Abstract—Water utilities across the globe are concerned with the inspection and replacement of buried metallic water pipes due to corrosion-related structural damages. Internal pipe linings are commonly used as a renewal method to improve structural strength as they are regarded to be a less expensive alternative to costly and time-consuming pipe replacements. However, linings are also prone to failure as well. Therefore, water authorities regularly monitor lining performance, where defect evolution over a long period of time is an important parameter to note. It requires an accurate in-pipe robot localization technology. In this article, we propose a novel method for in-pipe robot localization and tag mapping that uses battery-free ultra high frequency (UHF)-radio-frequency identification (RFID) sensor wireless signals. It utilizes a signal mapping approach in combination with a tailored pose-graph simultaneous localization and mapping (SLAM) algorithm. Evaluation results of a field-extracted pipe sample from Sydney Water’s distribution network show that the proposed approach is capable of localizing the robot within 2.5 cm accuracy in a 50-m equivalent pipe with an unknown UHF-RFID distribution. The proposed approach outperformed other reported similar work in the literature.

Index Terms—Battery-free sensors, field robotics, infrastructure robotics, infrastructure sensing, pipe robotics, pipe sensing, robot localization, robot perception, sensor applications, simultaneous localization and mapping (SLAM), ultra high frequency (UHF)-radio-frequency identification (RFID) sensors.

I. INTRODUCTION

Many cities around the world experience greater incidences of water and wastewater pipe leaks and breaks, both of which cause significant economic, social, and environmental damage [1], [2], [3]. This is exacerbated by aging assets, and hence timely monitoring of them is essential for identifying faults and determining the most effective ways of renewal [4]. Cured in place pipe (CIPP) [5] or spray techniques [6] are widely utilized in the “lining” process, which is a popular form of renewal. Despite the fact that a variety of robotic technologies are available for the condition assessment of host pipes [7], [8], they do not provide critical information about the quality of the liners and their long-term performance. Common defects of liners are folds, bulges, wrinkles, dimples, thickness variations, and so on [9], [10], [11], [12]. Postapplication condition assessment of liners improves the confidence in the application, whereas long-term monitoring can identify defects that can potentially lead to pipe failures. Currently, it is accomplished through the use of closed-circuit television (CCTV) technology, either based on subjective visual analysis or through the experience of an operator.

Laser profiling and ultrasound technology are two examples of emerging technologies that can be used to monitor the quality of water pipe linings. The improved solution for laser profiling that we proposed in our previous work [12], [13] has the capability of taking measurements with millimeter-level accuracy. When it comes to reconstruction in the radial direction, the solution is effective and efficient. However, it has limitations as a result of longitudinal errors accumulating over time and distance when encoder-based localization is employed. This is particularly unacceptable in the context of long-term defect monitoring, where it is necessary to correlate
a specific defect across multiple deployments occurring at different time intervals. Flying and floating robots are not meant for encoder-based localization. Due to the inherent visual feature changes caused by the application of liners, emerging corrosion patches, and possible alien buildups, popular outdoor localization methods such as visual simultaneous localization and mapping (SLAM) become infeasible in underground pipeline infrastructure. This necessitates the development of an alternative and more efficient contact-less localization method.

Many different wireless technologies and algorithms are being researched for use in indoor and outdoor environments [14], [15], [16], [17], [18], [19]. The use of radio-frequency identification (RFID) localization technology has produced reasonable localization results for indoor and outdoor environments [20], [21], [22], [23], [24], [25]. Therefore, we attempted to use RFID in in-pipe environments. They also have other benefits, such as cost-effectiveness and the ability to measure various environmental conditions inside pipelines, such as temperature, moisture, and acidity levels, by embedding them as linear embedded sensing technologies [26], [27], [28]. Temperature is a good proxy for liner curing, moisture can indicate leaks, and acidity level is a corrosion indication. As a versatile sensor, RFID has numerous advantages in in-pipe applications. Unfortunately, there has not been much research on subsurface pipeline robot localization utilizing RFID sensors as of yet. This could be owing to the application’s intrinsic complexities. Unlike RFID localization in outdoor or indoor applications, the highest peak of signal intensity is not always referring to the most likely location of the RFID tag [29], [30]. The pipe surface behaves like a waveguide causing the signal inside to bounce leading to various peaks and ripple effects in the signal strength [31], [32]. Furthermore, commercial off-the-shelf (COTS) RFID readers offer erratic measurements, only capable of accurately localizing the RFID tag within a square meter area [20], making the process difficult and unique.

