A UHF-RFID gate control system based on a Recurrent Neural Network

Guillermo Alvarez-Narciandi, Andrea Motroni, Marcos R. Pino, Alice Buffi and Paolo Nepa

Abstract—**This paper presents a novel, cost-effective and easy-to-deploy solution to discriminate the direction of goods crossing a UHF-RFID gate in warehouse scenario. The system is based on a grid of UHF-RFID tags deployed on the floor underneath the gate equipped with a single reader antenna. When a transpallet crosses the gate, it shadows the tags of the deployed grid differently, according to the specific direction, namely incoming or outgoing. Such distinguishable signature is employed as input of a recurrent neural network. In particular, the number of readings for each tag is aggregated within short time-windows and a sequence of binary read/missed tag data over the time is extracted. Such temporal sequences are used to train a Long Short-Term Memory neural network. Classification performance of the proposed method is shown through a set of measurements in indoor scenario.**

Index Terms—**UHF-RFID Gate; RFID machine learning; RFID neural network; Recurrent neural network.**

I. Introduction

THE use and development of Radio Frequency IDentification (RFID) technology led to a growing number of applications based on it. In 2018 more than 15 billion of RFID tags were sold (a 23% increase with respect to 2017) [1], showing the technology growth. In particular, the RFID technology was successfully used in the context of access control, warehouse management and logistics. One specific problem in warehouse scenario is the correct discrimination of goods or pallets transiting through a gate or between two warehouse areas. For such purpose, a UHF-RFID gate can be installed at the points of interest. To correctly discriminate if the pallet is incoming, outgoing or not-crossing the gate, several systems were proposed in the state of the art. Since a warehouse is a harsh environment due to multipath propagation and the presence of a large number of RFID tags, several setups were proposed apart from conventional localization systems [2]. Some solutions rely on creating shielded reading zones using tunnel gates [3] or using additional hardware such as light or motion sensors [4] or cameras [5] to determine the movement direction of goods, at the expense of higher complexity and cost of the system. Moreover, the use of cameras may raise privacy issues. Other solutions employ more than one antenna to estimate the motion direction of the goods by comparing the signature of tagged items measured from each antenna [6] or creating different interrogation zones [7]. Keller et al. [8] suggest to use various aggregated features based on the low-level reader data (Electronic Product Code, *Received Signal Strength Indicator* - RSSI, timestamp, reading antenna) to discriminate moving tags in forklift truck applications, with multiple antennas. Other solutions exploited the phase of the tag backscattered signal to discriminate tags carried out by a forklift [9] or moving along a conveyor belt [10].

Recently, machine learning techniques were employed in RFID systems for localization purposes [11], [12] and for classification of tag actions in UHF-RFID gates [13]. This paper presents a novel solution to discriminate the crossing goods from the not-crossing throughout a UHF-RFID gate in a warehouse scenario. Furthermore, the crossing goods are distinguished between incoming or outgoing. The system employs a Recurrent Neural Network (RNN) exploiting data acquired by a single reader antenna and a grid of UHF-RFID reference tags.

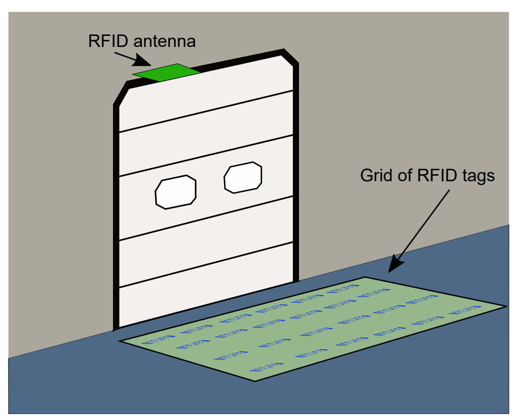

Figure 1. Basic scheme of the UHF-RFID gate control system with a single reader antenna and a grid of reference tags.

