Using Machine Learning and RFID Localization for Advanced Logistic Applications

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***Abstract*—Human supported picking stations are commonly used in warehouses across various business sectors. So called goods-to-man picking processes are usually guided by simple cross-checks to minimize picking errors. These cross-checks typically utilize binary light-barriers and are hence not able to accurately identify wrong picks or even provide early warnings to operators. In this work, we present an approach which tackles this problem by exploiting data gathered through RFID localization technologies in combination with machine learning methods. We are able to predict the picker's intended movement at an early stage which is a first step towards the interception of potential picking errors and hence leading to an improvement of the overall picking performance and accuracy.**

I. Introduction

Picking stations are a crucial component of classical warehouse systems, especially in fashion retail where sorting and picking are frequently performed by human operators due to the mechanical challenges of autonomously picking textiles. In practice, these human supported picking tasks are subject to a non negligible error rate that induces costs for later error and exception handling. The currently available mechanisms to combat picking errors utilize binary light-barrier sensors to confirm the placement of the item. However, these mechanisms do neither ensure that items are actually placed in the correct box nor provide predictive capabilities. This work presents an approach to reliably predict picking errors by combining Radio Frequency Identification (RFID) localization technologies with advanced machine learning methods. By means of that, the proposed system is able to accurately monitor the picking process, predict the intended movement, and signal a warning in case of a potential picking error.

II. Related Work

Item-level localization using RFID technology is a highly active research field and the fundamental limitations and the resulting accuracy have been exhaustively discussed [1]. Similar to various other research areas, machine learning approaches and in particular neural networks form a promising class of algorithms to deal with inherent uncertainty and provide predictive capabilities. In general, neural networks are well-suited for pattern recognition or classification problems. The class of recurrent neural networks (RNN) provides possibilities of storing outputs [2], [3] which makes them especially suitable for time-series prediction [4] under uncertainty.

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III. Experimental Setup

Our experimental setup is based on a simulation framework that uses realistic channel and system parameters gathered during an extensive measurement campaign [1]. Besides the channel characterization, the measurement campaign is used for the evaluation of a novel ranging algorithm which can be applied to off-the-shelf UHF-RFID equipment [5]. The used setup emulates a classical *goods-to-man* picking scenario and consists of a conveyor belt (providing source boxes) and three different target boxes for the actual picking.

Within this setup, we simulate three different datasets (DS1-DS3) with different channel parameters (i.e., Rician K-factor for the line-of-sight component and root-mean-square delay spread) and transmitter/receiver settings (i.e., single input single output—SISO & single input multi output—SIMO). For each dataset, we generate location data for 3000 items (1000 per box). To generate DS1 and DS2, we use the arithmetic mean values of the channel parameters measured in an industrial hall and a laboratory respectively (cf. Table I). The third dataset, DS3, is based on distance dependent values. For further details concerning data generation, we refer to [1].

IV. Method

Given a discrete sequence of measurements which describes the path of an item from the conveyor belt (i.e., source box) into the target box, all subsequences of length four are extracted. Each measurement comprises the estimated x and y position, and corresponding covariances which are used as features for the RNN.

For all subsequences in which an item is moved by the picker (i.e., from the source box towards a target box), the target class is set to the target box. All remaining subsequences are assigned to the target class "source box".

TABLE I
Results. Settings used to generate the dataset and the results in terms of the averaged AUC and F1 score across a 10-fold cross-validation for each dataset.

	Dataset	K_{LOS} in dB	τ_{rms} in ns	**AUC**		**F1**	
				1NN	**RNN**	**1NN**	**RNN**
SISO	DS1	0.22	18.4	0.984	0.998	0.917	0.9631
	DS2	-3	18.6	0.824	0.923	0.653	0.743
	DS3	nA	18.6	0.993	1	0.955	0.985
SIMO	DS1	0.22	18.4	0.984	0.998	0.92	0.965
	DS2	-3	18.6	0.966	0.993	0.866	0.927
	DS3	nA	18.6	0.995	1	0.969	0.986