The Gaussian process combined particle filter localization methodology using ultra high frequency (UHF)-RFID signals has been proposed in our previous research [31], [32], [33], and it takes advantage of both received signal strength indicator (RSSI) and phase data values to improve accuracy. It works well with known RFID distribution maps (RFID tag locations are known), and it has millimeter-level accuracy when using known RFID distribution maps. In practice, however, the premise of the availability of an accurate RFID distribution map, to begin with, is less practical than it appears in theory. As a result, we present in this study an RFID localization system that employs a signal mapping approach in combination with a customized SLAM algorithm which does not require the RFID distribution map to be known as a priory. The main contributions of this article are briefly elucidated as follows.

1) Development of an in-pipe robotic prototype for simultaneous localization and mapping with a custom measurement model using dual-antenna UHF-RFID RSSI signal cross correlation.

2) The system can be deployed from any location within a pipe to travel in either direction while building RFID tags location maps and localizing the robot simultaneously with approximately 2.5 cm accuracy.

3) The system works independently without the aid of any other odometry system and requires only a training dataset acquired in a laboratory pipe sample. It does not require any specific field calibration.

4) Demonstration of the superiority of the proposed localization by comparing it with industry standards and relevant localization approaches reported in the literature.

The rest of this article is structured as follows. Section II formulates the SLAM problem, while Section III formulates the pose graph optimization and UHF-RFID signal mapping. Section IV describes the RSSI cross correlation matching and Section V presents the experimental results. Section VI concludes the article by summarizing the key outcomes while briefing the intended future work.

II. SIMULTANEOUS LOCALIZATION AND MAPPING

The conventional pose-graph optimization problem solver [34], [35], [36] has been used to localize the robot inside the pipeline with respect to the UHF-RFID measurements received from the sensor model. The motion model of the robot’s movement along the pipe can be defined as follows:

\[
x_f^t = g (u_t, x_{f-1}) + \omega_t
\]

where \(x_f^t\) is the 1-D position of the robot along the axis of the pipeline at time instance \(t\), \(u_t\) is the input given to the robot at time instance \(t\), \(g\) is a nonlinear function for state transitions, and \(\omega_t\) is random Gaussian distributed noise where \(\omega_t \sim N(0, R_t)\).

Following that, the UHF-RFID (landmark) measurement model of the robot can be defined as follows:

\[
z_i^t = h \left(x_f^t, x^i\right) + v_i
\]

where \(z_i^t\) is the UHF-RFID measurement from the UHF-RFID tag landmark \(i\) at the time \(t\), \(x^i\) is the UHF-RFID RSSI measurement of the landmark \(i\), \(h\) is a nonlinear measurement model, and \(v_i\) is random Gaussian distributed noise for measurement, where \(v_i \sim N(0, Q_t)\). The robot only senses UHF-RFID tags that are closer to the robot. Therefore, for some time indices \(t\), there can be no measurements.

