An Intelligent Mobile Robot Navigation Technique Using RFID Technology

Wail Gueaieb, *Senior Member, IEEE*, and Md. Suruz Miah, *Student Member, IEEE*

***Abstract*—This paper presents an innovative mobile robot navigation technique using Radio Frequency IDentification (RFID) technology. Navigation based on processing some analog features of an RFID signal is a promising alternative to different types of navigation methods in the state of the art. The main idea is to exploit the ability of a mobile robot to navigate *a priori* unknown environments without a vision system and without building an approximate map of the robot workspace, as is the case in most other navigation algorithms. This paper discusses how this is achieved by placing RFID tags in the 3-D space so that the lines linking their projections on the ground define the "free ways" along which the robot can (or is desired to) move. The suggested algorithm is capable of reaching a target point in its *a priori* unknown workspace, as well as tracking a desired trajectory with a high precision. The proposed solution offers a modular, computationally efficient, and cost-effective alternative to other navigation techniques for a large number of mobile robot applications, particularly for service robots, such as, for instance, in large offices and assembly lines. The effectiveness of the proposed approach is illustrated through a number of computer simulations considering testbeds of various complexities.**

***Index Terms*—Fuzzy logic, mobile robots, navigation, position control, Radio Frequency IDentification (RFID), robot sensing systems.**

I. Introduction

MOBILE robot navigation has stood as an open and challenging problem over the last few decades. Despite the significant advances in this field, researchers have yet to reach a comfortable level of satisfaction. To date, most of the robot navigation algorithms proposed in the literature are either tailored toward particular structured environments or driven by an overwhelming degree of computational complexity [1]. In some cases, the hardware needed to implement the algorithm can be more costly than the robot itself. This makes the practical realization of such algorithms in most real-world robotic systems questionable. This paper contributes to the efforts of developing practical, modular, and easy-to-implement robot navigation algorithms that are both cost and computationally effective. The proposed algorithm takes advantage of the emerging Radio Frequency IDentification (RFID) technology and a fuzzy logic controller (FLC) to guide the robot to navigate in its working space.

Numerous robot navigation methods have been suggested over the past few years. These systems generally fall under one of the following categories: dead-reckoning-based, landmark-based, vision-based, and behavior-based techniques. The fundamental idea behind dead-reckoning navigation systems is the integration of incremental motion over time [2]. This navigation method is based on continuous encoder readings that provide the position, orientation, and linear and angular velocities of the robot. This type of navigation is widely used due to its simplicity and ease of maintenance. However, small precision errors and sensor drifts inevitably lead to increasing cumulative errors in the robot's position and orientation, unless an independent reference is periodically used to correct the error [3].

Given these shortcomings, researchers shifted their interest to vision-based navigation to improve the robot position estimation by tracing the visual features in the environment and using them as landmarks [4]. This measurement usually returns bearing to the visual features only, with no *a priori* knowledge of the landmark positions. Nevertheless, such a technique also has its own disadvantages, which include the lack of information depth, complex image processing algorithms with high computational burden, and its dependence on the working environment. This problem can be alleviated by adopting behavior-based navigation systems, as they can incorporate a relatively large number of sensors, making them suitable for navigation in unstructured environments. However, relying on numerous sensors makes the system vulnerable to their drifts and cumulative errors. To overcome this shortcoming, some researchers used artificial landmarks to compensate for these errors. For example, in some studies, RFID tags were placed in particular locations in the workspace, and the robot was equipped with an RFID reader to communicate with the tags to estimate its position.

In cases where the RFID systems were applied to mobile robot systems, they were mainly used for robot localization but not directly for navigation [5]. In this paper, we describe a novel navigation technique in which RFID tags are mounted in fixed locations in the 3-D space. The tags are used to define the desired trajectory of the robot. The aim of the navigation algorithm is then to make the robot navigate along the virtual lines on the ground, linking the orthogonal projection points of the tags on the ground. Unlike other studies of this kind reported in the literature, there is no restriction on where the tags should be mounted. For indoor applications, they can be mounted on the ceiling, whereas outdoors, they can be mounted, for example, on posts. A two-antenna RFID reader is mounted on

Manuscript received November 15, 2006; revised February 10, 2008. This work was supported in part by the Natural Sciences and Engineering Research Council of Canada, the Canada Foundation for Innovation, and the Canadian Microelectronics Corporation.

The authors are with the Machine Intelligence, Robotics, and Mechatronics (MIRaM) Laboratory, School of Information Technology and Engineering, University of Ottawa, Ottawa, ON K1N 6N5, Canada (e-mail: wgueaieb@site.uottawa.ca; suruz.miah@uottawa.ca).

Color versions of one or more of the figures in this paper are available online at http://ieeexplore.ieee.org.

Digital Object Identifier 10.1109/TIM.2008.919902

the robot to communicate and determine the robot's relative position with respect to the tags. The sampled information is continuously fed to a fuzzy logic engine to tune the robot's orientation and to guide the robot to navigate as close as possible to the virtual line defining the desired trajectory on the ground. To the best of the authors' knowledge, this is the first attempt to use RFID technology for the true real-time navigation (not localization) of mobile robots. It is also worth mentioning that this paper represents the first milestone of a larger project to provide a fully fledged practical nonvision-based navigation solution. Vision-based navigation may still be necessary in some cases. If not, however, the proposed technique represents a promising alternative solution. Although several modules are involved in operating mobile platforms, such as, for example, the localization, navigation, obstacle detection, obstacle avoidance, and path planning modules, only the former two are considered here. The other modules are out of the scope of this paper. The rest of this paper is organized as follows. A brief literature review of robot navigation systems and their common techniques is given in Section II. In Section III, we give a brief general overview of the RFID systems. Then, we detail our proposed navigation system in Section IV. A thorough evaluation of the technique in hand is provided in Section V before concluding this paper in Section VI with some highlights, the pros and cons of the proposed navigation method, and how it can be further extended.