II. Classification Method Description

The proposed system for the UHF-RFID gate is based on a grid of reference tags deployed on the floor underneath the gate and a single reader antenna (Figure 1). Therefore, when a transpallet moves over the grid, tags are shadowed due to the

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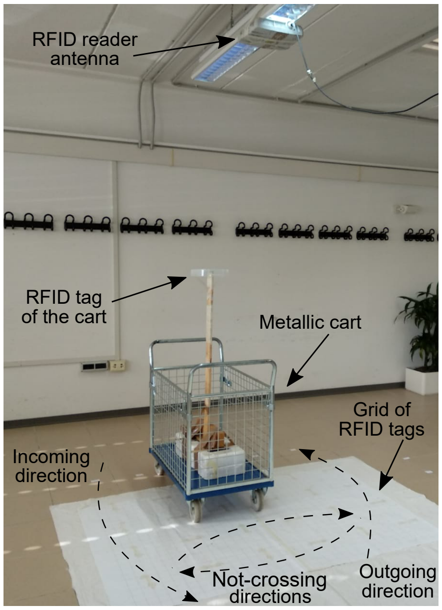


Figure 2. Measurement setup of the proposed system for the UHF-RFID gate.

presence of metallic parts and some of them are not detected by the reader antenna. Thus, the pattern of shadowed tags can be used as a signature of the transpallet incoming, outgoing or not-crossing actions. Such principle resembles the solutions proposed in [14], [15] which are based on the shadowing of the signal backscattered by a set of RFID tags deployed within the area of interest for localization purpose.

An important design consideration is the size of the grid of reference tags. The grid width should be at least similar to the width of the gate to be monitored. In the other dimension, the number of grid rows (i.e. the length of the grid) should be at least three or four, so that the transpallet movement causes a consecutive shadowing of tag rows, which is a useful information for direction discrimination. On the other hand, the number of tags should not grow indefinitely as the reader must be able to detect all of them within a certain time window. In this regard, it should also be considered that other tags will be in the gate surroundings identifying different goods stored in the warehouse. The distance between the reference tags should be large enough to reduce the coupling effect, while ensuring the tag shadowing during the transpallet motion.

A. The Recurrent Neural Network

To perform the transpallet action classification a Recurrent Neural Network (RNN) was trained. This type of neural network was proven to be very successful in sequence processing or sequential processing of non-sequence data [16]. The basic working principle of a RNN is that when there is an input to the network, x_t, it computes the new state, h_t, based on the previous state h_{t-1} and the input according to an activation function f:

$$h_t = f(W_{hh}h_{t-1} + W_{xh}x_t). \tag{1}$$

Then, in sequence-to-one (or sequence labeling) problems (as the problem discussed in this paper) the output is usually computed based on the last state. In the proposed system, we employed a particular kind of RNN, that is the Long Short-Term Memory (LSTM) network [17]. LSTM networks solve the problems of vanishing or exploding gradient, and have shown great performance in speech recognition [18] or image caption generation [19] applications. They have a block structure where each cell has an internal cell state, $\boldsymbol{c}_t$ and a hidden state $\boldsymbol{h}_t$. The above parameters are updated based on the network input $\boldsymbol{x}_t$ at time t, and the previous hidden state, $\boldsymbol{h}_{t-1}$, as follows:

$$\boldsymbol{c}_t = \boldsymbol{f} \circ \boldsymbol{c}_{t-1} + \boldsymbol{i} \circ \boldsymbol{g}, \tag{2}$$

$$\boldsymbol{h}_t = \boldsymbol{o} \circ \tanh(\boldsymbol{c}_t), \tag{3}$$

where $\circ$ denotes the element-wise product. The other parameters are the network input gate $\boldsymbol{i}$ and the cell candidate $\boldsymbol{g}$, which control the input amount which is written into the cell; the forget gate $\boldsymbol{f}$, which controls how much the cell state of the previous time step is forgotten; the output gate $\boldsymbol{o}$, which computes the hidden state of the current time state. These parameters can be calculated throughout the following equation:

