Deep Learning Enables Robust Drone-based UHF-RFID Localization in Warehouses

Chenglong Li*(1), Emmeric Tanghe(1), Pieter Suanet(2), David Plets(1), Jeroen Hoebeke(3), Luc Martens(1), Eli De Poorter(3), and Wout Joseph(1)
(1) WAVES, Department of Information Technology, Ghent University-imec, 9052 Ghent, Belgium
(2) Aucxis cvba, 9190 Stekene, Belgium
(3) IDLab, Department of Information Technology, Ghent University-imec, 9052 Ghent, Belgium
* Email: *chenglong.li@ugent.be*

Abstract

Radio frequency identification (RFID) localization technology has attracted great attention in stocktaking in warehouses. In this paper, we investigate drone-based RFID localization for fast and accurate inventory management. Considering the drone trajectory errors, we propose a robust RFID lateral localization method based on the unwrapped phase, in which a temporal convolutional network (TCN) with non-causal convolutions is designed for the phase unwrapping. The tagged assets are localized via the nonlinear optimization upon the unwrapped phases. The experiment results in a logistic warehouse show that the proposed algorithm achieves RFID localization with 0.17-meter mean absolute errors and 0.4-meter 90-th percentile errors, respectively.

1 Introduction

Radio frequency identification (RFID) technology has attracted great attention for fast and accurate inventory management. However, the stocktaking in warehouses remains labor-intensive and time-consuming. To handle this problem, automatizing the stocktaking with the help of unmanned vehicles has been proposed during the last few years [1, 2]. When considering that most of the pallets are stored vertically with large altitudes, drone-based platforms are more suitable and flexible than ground vehicles. As the physical-layer metric (i.e., phase) has been available for commercial off-the-shelf (COTS) RFID devices [3,4], the positioning accuracy of RFID has been increased greatly from meter level to centimeter level. During the last few years, various RFID localization algorithms have been developed, mainly including the model-based [5–7] and pattern-based solutions [2,8,9]. The model-based solutions generally require the accurate positions of the multiple RFID readers or the trajectory of the moving reader (*a.k.a.*, the idea of synthetic aperture radar). Besides the model-based algorithms, another popular direction for RFID localization is based on the patterns of the received signal strength indicator (RSSI) or phase profile. The pattern-based solutions generally obtain the one-dimensional (1-D) locations or the relative orders of the RFID tags, e.g., the order of luggage on a conveyor belt.

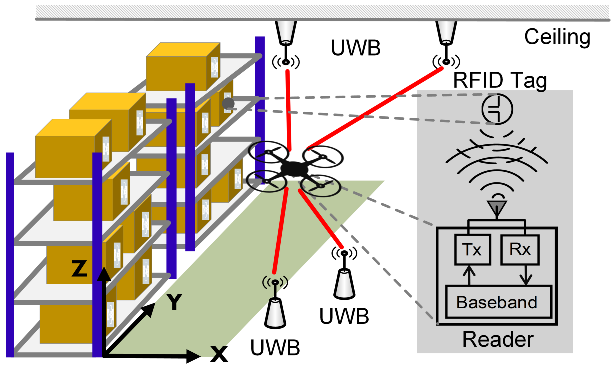


Figure 1. Drone-based RFID localization system design for the inventory management in warehouses.

In this paper, we focus on the drone-based ultra-high frequency (UHF) RFID localization problem for inventory management in warehouses. As shown in Fig. 1, the RFID-mounted drones fly between the vertical racks along the straight aisle to gather the inventory information. The trajectory of the drone is generally predefined and parallel to the plane of racks. So the drone-based RFID positioning can be regarded as a two-stage localization, which reports the location of the pallets or goods with respect to the flying reader. However, considering the drone may not be fully controlled along the predefined trajectory, it is required to track the drone and obtain its instant locations during the interrogation. Considering the payload and cost, the radio frequency (RF)-centered sensor fusion framework had been proposed for the 3-D drone tracking [1, 2], which involves the COTS ultra-wideband (UWB) modules and other low-cost sensors, e.g., inertial measurement unit (IMU), magnetometer, etc. Although the sensor-fusion-based solution can achieve quasi-centimeter-level mean accuracy, it is not sufficient for the second-stage RFID localization [2]. Specifically, the phase is sensitive to the distance variation as one quarter-wavelength (e.g., about 8.2 cm for 917.5 MHz) changing will cause π-radian phase shifts, which makes the model-based solutions unreliable [5–7].