II. Related Work

In recent years, significant research has been conducted on mobile robotics that incorporate several sensors and landmarks as navigation media in the environment. In this section, we provide a briefing on some of the recent research related to mobile robot navigation, e.g., those dealing with landmark-based, dead-reckoning-based, and behavior-based navigation.

The indoor mobile robot navigation presented in [6] uses a global ultrasonic system for the robot's position estimation while navigating in an environment. The global ultrasonic system consists of four ultrasonic generators fixed at *a priori* known positions in the workspace and two receivers mounted on the mobile robot. An extended Kalman filter is opted to process the sensory data to locate the robot. Hallmann and Siemiatkowska [7] developed a mobile robot B14 to navigate in a partially known environment. The vehicle is equipped with 16 sonars, 16 infrared sensors, an onboard Pentium computer, and a gray-scale camera. A map of the robot's environment is built based on the information fed by the sonar and infrared sensors mounted on the robot. Artificial landmarks with predefined shapes and colors are placed in specific locations to help, together with some image processing and pattern recognition algorithms, the robot locate itself.

In addition to artificial landmarks, natural landmarks have also been exploited in a number of robot navigation algorithms. For instance, Betge-Brezetz *et al.* [8] focused on the high-level representation of the natural scene to guide a mobile robot in an *a priori* unknown environment. The landmarks in this case are defined as natural objects extracted from perceptual data. The scene is structured into elements corresponding to its main entities, and only the parametric description is employed to characterize the shape of every entity. A segmentation algorithm was adopted to distinguish different components in the 3-D scene. After that, the object models are built using a quadratic representation. Finally, the objects and the topological models are merged to construct the scene model, which is ultimately used for navigation control. Wijk and Christensen developed a similar algorithm for natural landmark extraction from sonar data streamed from a mobile platform [9]. In this paper, the robot's absolute position is determined through a matching procedure between the recently collected landmarks and the reference map. The adopted natural point landmark extraction method consists of a double-fold filtering process of sonar data, i.e., a triangulation-based fusion and a completion of the landmark hypothesis. In the first layer, 2-D data points are filtered out, and the best triangulation points from the first filtering stage are considered in the second layer. Then, in the second layer, these extracted landmark points are used to match the reference map to localize the robot in its working environment.

Among the dead-reckoning techniques investigated in this context is the one described in [10], which studied the integration of dead-reckoning and visual landmark recognition methodologies for the navigation control of a vehicle along a predetermined path in a forest. This research used a magnetic compass to measure the robot heading and a ground speed Doppler radar to measure distance. The desired path is marked with landmarks that are detected by a camera connected to a computer on the vehicle. The position and orientation of the vehicle are determined based on the relative proximity of the detected landmarks and through the fusion of the data continuously collected by the sensors onboard. Another algorithm to guide a robot to navigate along a predefined desired path is described in [11]. The proposed control scheme integrates the position estimation obtained by a vision system with the position estimated by an odometer, whereas an obstacle detection mechanism is implemented based on the information fed by a number of ultrasonic sensors mounted on the robot. Despite its satisfactory performance, the system is only suitable for structured or quasi-structured environments and requires *a priori* knowledge of the world model. An indoor autonomous goal-based mobile robot navigation technique is proposed in [12]. The adopted architecture relies on a cooperative strategy between odometric and visual self-localizing techniques. This way, only the relative motion is estimated to obtain the absolute position of the vehicle. Other dead-reckoning navigation systems were developed in [13] and [14], where encoder and gyroscope readings are fed to an indirect Kalman filter to compute reliable position and heading angle approximations of an autonomous mobile robot. A number of the aforementioned paradigms were accompanied with tools of computational intelligence, such as fuzzy logic, artificial neural networks, genetic algorithms, and several combinations of them. For example, a genetic algorithm was used in [15] to design a mobile robot navigation framework. However, among the main drawbacks of this strategy, and of the genetic-algorithm-based approaches in general, is that it is nondeterministic and, hence, cannot operate in real time. FLCs were also tested in [16] and [17] for the navigation of single and multiple mobile robots, respectively, with the ability to avoid collision in a dynamic environment.

Recent attempts in the area of mobile robot navigation have witnessed an increasing interest in the emerging RFID technology as a promising alternative technique to the aforementioned strategies due to its ease of use, flexibility, and low cost. Khubitz *et al.* presented a navigation system that uses RFID tags as artificial landmarks [18]. The tags' global position, environment class, environment position, and further optional data are prestored in the tags' memory. The system also employs a behavior-based control architecture that enables the robot to reach any landmark within its working environment through a topological robot positioning approach. The behavior-based control architecture is specially designed to be able to integrate several position sensors with different accuracies and error categories while enabling the robot to navigate. A new navigation system in man-made environments, such as hallways, was developed in [19], where RFID tags are used as artificial landmarks, and the mobile robot is equipped with an onboard laptop computer, an RFID tag sensor, and a vision system. The RFID reader is mounted on the robot itself, whereas the tags are pasted at particular locations on walls. At the junction of two passages, the RFID tag sensor reads the unique tag identification numbers and infers the necessary actions (turn left, right, or remain straight) to reach the desired positions. In 2005, another technique was proposed by Tsukiyama [20], where the robot tries to build a topological map of its surrounding environment to be used in path planning and navigation. Each node in the topological map is the intersection point of two passages. At these points, the robot has to decide on the next action according to a plan stored in the robot's memory to reach the target position. The robot then follows certain paths using an ultrasonic range finder until a tag is found. However, such a methodology is specific to a particular workspace and requires a substantial amount of customization for it to operate in a new environment. Chae *et al.* proposed a mobile robot localization method with the help of a combination of RFID and vision technologies [21]. The global localization of the robot is performed by incorporating signal detection from artificial landmarks represented by RFID tags. The tags are assigned different weights, which are determined by the RFID reader mounted on the robot. The algorithm takes advantage of a vision system incorporating a feature descriptor derived from a scene view of the robot environment, which provides the fine position and orientation of the robot. Although this algorithm offers an efficient localization method, in general, it naturally inherits the typical shortcomings of vision-based techniques.