The conventional pose-graph optimization problem [34] cost function can be defined as

\[
J = x_0^T \Omega_0 x_0 + \sum_t \left( x_f^t - g (u_t, x_{f-1}) \right)^T R_t^{-1} \left( x_f^t - g (u_t, x_{f-1}) \right) + \sum_t \sum_i \left( z_i^t - h \left(x_f^t, x^i\right) \right)^T Q_i^{-1} \left( z_i^t - h \left(x_f^t, x^i\right) \right)
\]

where \(x_0\) is the initial state of the robot, \(R_t^{-1}\) is the covariance of motion noise, and \(Q_i^{-1}\) is the covariance of measurement noise. Signal cross correlation is used to estimate the distance from the robot to an RFID tag. The uncertainty values returned from the signal cross-correlation mapping are used as the
covariance of $Q$. Motion model-related uncertainty was tuned based on the performance. $\Omega_0^{-1}$ is an information matrix. In this matrix, the off-diagonal elements are all zero other than between any two consecutive robot poses or any element between a map feature and a robot pose, if a map feature was observed by the robot at that time instant. Entries relating to pair of features are zero. $r$ is the number of time steps for the robot, and $I$ is the number of features. The defined problem in (3) can be solved as an optimization problem using the following equation:

$$x^* = \arg \min_x J(x) \tag{4}$$

where $x$ is given as

$$x = \begin{bmatrix} x_{r,t}^T \\ x_{0:t}^T \end{bmatrix} \tag{5}.$$

Using numerical methods, this optimization problem has been solved iteratively to compute the gradient.

III. Pose-Graph Optimization With RFID Signal Mapping

The robot trajectory path estimations and the UHF-RFID sensor (landmark) location estimations need to be simultaneously optimized. Therefore, UHF-RFID RSSI signal measurements need to be incorporated into the optimization problem. This has been achieved by incorporating the RSSI signal $s_t$ into the pose-graph optimization problem in (3) with an additional cost function $\phi$ that denotes the inconsistency of the signal measurements along the pipe traverse. The updated equation is defined as

$$J = x_{0:T}^T \Omega_0 x_0 + \sum_{t=1}^r (x_{r,t}^T - g(u_t, x_{r,t-1}^T))^T R_t^{-1} (x_{r,t}^T - g(u_t, x_{r,t-1}^T))$$

$$+ \sum_{t=1}^r \sum_{i} (z_{i,t}^T - h(x_{r,t}^T, x_{s,t}^T))^T Q_{t}^{-1} (z_{i,t}^T - h(x_{r,t}^T, x_{s,t}^T))$$

$$+ \sum_{t} \phi(t, x_{0:t}^T, s_{0:t}) - P_t^{-1} \phi(t, x_{0:t}^T, s_{0:t}) \tag{6}$$

where $x_{0:t}^T$ is the robot positions along the pipe, $s_{0:t}$ is the RFID signal measurements along the pipe, and $P_t$ is the covariance of the measurement model noise. Function $\phi$ can be defined as

$$\phi(t, x_{0:t}^T, s_{0:t}) = y(t, x_{0:t}^T, s_{0:t}) - f(t, x_{0:t}^T, s_{0:t}) \tag{7}$$

where $y$ is a function that calculates the distance between matching points of the signal $s$, and $f$ is a function that calculates the distance between matching points in the estimations of $x$.

IV. RSSI Signal Cross-Correlation Matching

Let $[x_{p1}^T, s_{p1}]$ be the training data collected from the robot at the initial deployment in the lab pipe environment, and $[x_{p2}^T, s_{p2}]$ be the data received from the robot during the localization task. Before performing cross-correlation, an equal number of comparison data points are generated with data interpolation. Let the new sets of points be $[x_{p1}'^T, s_{p1}'^T]$, $[x_{p2}'^T, s_{p2}'^T]$, where $[x_{p1}'^T, s_{p1}]$ and $[x_{p2}'^T, s_{p2}]$ be the subsets of points. The normalized cross-correlation coefficient $\gamma$ between the two sets of data can be calculated using

$$\gamma = \frac{\sum_{i} (s_{p1}(x) - \overline{s_{p1}}) (s_{p2}(x) - \overline{s_{p2}})}{\sqrt{\sum_{i} (s_{p1}(x) - \overline{s_{p1}})^2 \sum_{i} (s_{p2}(x) - \overline{s_{p2}})^2}} \tag{8}$$