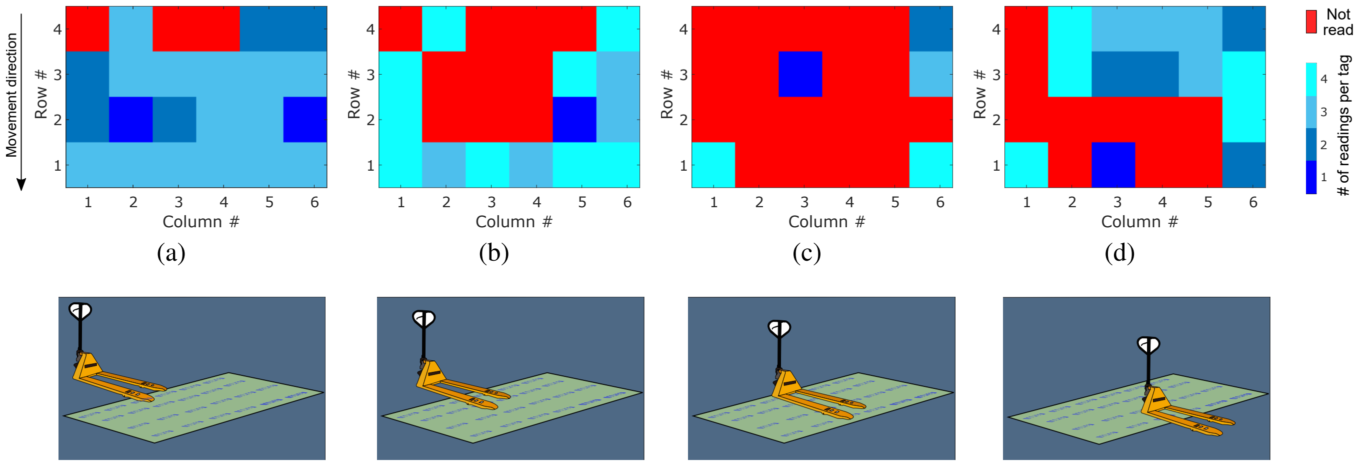
$$\begin{pmatrix} \boldsymbol{i} \\ \boldsymbol{f} \\ \boldsymbol{o} \\ \boldsymbol{g} \end{pmatrix} = \begin{pmatrix} \sigma \\ \sigma \\ \sigma \\ \tanh \end{pmatrix} \boldsymbol{W} \begin{pmatrix} \boldsymbol{h}_{t-1} \\ \boldsymbol{x}_t \end{pmatrix} , \tag{4}$$

Where $\boldsymbol{W}$ is the weighting matrix; σ is the sigmoid function, and $tanh$ is the hyperbolic tangent function. The size of the network input, $\boldsymbol{x}_t$, corresponds to the number of input features of the network, N_{feat}. The size is of the hidden state vectors, $\boldsymbol{h}_t$, as well as the size of the internal cell state, $\boldsymbol{c}_t$, $\boldsymbol{i}$, $\boldsymbol{f}$, $\boldsymbol{o}$ and $\boldsymbol{g}$, is given by the number of hidden units (NHU) of the cell, which controls the amount of information remembered between time steps. Finally, the size of the weighting matrix $\boldsymbol{W}$ is $(4 \cdot NHU) \times (N_{feat} + NHU)$.

B. Data Pre-processing

The input features of the neural network should provide representative and distinguishable signatures of each type of movement of the transpallet. In addition, they should be chosen to make the system independent on the application scenario, and to avoid any calibration step to minimize deployment time.

First, it should be noted that, as the existence of moving goods and their direction discrimination are based on the information collected from a set of reference RFID tags, an appropriate acquisition time must be defined. The latter, denoted as t_{win}, must be long enough to query all reference tags. The duration of the time windows should be adjusted so that the transpallet movements can be captured. This means that, if the time window is too long with respect to the transpallet moving speed, some movements could be filtered out. On the other hand, if the time window is too short the reader may not be able to read all the reference tags within the same time window, and the system can misinterpret that phenomenon as a shadowing effect.



(e) (f) (g) (h)

Figure 3. Number of readings of each grid tag during a sample incoming movement of the metallic cart. Consecutive time windows of duration of 200 ms were shown from (a) to (d). Missed tags are depicted in red. A schematic representation of the metallic cart position within the setup corresponding to the snapshots presented from (a) to (d) is shown from (e) to (h), respectively.