III. RFID Systems

RFID is an automatic identification method that relies on storing and remotely retrieving data using data-carrying devices called RFID tags or transponders. The power required to operate the data-carrying device is transferred using a contactless technology from a data-capturing device called an RFID reader. The basic communication between the reader and the transponder of an RFID system is based on radio frequency (RF) technology. A simplified RFID system's architecture is depicted in Fig. 1. A communication antenna is usually built within the tag, whereas the reader is typically equipped with one or two antennas. The RF transceiver on the reader illuminates a short pulse of electromagnetic waves. The transponder receives the RF transmission, rectifies the received signal to obtain the dc power supply for the IC memory, reads the ID stored in the memory, and backscatters it in response to the interrogation. The signal generated by the transponder is then received by the reader to extract the tag's ID number. Due to its simplicity, flexibility, and low cost, the RFID technology has quickly gained an increasing popularity in a large number of applications, such as personal identification, food production control, security guard monitoring, and inventory management, to name a few.

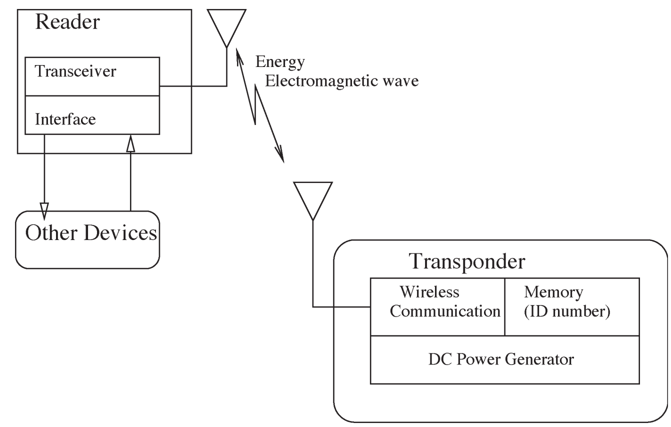


Fig. 1. Simplified RFID system's architecture.

The RFID sensing method used in this paper relies on processing the backscattered signals within a specific frequency range. The wave broadcasted by the reader is in the form of single-tone sinusoidal signals with different frequencies using time multiplexing. In this paper, we are particularly interested in the phase of the baseband signal received at the reader's end as a result of the tag's response. This phase ϕ is derived from the in-phase (I) and quadrature (Q) components of the received signal and is defined by

$$\phi = \tan^{-1}\left(\frac{I}{Q}\right). \quad (1)$$

IV. Proposed Approach

The general high-level architecture for the proposed navigation system consists of an RFID communication module and an FLC, in addition to the software performing data processing and computing the necessary control actions. The proposed technique relies on RFID tags placed in 3-D space so that the lines linking their projections on the ground virtually define the "free ways" along which the robot can (or is desired to) navigate. The locations of the tags are unknown to the robot. The robot is preprogrammed with an ordered list of tag ID numbers defining its desired path. For instance, if the robot is given the list (4, 9, 1, 5), then it is supposed to navigate to the closest point it can reach to tag number 4, then move in a straight line to the closest point it can reach to tag number 9,

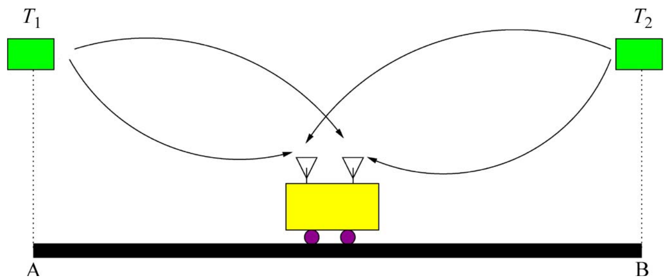


Fig. 2. High-level system configuration with two RFID tags.

and from there to tag number 1, and then to tag number 5. The closest point to a tag that the robot can reach is usually the orthogonal projection point of that tag on the ground. During navigation, the robot continuously reads the ID's of all the tags within reach but will only process the signal coming from the destination tag at that time instant. The communication with the tags is performed through an RFID reader with two receiving antennas mounted on the robot. A high-level configuration setup of this system with two RFID tags is depicted in Fig. 2. In this configuration, the robot's desired path is the straight line segment between the tags' orthogonal projection points on the ground, i.e., A and B. In the following, we provide a detailed description of each module of the proposed navigation system.

A. RFID Communication Module

During the robot's navigation, the RFID reader sends time-multiplexed single-tone sinusoidal signals with different frequencies and then listens to the backscattered signals from the RFID tags. Particularly, we are interested in the signal broadcasted by the tag representing the robot's destination at that time instant. Let ϕ_1 and ϕ_2 be the phase angles of the signal received by the reader's reception antennas 1 and 2, respectively [as defined in (1)]. This information is then used to calculate the signal's phase difference as it will be later used by the FLC to decide on the necessary control action. The phase difference is computed as

$$\Delta\phi = \phi_1 - \phi_2. \tag{2}$$

It is worth mentioning, however, that none of the commercially available RFID readers to date is capable of providing the necessary information to perform these calculations. This is simply because all that these readers currently offer is the ID number of the transponders within its communication range. As a result, preliminary studies were conducted using a custom-made RFID reader and a digital oscilloscope to confirm the fact that the phase difference defined in (2) can indeed be used to know if the tag lies on the left or the right of the vertical plane perpendicular to the ground and dividing the line segment connecting the two receiving antennas of the RFID reader at its midpoint. Nevertheless, this technique can be easily implemented in the future using any commercial reader capable of providing either the signal's phase directly or some sort of other relevant data through which it can be computed.

The custom-made RFID system consists of a signal generator that generates continuous-wave signal with an embedded BPSK-modulated p-n sequence [22]. The two directional antennas on the reader are then used to receive the backscattered signal. The in-phase (I) and quadrature (Q) components of the received baseband signal are sampled and stored using the digital oscilloscope. This information is then fed to the high-level navigation algorithm to compute the phase difference defined in (2). A high-level architecture of this custom-made RFID setup is given in Fig. 3. The data collected offline in this experiment is used later to model the RFID module in the simulation.