For each window, when the signals are aligned properly, the difference (Euclidean distance) between the signals is calculated using the following equation as a confidence $\eta$ parameter for later use in the optimization:

$$\eta = \frac{1}{\sum_{i} (s_{p1}(x) - s_{p2}(x))^2} \tag{9}$$

The final confidence parameter $\epsilon$ is calculated using the results of both (8) and (9) as

$$\epsilon = ((1 + \gamma) \eta)^2 \tag{10}$$

where best matching poses can be filtered by setting a threshold value to the calculated $\epsilon$. The corresponding poses that represent the filters $s_1$ and $s_2$ are added to the cost function (7) where measured distance and expected distance are given by the following equations:

$$y_t = 0 \tag{11}$$

$$f_t = x_{t}^2 - x_{t}^2 \tag{12}$$

where $x_{t}^1$ and $x_{t}^2$ are the corresponding poses when $s_1$ and $s_2$ signals are matching signals. The signal mapping process depends on the many numbers of poses in $x_{0:T}$, which can be a heavy computational cost. Therefore, the signal noise covariance $P_t$ has been used as inversely proportional to $(\gamma \times \eta)$, so that stronger matches effectively weight the cost function in (3).

V. Experiments and Results

A. Development of an In-Pipe Robotic Prototype for SLAM

The developed in-pipe robotic system and two-layer system architecture utilized are shown in Figs. 1 and 2.

1) Hardware Developments: The RFID unit mounted on top of the robot has been built using commercially available off-the-shelf components. Thingmagic M6e Micro-LTE UHF 2-port RFID reader module with embedded developer kit has been used to implement the proposed system. Two 915 Mhz general purpose panel RF antennas in the 902–928 MHz range with 5.5-dBi gain were used as the receiver antennas. The two antennas are directed in the travel direction of the robot. It can be analogously similar to a stereo camera system. UHF-RFID Tag types A and B discussed in [31] have been used to conduct experiments. An industry standard infrared laser distance sensor with 80-m range and 1-mm accuracy has been used as the robot’s location ground truth. When the robot is moving forward, the distance to the object is decreasing and hence the laser-based distance to the object. Even though laser localization is quite accurate, to perform laser-based localization, the pipe needs to be straight, so that the laser pointer can be focused from the robot to an object.
at the end of the pipe during the whole journey. Underground pipelines are not perfectly straight, and the robot can have pan and tilt movements causing the laser pointer to incident on pipe surfaces rather than the end of the pipe object causing localization errors. Although the laser system is cheap, it is not practical to use it as a general localization method in this application. In our experiments, the laser localization is used only for a shorter pipe length to create the measurement model and finally compare the accuracy of localization by using it as the ground truth. To compare the performance with the standard wheel encoder-based odometry, a calibrated, industry-standard 2400 pulses per revolution rotary encoder has been used to record the odometry by attaching it to the robot wheel. The Jetson Nano Developer kit board with a Quad-core ARM 1.43 GHz CPU and 4 GB 64-bit LPDDR4 RAM was used as the central processing unit to run the implemented system. The whole hardware system was assembled inside an enclosure and mounted on the robotic platform, miniPIRO as shown in Fig. 1.

2) Software Developments: The software components were implemented with the robot operating system (ROS) framework to gain the flexibility to modularize each component and to gain cross-language software support. Each individual component has been implemented as an ROS node to communicate with each other effectively. UHF-RFID-related components are implemented in Python as they are supported by the open-source Python Mercury application programming interface (API) library. To gain more structure and flexibility to implement the algorithms, the core integration has been implemented as C++ components. The laser distance sensor that tracks the odometry of the robot has been implemented with Arduino components. As the diagram elaborates, the UHF-RFID component receives the RSSI and Phase data signals from the robot and publishes the data to the receiving components. In the training phase, the location mapper will combine the data with robot odometry data that is received from the laser data publisher node. The collected data will be stored as measurement data maps for later use in signal mapping. In the localization phase, the data received from the robot is mapped with the measurement model using the signal correlation algorithm. Based on the generated confidence value, the probabilities of robot location and tag locations are calculated within the SLAM algorithm for each UHF-RFID tag signal. Finally, using these calculated values, the highest probability of the robot localization and UHF-RFID tag locations are published to the location publisher node, which is displayed in robot operating system visualization (RVIZ)-like location visualizer systems.