The RFID reader is configured to perform continuous inventories and, as explained before, in order to introduce meaningful information to the neural network, the measured data is aggregated within time windows of a predefined duration. As a consequence, when the system is activated (for example when a tagged transpallet is detected in the surroundings of the gate) a set of features are extracted from the measured data in a $N_{feat} \times M$ matrix form. Then, such set feeds the network, where N_{feat} is the number of features and M is the number of time windows within the total acquisition time. Among the potential features, the two parameters described below were considered:

- The number of times each reference tag was read during each time window: in the absence of a moving transpallet the number of readings within each time window should be approximately constant depending on the number of RFID tags present on the surroundings of the gate. However, when a transpallet moves over the grid of reference tags, it shadows the tags underneath and, hence, the number of successful readings decreases. Therefore, a pattern can be extracted from the fluctuations on the number of readings during time windows of each reference tag.
- Whether each reference tag was read or was missed during each time window: this provides a binary information for each tag in each time window. If during a certain time window the tag was detected at least once, then the binary data is set to "read". In a similar fashion to the previously explained feature, if a tag is shadowed by a transpallet, it would not be read in that time window, so being classified as "missed".

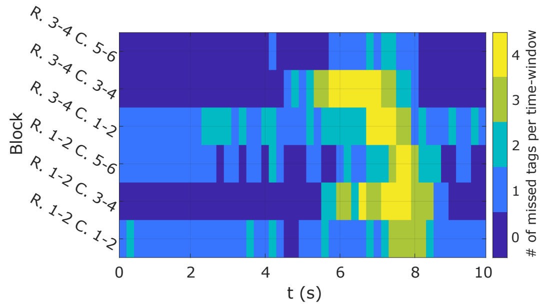
Both parameters provide analogous information, as it was observed during the experimental analysis of the system. However, since the number of readings depends on the amount of detected tags in the surroundings of the gate (i.e. tagged stocked goods waiting to be delivered), it was decided to use the binary read/missed tag data, for each tag in a specific time window. The binary data is equal to 1 if the tag is read or equal to 0 if it is undetected.

The use of RSSI values of the signals backscattered by the tags of the grid was discarded as this parameter depends on the distance from the reader antenna to the grid, the material of the floor under the gate grid, and on the multipath effect typical of an indoor scenario.

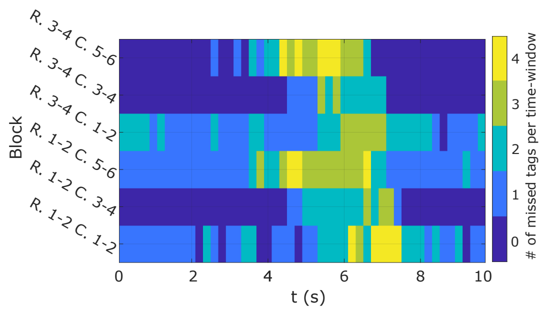
Thus, the input of the neural network consists of one sequence, i.e. one feature, per reference tag with the read/missed, whose length depends on the duration of the time window and on the transpallet speed during the specific action.

III. Experimental Analysis

In order to validate the proposed system, laboratory tests were conducted at the research facilities of the Department of Information Engineering of the University of Pisa. The measurement setup is depicted in Figure 2. A total of 24 EasyRFID Dogbone tags were arranged in a 4×6 grid with a 30 cm separation between them. The size of the grid was selected so that it could be used to monitor the transpallet motion throughout a gate of width less than 2 m, a typical size for many warehouse and docking area doors. The reader antenna was fixed at the ceiling above the grid at a height of 2.6 m, and a 38 cm wide metallic cart was employed to emulate a transpallet. Then, a total of 159 trajectories were performed while recording data from the tags: 50 incoming, 49 outgoing and 60 passing nearby the grid without crossing the gate. For each test, the reference tags were queried continuously, thus before, during and after the metallic cart moved over the grid. This resembles the practical operation of the proposed system, ensuring that fluctuations in the tag readings are recorded. Each acquisition was around $T = 10\ s$ long, so the value $M = \lfloor T/t_{win} \rfloor$ ranged from $M = 50$ when $t_{win} = 200\ ms$ to $M = 12$ when $t_{win} = 800\ ms$. The obtained results were used to build a data set to train and test the neural network. The train and test data sets were built using 60% and 40% of the data respectively. The different measurements were randomly assigned to each group, but keeping the class balance, i.e. similar proportion of incoming, outgoing or not-crossing trajectories.