B. FLC

Many of the humans' actions and behaviors can be very effectively accomplished using a well-structured set of if–then rules that they implicitly developed over years of knowledge and experience. Fuzzy set theory has been developed to mimic this powerful capability and to design systems that can effectively deal with ambiguous processes. Among the main features of FLCs is their ability to generate adequate decisions inferenced through human-like linguistic descriptions [23]. This feature is quite convenient for the problem at hand, given that the system's behavior in analyzing the phase difference can be easily modeled through a human-like reasoning mechanism. The FLC represents its decision-making inference system through fuzzy rules based on heuristics, knowledge, and experience, which are often used to control a given ill-defined system. A special inference mechanism processes the information stored in the knowledge base to determine the adequate control action to be taken at any given situation.

In this paper, we use a single-input–single-output Mamdani-type FLC, as shown in Fig. 4. The aim of the FLC is to decide on the amount of tune-up $\Delta\theta$ that the robot has to apply to its direction θ to converge to its target position. The FLC's input is the phase difference $\Delta\phi$ provided by the two directional antennas mounted to the RFID reader on the robot. The robot then uses this information to update its direction following the update rule:

$$\theta^{(\text{new})} = \theta^{(\text{old})} + \Delta\theta. \tag{3}$$

The fuzzification and defuzzification membership functions are taken as linear triangular and trapezoidal membership functions for their higher computational efficiency. They are illustrated in Fig. 5. An empirical analysis was performed to optimize these membership function parameters to improve the FLC's performance. The "min" and "max" operators are adopted as t-norm and s-norm operators, whereas the defuzzification method is chosen to be the center of area. Three fuzzy rules are defined to reflect the fact that the phase difference of the signal is positive when the transmitting transponder is in on the left side of the reader and *vice versa*. These rules are defined as follows:

$$\begin{array}{llll} \textbf{If} & \Delta\phi \text{ is } Neg & \textbf{Then} & \Delta\theta \text{ is } CCW \\ \textbf{If} & \Delta\phi \text{ is } Zero & \textbf{Then} & \Delta\theta \text{ is } Zero \\ \textbf{If} & \Delta\phi \text{ is } Pos & \textbf{Then} & \Delta\theta \text{ is } CW. \end{array}$$

The rationale behind these rules is that the robot is supposed to turn left/right (*CCW*/*CW*, for counter clockwise and clockwise,

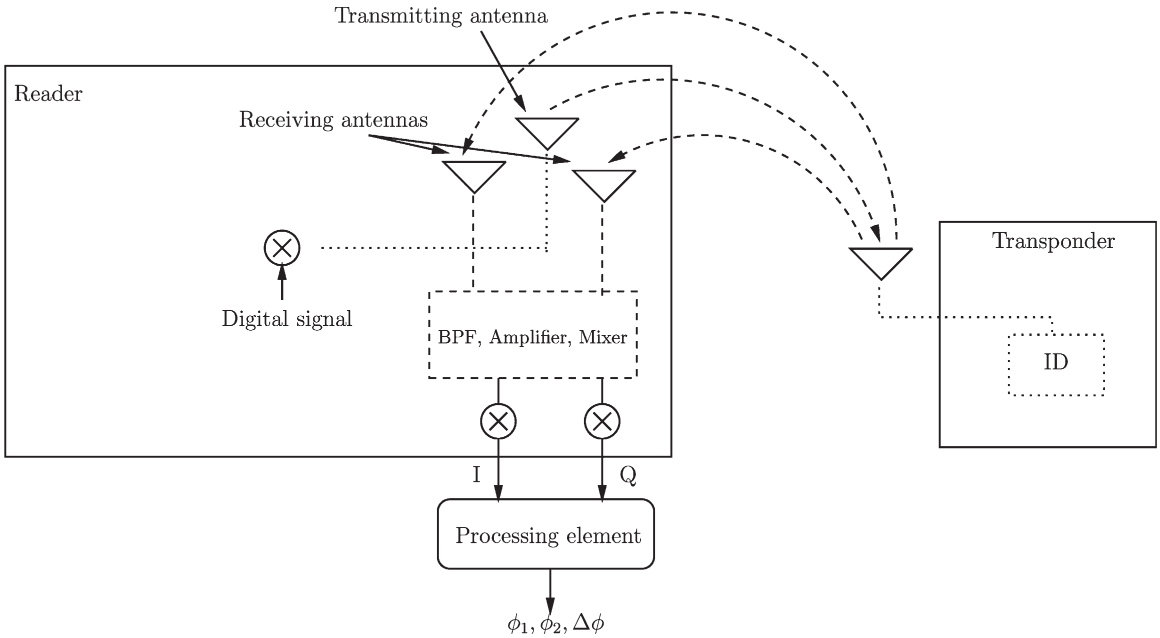


Fig. 3. RFID system setup to compute the phase difference.

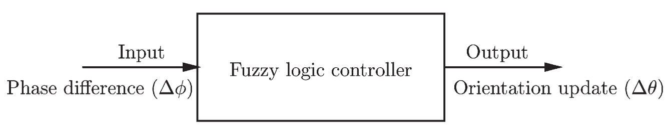


Fig. 4. FLC model used by the mobile robot.

respectively) if the RFID tag is on the left/right of the reader, where $\Delta\phi$ is negative and positive, respectively. Despite the simplicity of the adopted FLC, it proved to be quite efficient. It serves well the purpose of this paper in developing a modular computationally cost-effective yet powerful mobile robot navigation system.

C. Navigation Algorithm

A navigation algorithm is needed to act as a supervisory control layer to process and coordinate the efforts of the RFID communication module and the FLC on one hand and to pass the FLC's output control actions to the robot's relevant actuators on the other hand. A flowchart of the navigation algorithm is provided in Fig. 6. The following is a detailed description of the algorithm.

Step 1) The robot is preprogrammed with an ordered list of tag ID numbers defining its desired path.

Step 2) The target tag of the current navigation phase is determined from the ordered list of tags defining the complete robot's desired path.