B. Data Collection, Data Modeling, and Signal Mapping

Tethered heavy crawler robots are not preferred to be deployed in pipes with corners and bends as they tend to tangle or tear the tether. In practice, most of the water pipe inspections of medium-sized pipes (300–900-mm diameter pipes) are carried out over shorter distances (less than 500 m) and they are reasonably straight. In medium-sized nontraversable sewer pipes (900–1500-mm diameter), manhole-to-manhole deployments are generally carried out, ranging from 100 to 300 m. In Sydney, they are generally straight pipe sections, which led us to simplify the localization problem. However, in pipe environments with possible bends, this system can be modified with an inertial measurement unit (IMU) sensor and/or prior knowledge of network drawings to deal with the changes in orientation.

Data for training the measurement model was collected by placing UHF-RFID tags in the middle of the side wall of a 5-m long, 600-mm diameter pipe section. According to our previous studies [32], all tags perform similarly, and RFID tags did not interfere with each other. The closer the RFIDs were packed, the more the measurements were received. Having more measurements in the training model will help with the accuracy, however, it is costlier and time-consuming. Therefore, it should be a compromise between the required accuracy and time/cost. Next, we run the robot from one end to the other end, collecting the RSSI signal patterns for each tag along the pipe that maps to the robot’s location.
to generate the measurement model. The robot’s accurate location (ground truth) was determined using the laser distance measurement unit. For the test data, the robot was deployed ten times inside the 5-m pipe placing previously measured UHF-RFID tags approximately 1 m apart from each other, and in each deployment, we attached new sets of tags (a total of 50 different tags were used) that mimics approximately a 50-m long UHF-RFID pipe scan (see Fig. 3). RSSI data relating to the first ten UHF-RFID tags is shown in Fig. 4.

The robot is deployed in the pipe section, where the UHF-RFID locations are unknown. Fig. 5 shows an example result of the RSSI signal mapping for a given UHF-RFID tag and a given antenna. The top graph shows the measurement model signal that maps the laser distance reading to the signal pattern. The middle graph contains the received signal data (note the x-axis scale differences) that needs to be aligned with the measurement model to estimate the travel distance. The bottommost graph shows the results of mapping the received signal to the measurement model signal, which leads to correlating the data points with distance values.

C. In-Pipe Robot Localization and UHF-RFID Mapping

Robot localization accuracy calculated based on laser system is shown in Fig. 6. Fig. 7 shows the mean error graph where it has an initial slightly poor performance. It is due to a lack of received UHF-RFID signal data points, however, it improved significantly within the first 3 m. This can be alleviated by adding several RFIDs at the beginning of the pipe section.

It is to be noted that the currently used hardware can only receive data at an approximate 50-Hz rate. Therefore, the density and the quality of the received signal data depend on the robot’s speed. Higher robot speeds lead to larger errors as shown in Fig. 8. Fig. 9 shows the UHF-RFID signals received from the two antennas while traveling inside the pipelines.

D. Performance Evaluation

Performance of the proposed algorithm was compared with industry-standard, commonly used encoder odometry-based robot localization (OD) and also with the Gaussian process combined particle filter-based two antenna model localization method (GPPF2) that we have proposed in our preliminary research work [31], [32].

As in Fig. 10, the GPPF2 shows higher accuracy, however, it requires the exact locations of the RFID tags to be known. The proposed SLAM approach managed to achieve a slightly
lower accuracy without any knowledge of the RFID tag distribution.

