo.

The RFID array was mounted at $z = 1.15$ m from the ground. An operator equipped with a Dogbone inlay RFID tag with MZ-6 chip (-22.1 dBm sensitivity) performed a total of 282 portal crossings. Tag trajectories are straight with different speeds, and with a distance of around 1 m, 1.5 m, and 2 m from the antenna (i.e., $y = 1$ m, $y = 1.5$ m, and $y = 2$ m). Within 162 trials, two RFID tags were placed hanging from the ceiling close to the antenna at the locations $\mathbf{p_{tag_1}} = [x_{tag_1}, y_{tag_1}, z_{tag_1}]^T = [0.90, 0.75, 1.50]^T$ m and $\mathbf{p_{tag_2}} = [x_{tag_2}, y_{tag_2}, z_{tag_2}]^T = [2.15, 1.20, 1.50]^T$ m, respectively. When the person crossed the gate, the responses of the three tags, i.e., the crossing tag and the two static tags, were gathered by the reader by collecting the RSSI changes with an Impinj Speedway R420 UHF-RFID reader, set with a transmitting power of 20 dBm at $f_0 = 865.7$ MHz. A total of 282 data sequences from the crossing tag, 162 sequences from static RFID tag #1, and 162 sequences from static RFID tag #2 were recorded, by obtaining a dataset of $N_{Tot} = 606$ sequences.

It is noteworthy that, it is usually recommended to hide the array so as not to be visible to the eyes of a possible thief. Many solutions foresee the integration in the floor of the antenna which was not done in this work for practical matters.

C. Classification performance

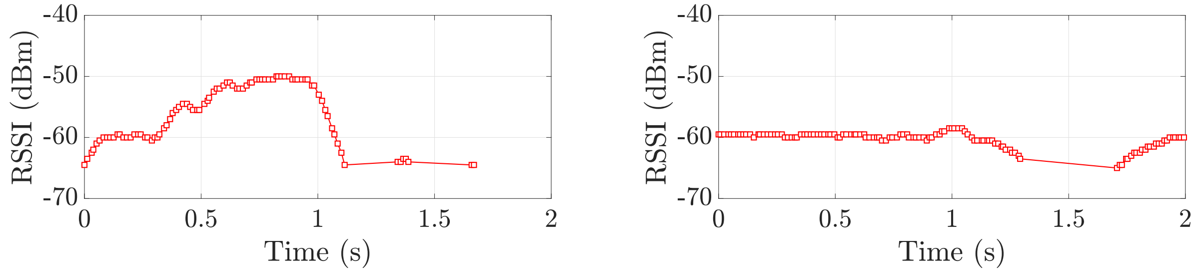
The RSSI sequence gathered from a *crossing* tag and the RSSI sequence acquired at the same time by a *static* tag are depicted in Fig. 4a and Fig. 4b, respectively. Although apparently the two sequences are different, they cannot be used as is to distinguish the two tag categories. This motivates the choice of the input features already described in the previous paragraph. Specifically, the *moving RSSI average* and the *moving RSSI variance* for all RSSI data acquired in the dataset are obtained with a window size of $L = 50$ samples. An example of the novel features is shown in Fig. 5. As noted, they have a different shape and thus represent valid candidates to be the input of an LSTM neural network.

Moreover, the LSTM network can also take multiple sequences as inputs, so both the sequences of moving RSSI average and moving RSSI variance can be jointly used in the LSTM. We divided the dataset consisting of 606 sequences into two subsets defined as *Training Set* and *Test Set*. The construction of these sets involves randomly selecting sequences that belong to either set so that both classes, i.e. *crossing* and *static* tags are represented. We varied the size of the Training Set by selecting the 50%, 60%, 70%, 80%, and 90% of the all available sequences. The size of the training set is therefore $N_{tr} = 303$, $N_{tr} = 363$, $N_{tr} = 424$, $N_{tr} = 484$, $N_{tr} = 545$. It follows that the test set size is $N_{test} = N_{Tot} - N_{tr}$ is $N_{test} = 303$, $N_{test} = 243$, $N_{test} = 182$, $N_{test} = 122$, $N_{test} = 61$.

Fig. 6a depicts the values of the training accuracy for the five analysed processing, namely SVM (circular blue markers), LSTM-RSSI (squared red markers), LSTM-Moving RSSI Average (triangular green markers), LSTM-Moving RSSI Variance (reverse triangular black markers), LSTM-Moving RSSI Average and Variance (diamond magenta markers). As expected, after fitting the SVM or after training the LSTM network, the classification accuracy on the training set decreases slightly as the size of the training set increases, while the accuracy on the test set increases. Processing sequences of RSSI, their moving average, or the moving RSSI average jointly with the moving RSSI variance does not produce good classification performance. The reason for this is that the data sequences are not significantly different between *crossing* and *static* tags and thus it is difficult, even for an artificial intelligence-based method, to perform classification. Moreover, this fact makes us understand how even through a deterministic algorithm it would be complex to discriminate the two classes. The use of the variance processed by a SVM and the moving RSSI variance processed by a LSTM instead allows to obtain good results, testifying that the RSSI variance is a good feature for classification. The SVM is the algorithm that has allowed to obtain values of 100% or close to 100% for all training set sizes. Table I and Table II resume all the obtained results.