In this paper, we propose a deep learning-based RFID positioning algorithm that is robust to the drone's (*i.e.*, the flying RFID reader) tracking errors. Specifically, a temporal convolutional network (TCN)-based phase unwrapping method has been proposed for the first time and different input features have been discussed. The experimental results validate the effectiveness of the proposed method.

2 Preliminaries

The RSSI reflects the signal strength which decays as $1/d^4$, where d is the antenna-to-tag distance. Meanwhile, the phase is monotonic with the distance. Taking advantage of these characteristics, the pattern-based approaches can pinpoint the tag's lateral location from the RSSI or phase profile. Specifically, the phase has been widely found to be finer-grained and less affected by the cluttered surroundings and can achieve much higher positioning accuracy than the RSSI-based solutions. In case that the RFID reader is not accurately tracked as mentioned above (Fig. 1), fortunately, the unwrapped phase still indicates the monotonicity with the antenna-to-tag distance in a large spatial scale [2]. In this way, we can pinpoint the lateral location of the RFID tag based on the unwrapped phase profile. But the reported phase by the RFID reader is wrapped generally, given by, $\phi_m = \mathrm{mod}\,(4\pi d/\lambda + \phi_0 + \omega)$, where $\mathrm{mod}\,(\cdot)$ is the modulo-π or -2π operator depending on the adopted RFID reader [3, 4]. ϕ_0 denotes the phase shift caused by the hardware. λ is the wavelength and ω is the measurement noise. So, the RFID localization becomes a phase unwrapping problem[1]. The conventional phase unwrapping method requires that the distance between two adjacent sampling points should be less than one quarter (or one eighth) wavelength for modulo-2π (or modulo-π) phases. The unwrapped phase ψ_m can be calculated by, $\psi_m[1] = \phi_m[1]$ and for $n > 1 \in \mathbb{Z}$,

$$\psi_m[n+1] = \phi_m[n+1] - \kappa\pi \left\lfloor \frac{\phi_m[n+1] - \psi_m[n]}{\kappa\pi} + \frac{1}{2} \right\rfloor, \quad (1)$$

where $\kappa = \{1,2\}$ for modulo-π and modulo-2π phase, respectively. Due to the spatial sampling constraint of the conventional phase unwrapping method, a high RFID reading rate is needed to unwrap the phase. But in practice (e.g., drone-based RFID system), the spatial sampling constraint is not easy to be satisfied. For (1), we can learn that phase unwrapping is related to the phase difference and the corresponding distance of two adjacent sampling positions. In this paper, we propose to model the phase unwrapping as a sequence-to-sequence (Seq2Seq) classification problem and solve it via a deep neural network, *i.e.*, temporal convolutional network (TCN).

[1]Note that in this paper we only consider the lateral positions of the tagged assets. Because of the limited size and carrying capacity of the drone, it is difficult to deploy multiple antennas vertically with a large aperture. Furthermore, inventory management in warehouses generally does not require fine-grained vertical accuracy but a layer-level granularity. In our previous works [2, 7], we adopted two tilted horizontal antennas [7] and a beam-steering patch antenna [2] to distinguish the layer of the tagged asset and achieved a satisfying level-identification accuracy. We refer to [2, 7] for the interested readers.

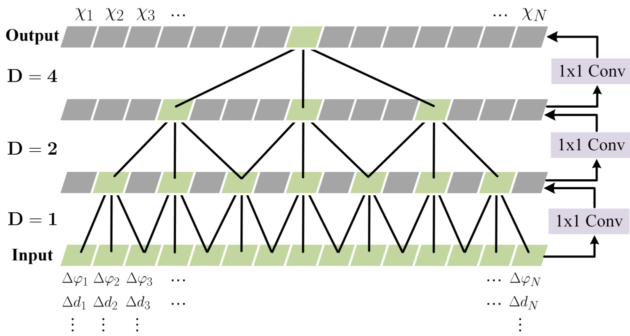


Figure 2. TCN architecture for phase unwrapping: dilated non-causal convolution with dilation factors $D = \{1,2,4\}$ and the filter size $k = 3$. Residual connection with 1×1 convolution will be applied in case that the number of channels between the input and output do not match.