Fig. 11 shows the comparison between the proposed SLAM, GPPF2, and OD. It shows errors caused by the accumulated drift of the odometry-based localization.

Fig. 12 shows the end results of a 50-m pipe deployment. A physical mark on the crown of the pipe has been used to correlate the localization errors. It is clearly seen that the OD localization is 0.817 m away from the ground truth. The GPPF2 with known RFID locations perfectly aligned with the ground truth with an insignificant (0.001 m) deviation. The proposed SLAM localization aligns within 0.021 m. Therefore, the most practically effective solution is the proposed UHF-RFID SLAM.

Table 1 summarizes the comparison results. The localization methods proposed in this journal show competitive accuracy compared with results for other methods reported in the literature. Two typical conventional localization methods [18], [19] show around 31- and 27-cm accuracy; two methods employing two UHF-RFID antennas in recent studies [20], [21] show around 59- and 50-cm accuracy; and an approach combining localization using IMU, gyro, and leak sensors [28] shows 250 mm accuracy. The encoder-based method [29] shows 833 mm accuracy with a standard deviation of 214 mm. The proposed GP-based PF method [33] shows 1.8 mm accuracy with a standard deviation of 1.62 mm. The proposed SLAM method shows the lowest error of 23.3 mm with a standard deviation of 3.8 mm.
VI. CONCLUSION AND FUTURE WORK

This article presents the development of battery-free UHF-RFID sensor-based SLAM for in-pipe robotic localization. A mobile robotic prototype that is capable of navigating in pipes with diameters ranging from 450 to 650 mm was developed. A signal cross-correlation mapping technique in combination with a customized SLAM algorithm was developed to estimate the location of the robot. It was tested up to a 50-m long pipeline using a sample pipe taken from the Sydney water underground pipe network.

The findings demonstrated that the proposed approach is capable of localizing the robot with an accuracy of approximately 2.5 cm while using UHF-RFID tag locations that are unknown. The effect of robot traverse speed on localization accuracy was investigated using a series of experiments. According to the experimental findings, faster speeds result in more errors since the number of data points received is reduced as a consequence. One way to improve the accuracy is to deploy RFIDs at shorter intervals.

Larger pipelines like the ones reported in this study are generally consisting of straight line sections. Hence, the localization is mostly 1-D and accurate enough for the application. Pipes are made of metallic cast iron and act as a Faraday cage, hence electromagnetic interference to RFID signals is negligible.

The initial cost estimate for a robotic system with an RFID dual antenna system costs $1250. For the RFID tags, it costs approximately $4 per meter. The encoder-based systems require neither the antenna cost which is U.S. $100 each nor the RFID tags cost, while it cannot produce the accuracy required for the application. Cost may be a factor to consider in making decisions about using the system. However, considering the millions of dollar budget allocated for condition assessment of pipes, this is a reasonable cost-effective solution. When compared with current literature and the most extensively used industry standard, encoder-based localization strategy, the proposed method outperformed in terms of accuracy.

In the future, we intend to test the technology in longer pipe sections under a variety of environmental circumstances when COVID constraints have been lifted. The research may be further developed in order to produce a more generalized signal model for enhancing the deployment efficacy of UHF-RFID tags by studying the signal repeatability characteristics of the UHF-RFID tags themselves.

REFERENCES

[1] K. Thiagajaran, S. Kodagoda, R. Ranasinghe, D. Vitanage, and G. Iori, “Robust sensor suite combined with predictive analytics enabled anomaly detection model for smart monitoring of concrete sewer pipe surface moisture conditions,” IEEE Sensors J., vol. 20, no. 15, pp. 8232–8243, Aug. 2020.

[2] N. Ulapanee, K. Thiagajaran, J. V. Miro, and S. Kodagoda, “Surface representation of pulsed eddy current sensor signals for improved ferromagnetic material thickness quantification,” IEEE Sensors J., vol. 21, no. 4, pp. 5413–5422, Feb. 2021.