Steps 3) and 4) Once the target tag is known, the robot scans through the signals backscattered from all the tags within its communication range and records the phase angles ϕ_1 and ϕ_2 of the signal coming from the tag representing the target transponder at that time instant.

Step 5) The phase difference of the destination tag's signal is then calculated as defined in (2).

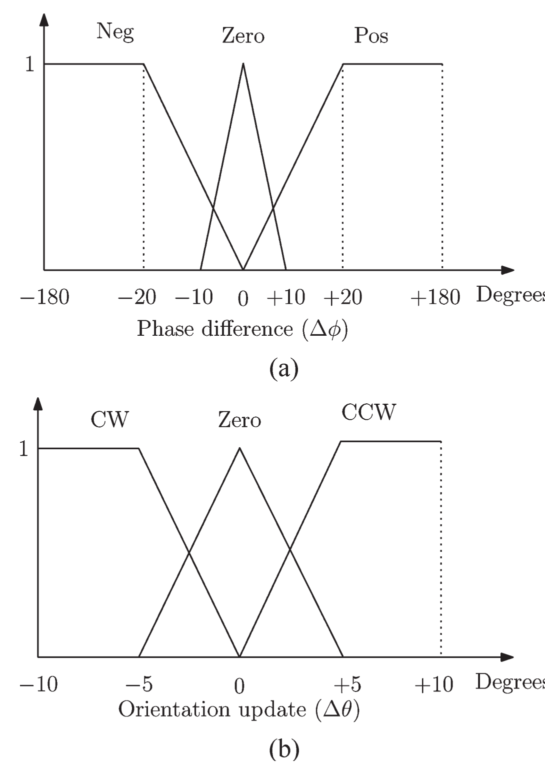


Fig. 5. FLC's membership functions. (a) Input membership functions. (b) Output membership functions (not to scale).

Steps 6) and 7) In these steps, the phase difference is passed to the FLC (described in Section IV-B) to quantize the tune-up the robot has to apply to its direction to better direct itself toward its destination. The robot then updates its heading by $\Delta\theta$ by dispatching the required control action to its relevant actuators.

Step 8) The robot checks if the destination tag is reached. This can be accomplished in various

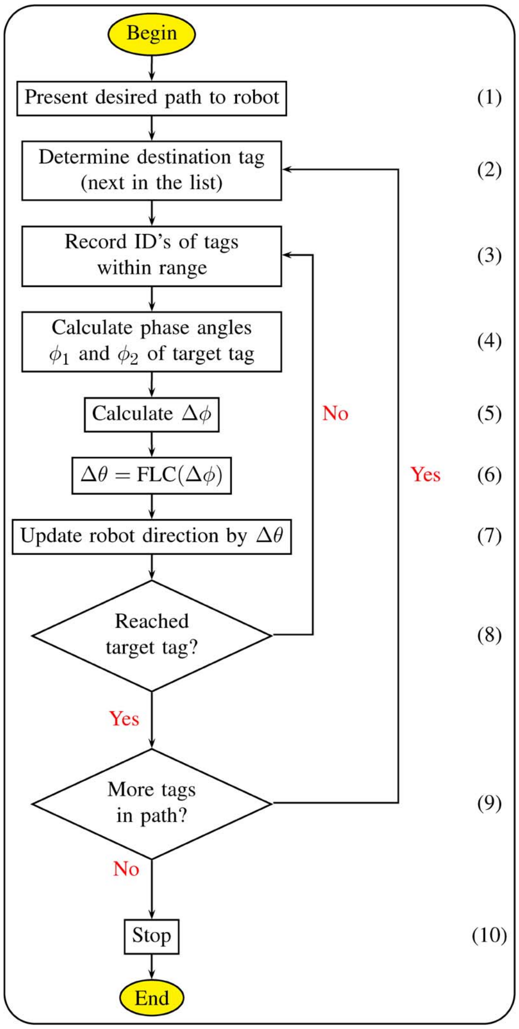


Fig. 6. Flowchart of the proposed mobile robot navigation algorithm.

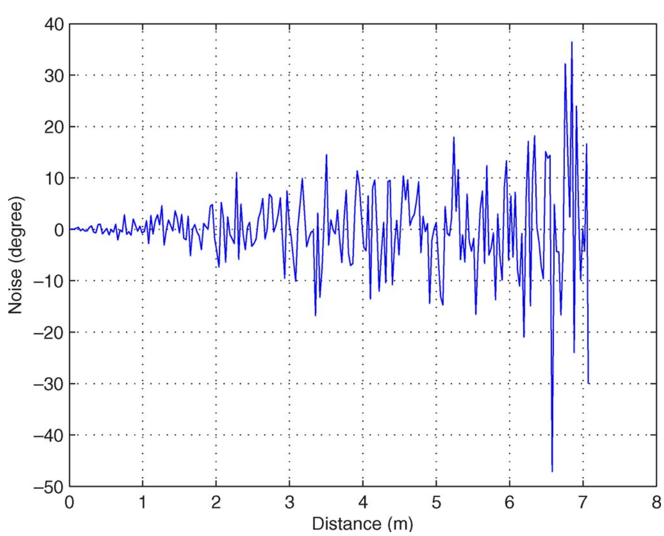


Fig. 7. Noise model of the received signal.

ways. Checking the target tag's signal strength is one option, which is currently under investigation. This can also be done by placing very short range RFID tags on the floor under each long-range tag used