(a)



(b)

Figure 4. Number of missed tags clustered in groups of 2×2 tags, for (a) an incoming trajectory of the metallic cart and (b) a not-crossing trajectory. The R. r_1 - r_2 indicates the rows of the clustered tags. The C. c_1 - c_2 indicates the columns of the clustered tags.

First, the two previously explained potential features during some trajectories of the cart were observed. In particular, the number of readings of the reference tags acquired during four meaningful time windows of 200 ms for an incoming trajectory is depicted from Figures 3a to 3d (from the beginning to the end). In addition, in order to clarify the position of the metallic cart during the four presented snapshots of the incoming trajectory, a schematic representation of the metallic cart and the setup is depicted for each time window from Figures 3e to 3h. The red blocks represent the missed tag data. As can be observed, when the transpallet moves forwards, it shadows mainly the reference tags aligned along columns #3 and #4. In addition, as the transpallet crosses the gate, moving out from the grid, the shadowed tags are read again.

Besides, just in order to facilitate the interpretation of the data, the tags in the grid were clustered in six blocks by grouping them in 2×2 sub-grids and their data were aggregated. In particular, the number of missed tags within each block is illustrated in Figure 4a for the same incoming trajectory summarized in Figure 3. The number of tags that are missed within each block for each time window ranges from zero (all tags are read) to four (none of the tags of the block were read during a given time window). As can be seen, during the cart movement over the grid (during the interval between 6 s and 8 s) there is a significant increase in the number of RFID tags that were missed. Another example for a not-crossing trajectory is depicted in Fig. 4b.

As previously explained, the data acquired during the laboratory tests were divided into a training data set with 60% of the trajectories and a test data set with the remaining ones. In addition, the network input consisted of $N_{feat} = 24$ features: one sequence of read/missed per each reference tag of the grid. Then, the LSTM network was trained using a different number of hidden units for different values of the duration of the time window. The obtained results are depicted in Figure 5 in terms of Test Accuracy, namely the ratio between the number of correctly classified actions and the total number of classified actions. As can be observed, the test accuracy approaches the value of 1 for 50 hidden units and a time window of 400 ms. The usage of 50 hidden units also provides an accuracy greater than 0.9 for the other studied values of time window duration. The test accuracy obtained using more than 50 hidden units decreases showing that the network might be overfitting.

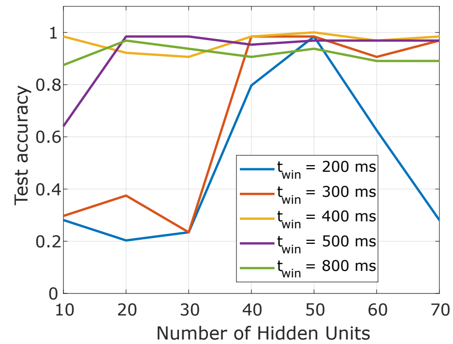


Figure 5. Test accuracy as a function of the number of hidden units of the LSTM network for different duration values of the time windows.

IV. Conclusion

A novel system to discriminate the direction of pallets crossing a UHF-RFID gate in a warehouse scenario was presented. The system is based on an easy-to-deploy grid of reference tags placed underneath the gate and a single reader antenna placed at the gate top over of the grid, making the system cost-effective. The transpallet movement causes the shadowing of the reference tags producing a distinguishable signature of its trajectory. The architecture of the proposed system exploits the shadowing effects of the transpallet on the reference tags close to it, which is predominant with respect to the multipath phenomena. The number of readings of each reference tag is aggregated within time windows using a binary attribute per tag (read or missed) as input features (one for every reference tag deployed on the grid) of a Long Short-Time Memory recurrent neural network. The test accuracy can approach the value of 100% for a proper time-window duration and number of hidden units. Although other state-of-the-art systems show similar performance, the required hardware infrastructure of the proposed system is cost-effective and easy-to-deploy. In addition, the system is more robust against multipath and should be adaptable to other scenarios without the need of retraining the network. The proposed system can find application also for discriminating the transit of a forklift through a point of interest. Furthermore, the proposed system is able to deliver real-time results as, once the neural network was trained, the transpallet action classification can be performed in a few milliseconds.

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