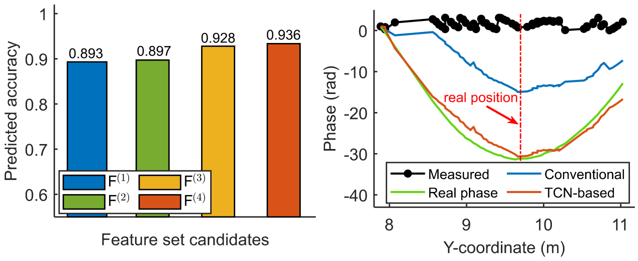
3 Algorithm Design

Although Seq2Seq problems are generally solved with recurrent neural network (RNN) architectures, [10] show that convolutional neural networks can operate on variable-length input sequences and outperform the recurrent networks. Compared with RNN and the iterative random forest classifier in [2] for phase unwrapping, the benefits of using TCN are better parallelism, better control over the receptive field size, and no tedious iterations. However, instead of using causal 1-D convolutions [10], we have adopted non-causal convolutions because the sampled phase is closely related to adjacent samples within a local neighborhood. The proposed non-causal TCN architecture for phase unwrapping is shown in Fig. 2. Besides phase difference and spatial distance of two adjacent samples, we also have considered the inevitable fluctuations of the drone's trajectory along the 3-D coordinates for TCN training. Moreover, the RSSI profile may be informative for phase unwrapping because it also identifies the inflection point of the unwrapped phase roughly. The output label is how many times of π used for phase unwrapping between two adjacent samples[2], namely $\chi = \{0, \pm 1, \pm 2, \cdots\}$. After obtaining χ for the whole phase sequence, we can unwrap the measured phase via,

$$\psi_m[n+1] = \phi_m[n+1] + \pi \sum_{i=1}^{n} \chi(i). \quad (2)$$

Before inputting the features into TCN, preprocessing or normalization is required. The phase differences and the adjacent distances are divided by π and $\lambda/8$, labeled as $\Delta\varphi$ and Δd, respectively. The trajectory fluctuation is defined by the adjacent coordinates offsets, given by Δx, Δy, and Δz. The RSSI profiles are normalized between zero and one, labeled as $\bar{S}$. So the candidate feature sets can be expressed as $\mathsf{F}^{(1)} = \{\Delta\varphi, \Delta d\}$, $\mathsf{F}^{(2)} = \{\Delta\varphi, \Delta d, \Delta x, \Delta y, \Delta z\}$, $\mathsf{F}^{(3)} = \{\Delta\varphi, \Delta d, \bar{S}\}$, and $\mathsf{F}^{(4)} = \{\Delta\varphi, \Delta d, \Delta x, \Delta y, \Delta z, \bar{S}\}$. In-

[2]In this paper, we adopted ThingMagic M6E-Micro RFID reader [4] that reports the wrapped phase between zero and π radian. The maximal absolute times of phase calibration is four according to our experimental observation, i.e., $\chi = \{0, \pm 1, \pm 2, \pm 3, \pm 4\}$.



(a) Prediction accuracy comparison (b) Phase unwrapping

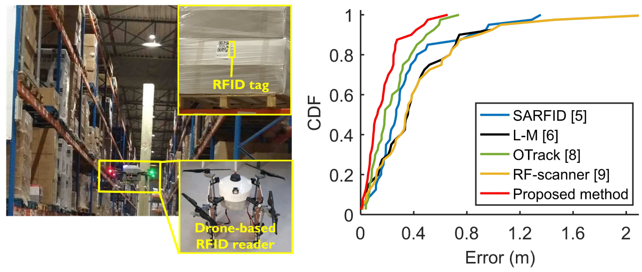
Figure 3. Phase unwrapping: (a) Prediction accuracy of TCN based on different feature sets $\{\mathsf{F}^{(1)}, \mathsf{F}^{(2)}, \mathsf{F}^{(3)}, \mathsf{F}^{(4)}\}$. (b) An example of phase unwrapping results.

stead of conducting extensive experiments to collect the dataset, we train the neural networks based on a synthetic dataset. The trained model can be adapted to the targeted scenario via transfer learning using a tiny part of experimental data, which relieves the data-collection cost and becomes easier to generalize for the scene variation. We refer to [11] for the RSSI and phase datasets generation considering the multipath effect and antenna patterns. Moreover, in practice, the sampling number of RSSI/phase is generally different from each measurement. The profiles' delay intervals are varied resulting from the uneven sampling. To this end, the varied number of samples, uneven sampling interval, and antenna tracking errors also should be considered to generate a synthetic dataset. Fig. 3(a) presents the prediction accuracy for phase unwrapping based on the four feature set candidates. The feature set $\mathsf{F}^{(4)}$ achieves the highest accuracy whereas $\mathsf{F}^{(3)}$ is slightly worse, which indicates the RSSI profile can assist to unwrap the measured phases. Fig. 3(b) shows an example of comparing TCN-based unwrapping results using $\mathsf{F}^{(4)}$ and the conventional method in (1). We can observe that the proposed TCN-based method can predict the unwrapped phase with accurate tendency and inflection point in spite of limited mispredictions.