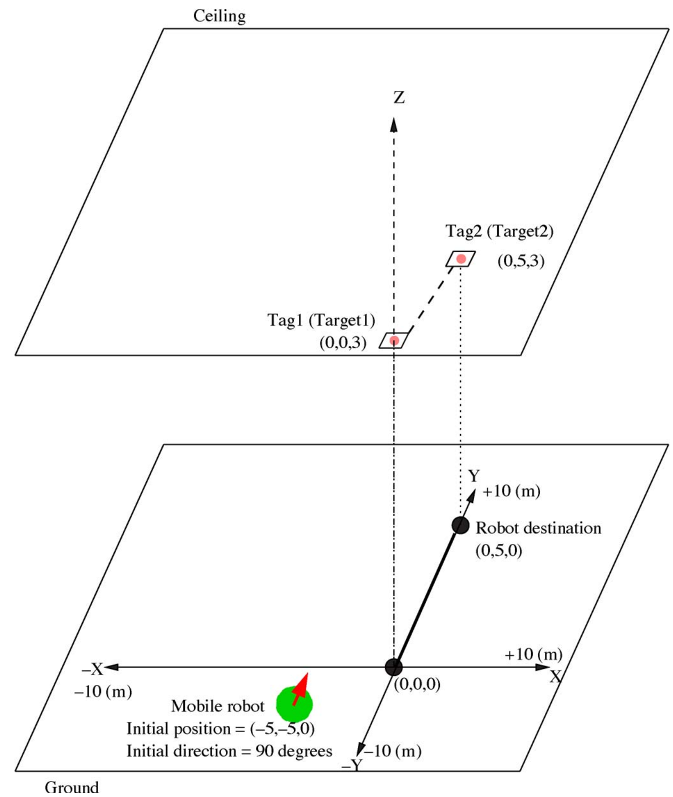


Fig. 8. Experimental setup for following a line segment.

to define the robot's target. Like that, the robot becomes aware that it has reached its destination if its RFID reader detects the signal sent by the short-range tag. This is the method used in the simulations described in Section V. Although this method is easy to implement, it restricts the algorithm's portability to only fully controlled environments. For this reason, we are currently investigating other techniques that can be used in this step. In the case in which the destination tag has yet to be reached, the algorithm restarts this inner loop, starting from Step 3).

Step 9) Once the path's current destination is reached, the robot checks if it was the last tag in the path. If not, then the algorithm passes the control back to the first step in this outer loop, i.e., Step 2).

A thorough evaluation of this algorithm's performance is provided in the following section.

V. EXPERIMENTAL RESULTS

A set of numerical experiments is conducted to test the different aspects of the proposed navigation algorithm and to demonstrate its performance under various configurations. The simulations are carried out using the 3-D robot simulation platform Simbad.[1] The environment considered in the simulation

[1] http://sourceforge.net/projects/simbad.

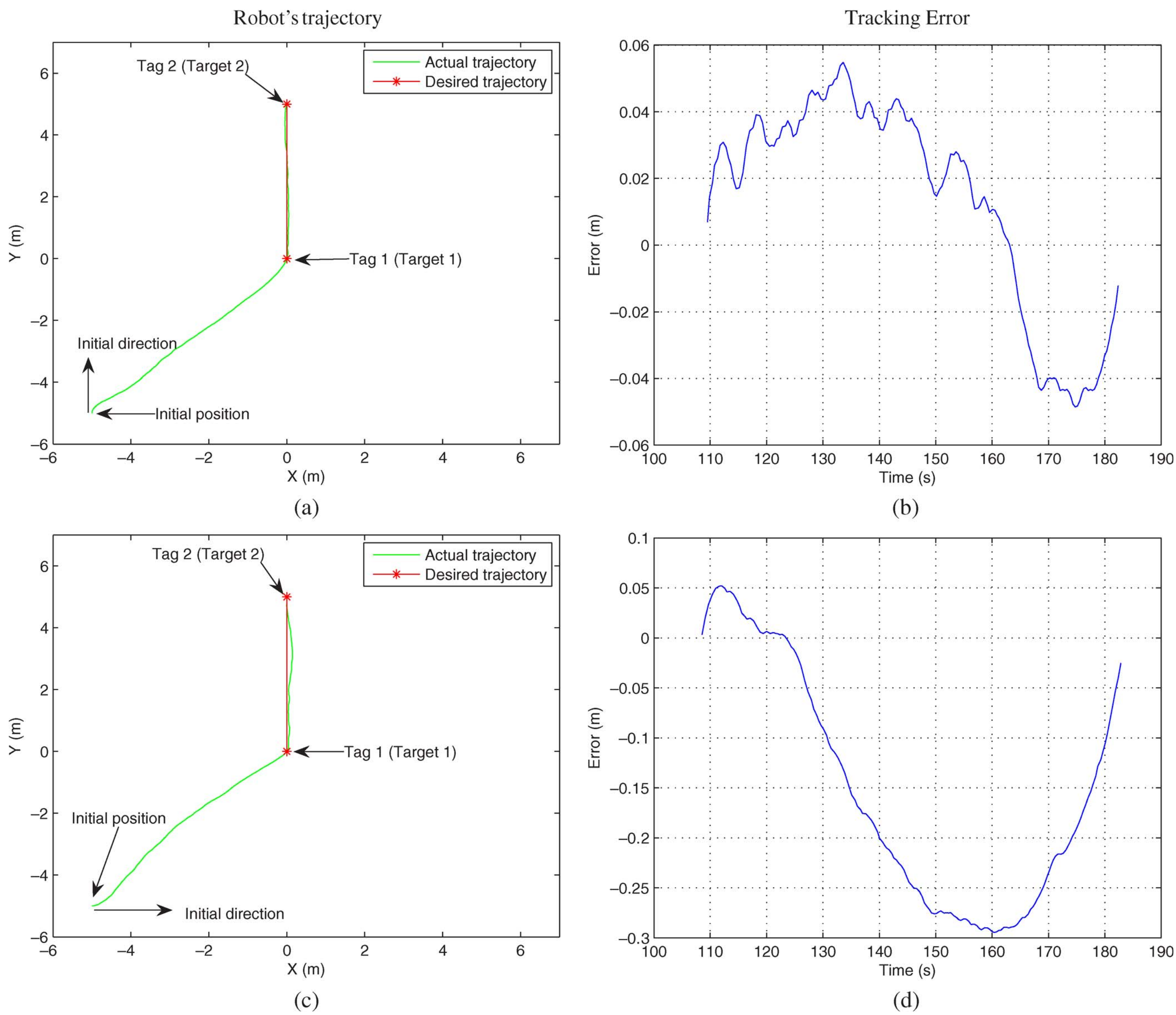


Fig. 9. Proposed algorithm's performance in following a line segment with an initial orientation of (a) and (b) 90° and (c) and (d) 0°.

is a workspace with a 3-m-high ceiling to which all the tags are attached. In all the experiments, the robot's speed is fixed to 0.2 m/s, whereas its direction is controlled by the proposed algorithm throughout the navigation.