[3] K. Thiagajaran, S. Kodagoda, R. Ranasinghe, D. Vitanage, and G. Iori, “Robust sensing suite for measuring temporal dynamics of surface temperature in sewers,” Sci. Rep., vol. 8, no. 1, p. 16020, Dec. 2018.

[4] S. Thiagajaran, S. Kodagoda, L. van Nguyen, and R. Ranasinghe, “Sensor failure detection and faulty data accommodation approach for instrumented wastewater infrastructures,” IEEE Access, vol. 6, pp. 56562–56574, 2018.

[5] J. C. Matthews, A. Selvakumar, and W. Condit, “Demonstration and evaluation of an innovative water main rehabilitation technology: Cured-in-place pipe (CIPP) lining,” Water Pract. Technol., vol. 7, no. 2, pp. 1–10, Jul. 2012, doi: 10.1109/JSEN.2020.3040396.

[6] S. Kodagoda and K. Thiagajaran. (Oct. 2018). Performance Monitoring of Liners: Parameter Identification. [Online]. Available: https://www.waterportal.com.au/smartlinings/images/Deliverables/31_UTC_Literature_Review_FINAL.pdf

[7] L. Nguyen and J. V. Miro, “An efficient 3-D model for remeshing wall thicknesses of cast iron pipes in nondestructive testing,” IEEE Sensors Lett., vol. 4, no. 7, pp. 1–4, Jul. 2020, doi: 10.1109/JSEN.2020.303330.

[8] S. K. Kodagoda and K. Thiagajaran, “UHF-RFID SLAM proposed in this journal exhibits superior accuracy of 2.5 cm inside pipelines.”

[9] A. Gunatilake, L. Piyathilaka, A. Tran, V. K. Vishwanathan, K. Thiagajaran, and S. Kodagoda, “Stereo vision combined with laser profiling for mapping of pipeline internal defects,” IEEE Sensors J., vol. 21, no. 10, pp. 11926–11934, May 2021, doi: 10.1109/JSEN.2020.3040396.

[10] A. Vasilikis and M. Karamanos, “Mechanical behavior and wrinkling of lined pipes,” Int. J. Solids Struct., vol. 49, pp. 3432–3446, Nov. 2012.

[11] D. Sharma et al., Polymer Coatings Technology and Applications: Polymer Coating Methods. Boca Raton, FL, USA: CRC Press, Jan. 2021.

[12] A. Gunatilake, L. Piyathilaka, A. Tran, V. K. Vishwanathan, K. Thiagajaran, and S. Kodagoda, “Stereo vision combined with laser profiling for mapping of pipeline internal defects,” IEEE Sensors J., vol. 21, no. 10, pp. 11926–11934, May 2021, doi: 10.1109/JSEN.2020.3040396.

[13] A. Thitzisz et al., “Localization of RFID tags by a moving robot, via phase unwrapping and non-linear optimization,” IEEE J. Radio Freq. Identificat., vol. 3, no. 4, pp. 216–226, Dec. 2019.

[14] F. Bernardini et al., “Robot-based indoor positioning of UHF-RFID tags: The SAR method with multiple trajectories,” IEEE Trans. Instrum. Meas., vol. 70, pp. 1–15, 2021.

[15] S. Han, H. Lim, and J. Lee, “An efficient localization scheme for a differential-driving mobile robot based on RFID system,” IEEE Trans. Ind. Electron., vol. 54, no. 6, pp. 3362–3369, Dec. 2007.

[16] P. Yang, W. Wu, M. Moniri, and C. C. Chibelushi, “Efficient object detection model for smart monitoring of concrete sewer pipe surface moisture conditions,” IEEE Sensors J., vol. 20, no. 15, pp. 8232–8243, Aug. 2020.

[17] S. R. Rusu, M. J. D. Hayes, and J. A. Marshall, “Localization in large-scale underground environments with RFID,” in Proc. 24th Can. Conf. Elect. Comput. Eng. (CCECE), May 2011, pp. 1140–1143.