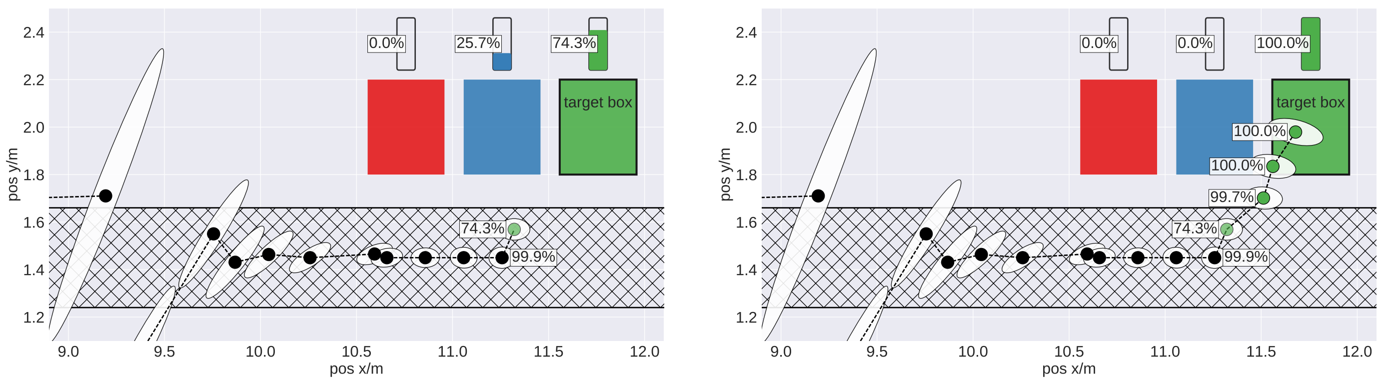

Fig. 1. **Illustrative Example.** Simulated path of a tag from the conveyor belt into the target box. The setup consists of three boxes (red, blue & green) and the conveyor belt (grid on the bottom) providing source boxes. For each step of the tag we show a circle filled with the color of the RNN's current prediction. The certainty of the current prediction is encoded as the points opacity. Additionally, we denote it as percentage next to the point and as bars above the boxes. Ellipses around position measurements represent their covariance (2σ). The figure depicts how early our method predicts the correct target box.

Thus, for items not leaving the source box no target box is predicted, but rather it is predicted that they stay in the source box. As soon as an item leaves the source box, the box into which the worker intends to place the item is predicted.

As baseline for this early prediction problem, we choose the well-established 1-Nearest-Neighbor (1NN) approach [4], [6]. The method proposed in this work outperforms 1NN by utilizing neural networks. In particular, we design a deep RNN which consists of an input layer, a recurrent layer, and a simple activation layer. We define the output layer as a softmax function over four neurons (i.e., one neuron per class) and train the neural network using stochastic gradient descent with cross-entropy as objective function.

The performance is measured using stratified 10-fold cross-validation in combination with two classification metrics—area under the curve (AUC) and F1 score [7]. To ensure that no information is shared across training and test set, the split is performed on sequence level. Finally, to avoid a bias in the results towards the overpopulated "source box" class, the test set is balanced by randomly removing samples of that class.

V. Results & Discussion

The proposed method is applied onto the datasets described in Section III. Fig. 1 illustrates an exemplary result. The results of all conducted experiments are denoted in Table I. For both performance metrics, the proposed method provides a highly accurate prediction. Moreover, it constantly outperforms 1NN, especially for the SISO setup in combination with F1 scores. It seems that the harder the prediction problem becomes, the stronger the proposed method outperforms the baseline. For example, for the SISO DS2 dataset 1NN achieves an AUC score of only 0.82. This can be attributed to the noisiness of the dataset which results from the specific data generation settings (cf. Table I). However, the RNN is able to handle such noisy data robustly, which is why it drastically outperforms 1NN in that case (i.e., AUC of 0.92). Hence, we think that the presented method is well-suited for real-world applications, in which noisy data is a common problem.

VI. Conclusion & Future Work

In this work, we presented a method that allows us to perform an accurate early prediction of intended picking motions, to minimize the error rate in typical, manual picking processes. The method utilizes a RNN that is fed with RFID based location estimates from a simulation framework based on empirical measurements. We showed that this approach is able to accurately predict the target box and is hence a promising step towards an intelligent supervision and guidance of manual processes within logistic applications.

As a concrete next step, we plan to include further developments of the RFID localization technology and build an end-to-end demonstrator setup using the discussed localization method. Moreover, we think that tuning and adapting the architecture of the used RNN will further increase the system's accuracy.

References

[1] S. Hinteregger, J. Kulmer, M. Goller, F. Galler, H. Arthaber, and K. Witrisal, "UHF-RFID backscatter channel analysis for accurate wideband ranging," in *2017 IEEE International Conference on RFID (RFID) (IEEE RFID 2017)*, Phoenix, USA, May 2017.

[2] A. Graves, A.-r. Mohamed, and G. Hinton, "Speech recognition with deep recurrent neural networks," in *Acoustics, speech and signal processing (icassp), 2013 ieee international conference on*. IEEE, 2013, pp. 6645–6649.

[3] H. C. Ravichandar, A. Kumar, A. Dani, and K. R. Pattipati, "Learning and predicting sequential tasks using recurrent neural networks and multiple model filtering," in *2016 AAAI Fall Symposium Series*, 2016.

[4] L. Wei and E. Keogh, "Semi-supervised time series classification," in *Proceedings of the 12th ACM SIGKDD international conference on Knowledge discovery and data mining*. ACM, 2006, pp. 748–753.

[5] F. Galler, S. Hinteregger, T. Faseth, N. Leder, K. Witrisal, G. Magerl, and H. Arthaber, "Performance evaluation and verification of Spread-Spectrum based UHF RFID ranging," in *2017 IEEE International Conference on RFID (RFID) (IEEE RFID 2017)*, Phoenix, USA, May 2017.

[6] E. Keogh and S. Kasetty, "On the need for time series data mining benchmarks: a survey and empirical demonstration," *Data Mining and knowledge discovery*, vol. 7, no. 4, pp. 349–371, 2003.

[7] M. Sokolova, N. Japkowicz, and S. Szpakowicz, "Beyond accuracy, f-score and roc: a family of discriminant measures for performance evaluation," in *Australasian Joint Conference on Artificial Intelligence*. Springer, 2006, pp. 1015–1021.