To make the computer simulation as realistic as possible, random noise was added to the phase corresponding to each of the reader's receiving antennas. Moreover, the noise was modeled in such a way to have a magnitude proportional to the distance between the transponder and the receiving antenna. Fig. 7 shows the noise signal generated from one simulation run.

To allow for a quantitative assessment of the proposed algorithm, the root mean squared error (RMSE) was used as a performance metric for the robot's trajectory tracking performance. The adopted RMSE is defined by

$$\mathrm{RMSE} = \sqrt{\frac{\sum_{t=1}^{T} [e(t)]^2}{T}} \tag{4}$$

where t is the discrete time index, T is the total navigation time, and $e(t)$ is the robot's trajectory tracking error at time t.

A. Following a Line Segment

The first experiment aims at testing the basic functionality of the proposed algorithm, i.e., guiding the robot to track a straight line. For that, two tags were pasted on the ceiling at positions (0, 0, 3) and (0, 5, 3) m to define a rectilinear-desired trajectory linking the virtual points (0, 0, 0) and (0, 5, 0) m in the world coordinate system. The robot's initial position and orientation were set to (−5, −5, 0) m and 90° on the trigonometric circle, respectively, as shown in Fig. 8. The robot's performance is illustrated in Fig. 9(a) and (b). The robot's first mission in this case is to find its way to the desired trajectory's starting point, i.e., (0, 0, 0). It took the robot about 110 s to be within 1 cm of this point. After that, the robot started to track its target trajectory. The tracking error of this phase is what is shown

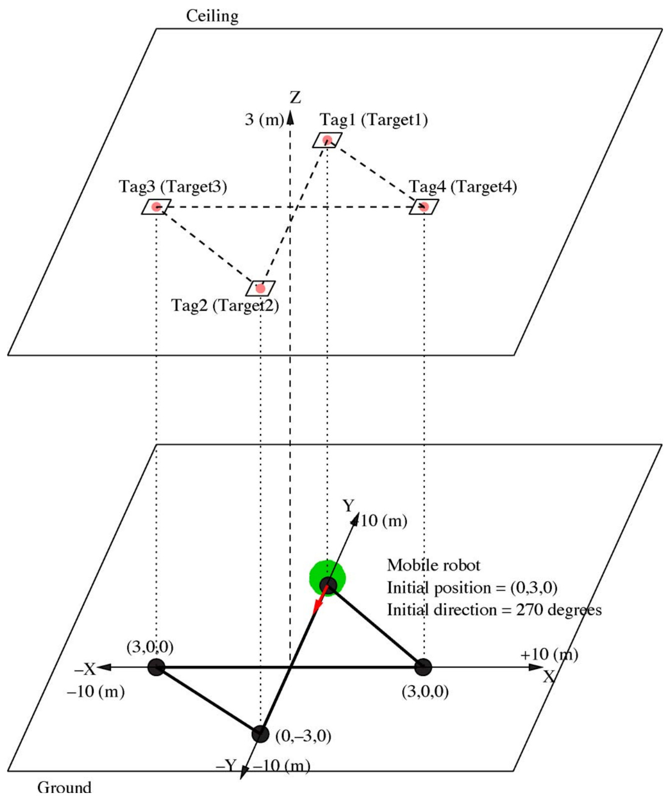


Fig. 10. Experimental setup for following a complex path.

in Fig. 9(b). As can be seen, this error is enveloped between −5 and +5 cm, despite the effect of the noise disturbance. The RMSE recorded in this experiment was 3.4 cm.

To ensure that this performance is independent of the robot's starting condition, the same experiment is repeated with the robot's initial orientation being zero this time. The results are shown in Fig. 9(c) and (d). This time, the tracking error ranged between −30 and +5 cm. The RMSE value for this experiment was found to be 9.3 cm. Despite the larger span of the error, it is important to notice the self-regulatory behavior of the proposed navigation algorithm. As soon as the tracking error starts to diverge, the algorithm automatically adjusts the robot's orientation to the proper direction so that it heads back toward the desired trajectory. This feature is ensured by the FLC designed for this purpose.

B. Following a Complex Path

To validate the proposed algorithm against a more complex trajectory, the robot is programmed to follow a multilinear path with acute angles, as demonstrated in Fig. 10. The robot was set to start at (0, 3, 0) m, right under tag 1, with an orientation of 270°. The tracking performance is visually summarized in Fig. 11. Although the tracking error recorded was between −5 and +50 cm with an RMSE of 17.5 cm, most of the error was due to its transient values at corner turns.

C. Following a Hallway

The last experiment in this series simulates the robot's trajectory on a synthetic terrain representing a hallway in a building, as depicted in Fig. 12. An RFID tag was mounted on a 3-m ceiling at each turn of the hallway. Therefore, in this case, seven tags were used to define the robot's free way. The navigation performance is revealed in Fig. 13. The experiment yielded an RMSE of 13 cm, which is insignificant relative to the length of the path the robot had to follow. The tracking