After obtaining the unwrapped phase, we can simply pinpoint the lateral position (y-coordinate) based on the minimum of the unwrapped phase, as shown in Fig. 3. But this method does not consider the possible trajectory fluctuations along the x- and z-scale. To handle this, we estimate the lateral position y_{tag} via the following maximum likelihood estimation (x_{tag} is set as zero for simplicity),

$$\underset{\{y_{\text{tag}}, z_{\text{tag}}, \varphi_0'\}}{\arg\min} \sum_{n=1}^{N} \left[\psi_m[n] - \left(\frac{4\pi}{\lambda} \| \mathbf{P}_{\text{ant}}^{(n)} - \mathbf{P}_{\text{tag}} \| + \varphi_0' \right) \right]^2, \quad (3)$$

where $\mathbf{P}_{\text{ant}}$ and $\mathbf{P}_{\text{tag}}$ are the positions of the RFID antenna and tag, respectively. φ_0' denotes the constant offset between the unwrapped phase and real phase. To estimate y_{tag}, the Levenberg-Marquardt (L-M) algorithm is adopted. Even though the optimization problem in (3) is non-convex, it presents locally strong convexity at an optimal solution. So the performance of the L-M algorithm depends on the initialization naturally. In this paper, we initialize y_{tag} using



(a) Measurement Campaign (b) Positioning errors

Figure 4. Experimental validation of the drone-based RFID system in a warehouse of the logistics company.

Table 1. Comparison of the statistical positioning errors of different algorithms in meter

Methods	SARFID	L-M	OTrack	RF-scanner	Proposed
MAEs	0.36	0.44	0.25	0.45	**0.17**
90-th	0.89	0.87	0.52	0.94	**0.40**

the estimated result via identifying the minimal of the unwrapped phase. Z_{tag} is initialized by the mean Z-coordinate of the drone during interrogation. φ_0' is initialized by zero.

4 Experimental Evaluation

To evaluate the positioning performance of the proposed method, we have conducted a drone-based RFID localization in a warehouse of a logistics company [2], as shown in Fig. 4(a). The drone with the mounted RFID reader and antennas flies along the planned trajectory, i.e., along Y-axis in Fig. 1, to gather inventory information. The drone (*i.e.*, the flying RFID reader) is tracked by a sensor fusion-based scheme that has fused the results from Decawave UWB and other low-cost directional sensors (IMU, magnetometer, etc.) based on an extended Kalman filter (EKF) [12, 13]. For the RFID interrogation, a lightweight reader ThingMagic M6E-Micro [4]) is utilized. The RFID tags (Avery Dennison AD661-R6P) are attached to the assets. The frequency of the RFID reader is 917.5 MHz. As mentioned, the TCN-based phase unwrapping model has been first trained on the mimicked dataset. Then transfer learning has been implemented to retrain the TCN model (by replacing the final fully connected layer and the classification layer) using part of measurement data (about 20%).

In this section, we compare the positioning results of the proposed method with different state-of-the-art (SOTA) methods. Fig. 4(b) shows the cumulative distribution function (CDF) of the absolute lateral positioning errors. Table 1 summarizes the mean absolute errors (MAEs) and 90-th percentile errors. We observe that the proposed method has achieved the best positioning accuracy (with 0.17-meter MAEs) compared with the other methods. Specifically, SARFID [5] performs poorly because it utilizes the measured phases directly which highly depends on the accurate antenna's locations. RF-scanner [9] and L-M [6] also have unsatisfying accuracy because they both have adopted the conventional phase unwrapping method, which is not suitable in our case (low sampling rate). Among the existing methods mentioned above, OTrack [8] is the only method that is based on RSSI profile and the reading rate. OTrack has achieved a promising accuracy with 0.27-meter MAEs, which outperforms the other phase-based SOTA solutions. We think it is because the RSSI is much less sensitive to the drone's tracking errors and sufficient for decimeter-level positioning for the short-distance scenarios, such as the stocktaking in warehouses.

5 Conclusion

In this paper, we have investigated robust RFID positioning for drone-based asset management in warehouses. A TCN-based phase unwrapping algorithm has been proposed for the first time. And the L-M algorithm has been introduced for the RFID lateral positioning, which is little affected by the drone tracking errors. The model is trained based on a synthetic dataset and generalized to real-world measurement data via transfer learning with little effort. According to experimental validation, the proposed method has achieved 0.17-meter MAEs and 0.4-meter 90-th percentile errors, which is promising for practical stocktaking in warehouses.