[18] C. Li, L. Mo, and D. Zhang, “Review on UHF RFID localization methods,” IEEE J. Radio Freq. Identificat., vol. 3, no. 4, pp. 205–215, Dec. 2019.
[24] E. DiGiampaolo and F. Martinelli, “A restarting paradigm for a range-only SLAM algorithm using the phase of passive UHF-RFID signals,” in *Proc. IEEE Int. Conf. RFID Technol. Appl. (RFID-TA)*, Sep. 2019, pp. 279–284.

[25] F. Martinelli, “Robot localization using the phase of passive UHF-RFID signals under uncertain tag coordinates,” *J. Intell. Robot. Syst.*, vol. 82, nos. 3–4, pp. 577–593, Jun. 2016.

[26] J. Virtanen, L. Ukkonen, T. Björninen, L. Sydanheimo, and A. Z. Elsherbeni, “Temperature sensor tag for passive UHF RFID systems,” in *Proc. IEEE Sensors Appl. Symp.*, Feb. 2011, pp. 312–317.

[27] E. M. Amin, M. S. Bhuiyan, N. C. Karmakar, and B. Winther-Jensen, “Development of a low cost printable chipless RFID humidity sensor,” *IEEE Sensors J.*, vol. 14, no. 1, pp. 140–149, Jan. 2014.

[28] Y. Wu, E. Mittmann, C. Winston, and K. Youcef-Toumi, “A practical minimalist approach to in-pipe robot localization,” in *Proc. Amer. Control Conf. (ACC)*, 2019, pp. 3180–3187.

[29] A. Buffi, P. Nepa, and R. Cioni, “SARFID on drone: Drone-based UHF-RFID tag localization,” in *Proc. IEEE Int. Conf. RFID Technol. Appl. (RFID-TA)*, Sep. 2017, pp. 40–44.

[30] F. Martinelli, “A robot localization system combining RSSI and phase shift in UHF-RFID signals,” *IEEE Trans. Control Syst. Technol.*, vol. 23, no. 5, pp. 1782–1796, Sep. 2015.

[31] A. Gunatilake, M. Galea, K. Thiyagarajan, S. Kodagoda, L. Piyathilaka, and P. Darji, “Using UHF-RFID signals for robot localization inside pipelines,” in *Proc. IEEE 16th Conf. Ind. Electron. Appl. (ICIEA)*, Aug. 2021, pp. 1109–1114.

[32] A. Gunatilake, K. Thiyagarajan, and S. Kodagoda, “Evaluation of battery-free UHF-RFID sensor wireless signals for in-pipe robotic applications,” in *Proc. IEEE Sensors*, Oct. 2021, pp. 1–4.

[33] A. Gunatilake, S. Kodagoda, and K. Thiyagarajan, “A novel UHF-RFID dual antenna signals combined with Gaussian process and particle filter for in-pipe robot localization,” *IEEE Robot. Autom. Lett.*, vol. 7, no. 3, pp. 6005–6011, Jul. 2022.

[34] S. Thrun, W. Burgard, D. Fox, and R. Arkin, *Probabilistic Robotics* (Intelligent Robotics and Autonomous Agents). Cambridge, MA, USA: MIT Press, 2005. [Online]. Available: https://books.google.com.au/books?id=2Zn6AQAAQBAJ

[35] W. Lin, J. Hu, H. Xu, C. Ye, X. Ye, and Z. Li, “Graph-based SLAM in indoor environment using corner feature from laser sensor,” in *Proc. 32nd Youth Acad. Annu. Conf. Chin. Assoc. Autom. (YAC)*, May 2017, pp. 1211–1216.

[36] H. Durrant-Whyte and T. Bailey, “Simultaneous localization and mapping: Part I,” *IEEE Robot. Autom. Mag.*, vol. 13, no. 2, pp. 99–110, Jun. 2006.

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