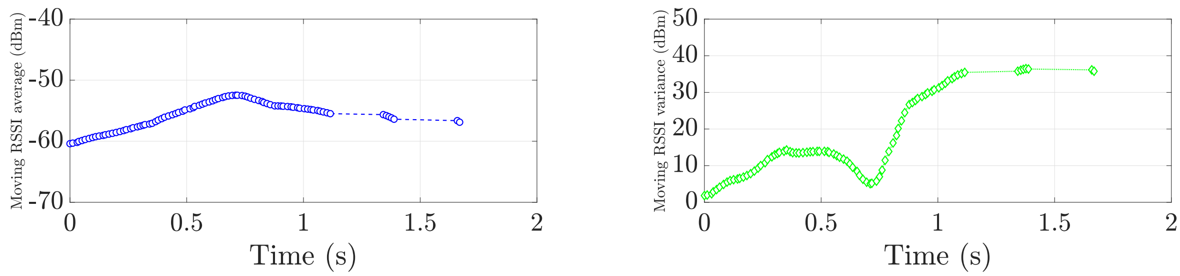
IV. Conclusion and Future Work

In this paper an UHF-RFID portal for anti-theft systems in fashion stores was investigated. The portal is composed by



(a) (b)

Fig. 4. (a) RSSI data gathered from a *crossing* tag, and (b) RSSI data gathered from a *static* tag during the motion of the *crossing* tag.



(a) (b)

Fig. 5. (a) *Moving RSSI average* and (b) *moving RSSI variance* of the RSSI data gathered during the crossing of the *moving* tag whose RSSI sequence is in Fig. 4a. The window size is $L = 50$ samples.

TABLE I
TRAINING ACCURACY WITH RESPECT TO TRAINING SET SIZE FOR ALL THE FIVE ANALYSED PROCESSING.

Training set / Dataset %	N_{tr}	**SVM**	**LSTM-RSSI**	**LSTM-Mov. Avg.**	**LSTM-Mov. Var.**	**LSTM-Mov. Avg. and Var.**
50%	303	99.99%	58.73%	59.55%	96.70%	56.47%
60%	363	99.99%	57.02%	58.02%	96.42%	55.10%
70%	424	99.99%	55.19%	57.64%	95.81%	55.24%
80%	484	99.98%	54.81%	55.66%	95.33%	53.76%
90%	545	99.97%	52.55%	53.80%	94.75%	52.74%

TABLE II
TEST ACCURACY WITH RESPECT TO TRAINING SET SIZE FOR ALL THE FIVE ANALYSED PROCESSING.

Training set / Dataset %	N_{test}	**SVM**	**LSTM-RSSI**	**LSTM-Mov. Avg.**	**LSTM-Mov. Var.**	**LSTM-Mov. Avg. and Var.**
50%	303	99.98%	52.81%	44.55%	96.30%	48.47%
60%	243	99.98%	53.02%	48.02%	95.42%	49.10%
70%	182	99.98%	54.19%	50.64%	95.18%	50.24%
80%	122	100%	53.81%	52.81%	95.12%	51.76%
90%	61	100%	51.81%	51.81%	94.75%	52.31%

a commercial RFID reader and an array antenna placed at the entrance of the store. RSSI data of crossing and static tags are gathered and processed both through a SVM and a LSTM neural network algorithms. An experimental analysis have been conducted in an indoor environment, and it has been demonstrated that by processing the variance of the measured RSSI through a LSTM, a classification accuracy around 95% can be reached, whereas when processing the data through a SVM, more than 99% of accuracy is achieved. In the future, a larger dataset combined with a more in-depth analysis of input features will be considered to obtain more robust classification approaches.

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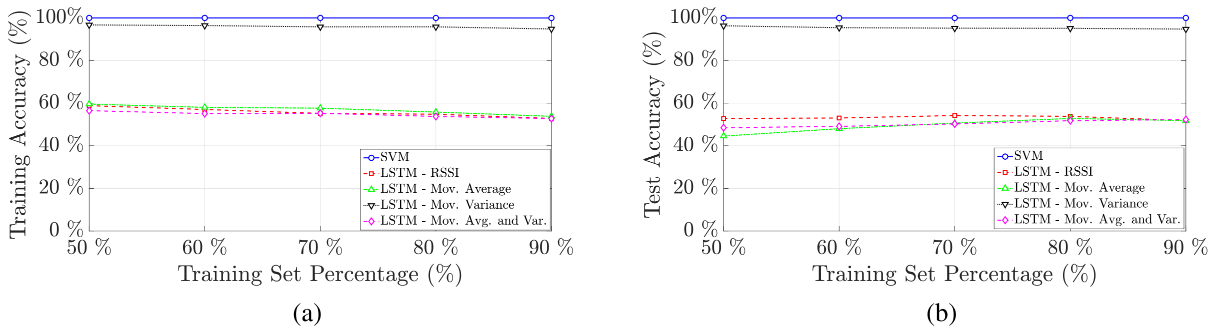

Fig. 6. a) Training accuracy and b) Test accuracy of the five analysed cases with respect to the size of the training set with respect to the entire dataset.

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