Acknowledgment

This work is supported in part by the Excellence of Science (EOS) project MUlti-SErvice WIreless NETworks (MUSE-WINET) and the imec ICON InWareDrones Project.

References

[1] I. Kalinov, A. Petrovsky, V. Ilin, E. Pristanskiy, M. Kurenkov, V. Ramzhaev, I. Idrisov, and D. Tsetserukou, "WareVision: CNN Barcode Detection-Based UAV Trajectory Optimization for Autonomous Warehouse Stocktaking," *IEEE Robotics and Automation Letters*, vol. 5, no. 4, pp. 6647–6653, Oct 2020.

[2] C. Li, E. Tanghe, P. Suanet, D. Plets, J. Hoebeke, E. De Poorter, and W. Joseph, "ReLoc 2.0: UHF-RFID Relative Localization for Drone-Based Inventory Management," *IEEE Transactions on Instrumentation and Measurement*, vol. 70, pp. 1–13, Mar 2021.

[3] Impinj, "Speedway Revolution Reader Application Note - Low Level User Data Support (Revision 3.0, 2013)," [Online]. Available: https://support.impinj.com/hc/en-us/article_attachments/200774268/SR_AN_IPJ_Speedway_Rev_Low_Level_Data_Support_20130911.pdf, Sep 2013.

[4] JADAK Technologies, "ThingMagic Micro and Micro-LTE User Guide," [Online]. Available: https://www.mouser.com/pdfDocs/TM_Micro_Micro-LTE-UG-Rev-06292018.pdf, May 2018.

[5] A. Buffi, P. Nepa, and F. Lombardini, "A Phase-Based Technique for Localization of UHF-RFID Tags Moving on a Conveyor Belt: Performance Analysis and Test-Case Measurements," *IEEE Sensors Journal*, vol. 15, no. 1, pp. 387–396, Jan 2015.

[6] H. Wu, B. Tao, Z. Gong, Z. Yin, and H. Ding, "A Fast UHF RFID Localization Method Using Unwrapped Phase-Position Model," *IEEE Transactions on Automation Science and Engineering*, vol. 16, no. 4, pp. 1698–1707, Oct 2019.

[7] C. Li, E. Tanghe, D. Plets, P. Suanet, J. Hoebeke, E. De Poorter, and W. Joseph, "ReLoc: Hybrid RSSI- and Phase-based Relative UHF-RFID Tag Localization with COTS Devices," *IEEE Transactions on Instrumentation and Measurement*, vol. 69, no. 10, pp. 8613–8627, Oct 2020.

[8] L. Shangguan, Z. Li, Z. Yang, M. Li, Y. Liu, and J. Han, "OTrack: Towards Order Tracking for Tags in Mobile RFID Systems," *IEEE Transactions on Parallel and Distributed Systems*, vol. 25, no. 8, pp. 2114–2125, Aug 2014.

[9] J. Liu, F. Zhu, Y. Wang, X. Wang, Q. Pan, and L. Chen, "RF-scanner: Shelf scanning with robot-assisted RFID systems," in *IEEE Conference on Computer Communications (INFOCOM)*, May 2017, pp. 1–9.

[10] S. Bai, J. Z. Kolter, and V. Koltun, "An empirical evaluation of generic convolutional and recurrent networks for sequence modeling," *arXiv preprint arXiv:1803.01271*, pp. 1–14, Apr 2018.

[11] P. V. Nikitin, R. Martinez, S. Ramamurthy, H. Leland, G. Spiess, and K. V. S. Rao, "Phase based spatial identification of UHF RFID tags," in *2010 IEEE International Conference on RFID (RFID)*, Apr 2010, pp. 102–109.

[12] J. A. Andersson, J. Gillis, G. Horn, J. B. Rawlings, and M. Diehl, "CasADi: a Software Framework for Nonlinear Optimization and Optimal Control," *Mathematical Programming Computation*, vol. 11, no. 1, pp. 1–36, Jul 2019.

[13] J. Vanhie-Van Gerwen, K. Geebelen, J. Wan, W. Joseph, J. Hoebeke, and E. De Poorter, "Indoor drone positioning: Accuracy and cost trade-off for sensor fusion," *IEEE Transactions on Vehicular Technology*, pp. 1–14, Nov 2021.