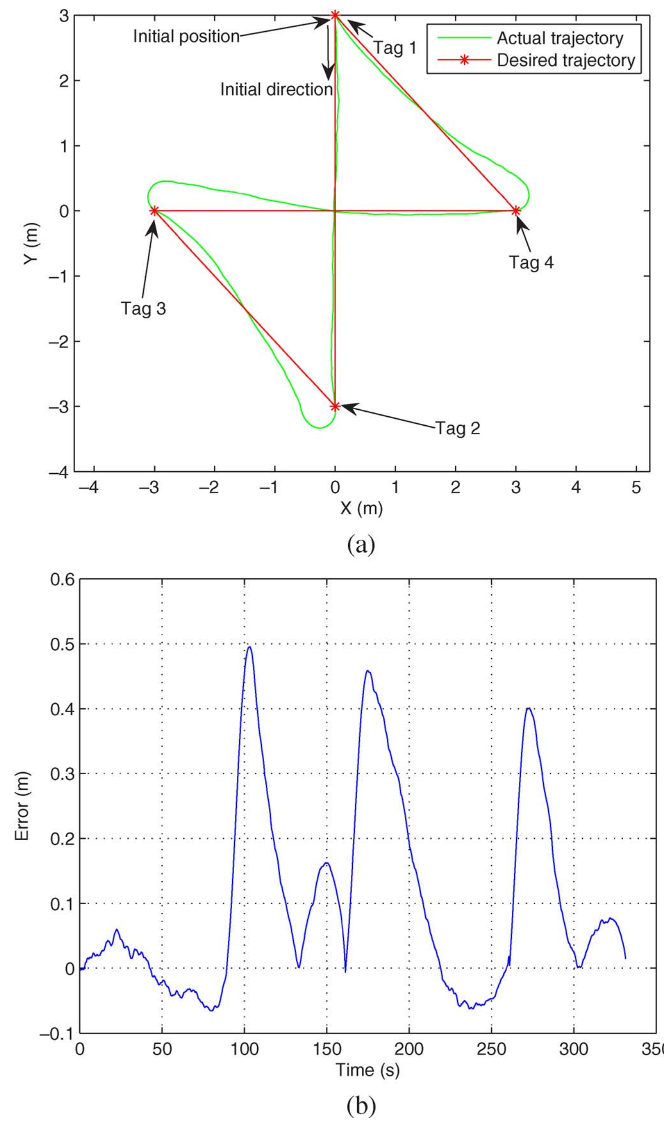


Fig. 11. Proposed algorithm's performance in following a complex path with acute angles. (a) Trajectory. (b) Tracking error.

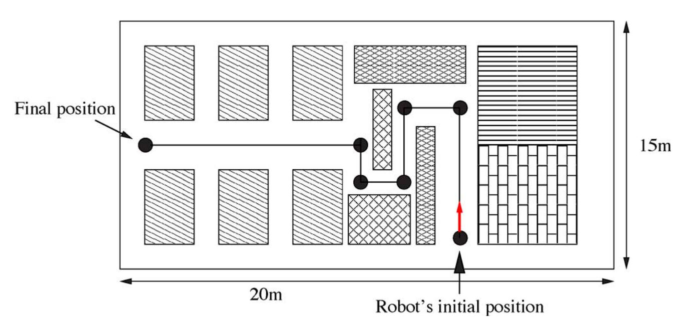


Fig. 12. Experimental setup for hallway following (not to scale).

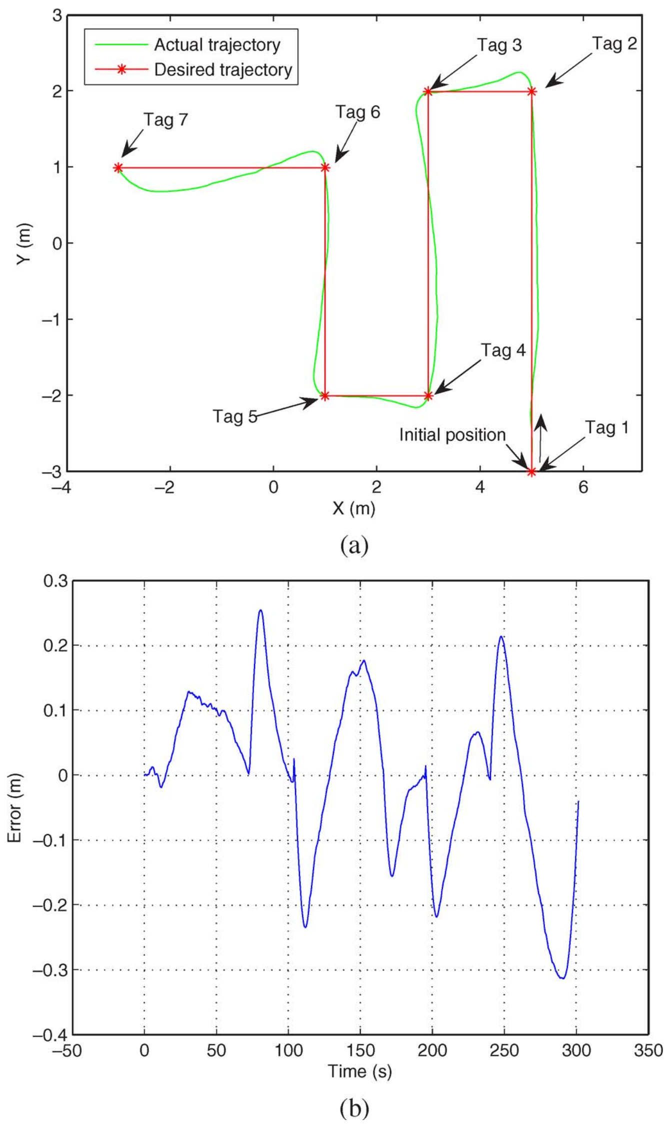


Fig. 13. Proposed algorithm's performance in following a hallway. (a) Trajectory. (b) Tracking error.

error was limited to the interval [−30, +25] cm, as shown in Fig. 13(b), which is much less than the typical width of the hallways in most buidings. Most of the error's extreme values were again due to the transient tracking phases around sharp corners, as is clear from Fig. 13(a).

VI. Conclusion

In this paper, we have presented a novel nonvision-based robot navigation algorithm using RFID technology. The algorithm is demonstrated to be highly effective in guiding the robot to under any RFID tag by a simple intelligent processing of the phase difference of the signal sent by the tag and received at both antennas of the RFID reader mounted on the robot. It is shown through computer simulations that neither the initial position nor the initial direction of the robot affects the algorithm's convergence performance as long as it is within an accessible range from the tag's transponder. In addition, the proposed algorithm is also shown to be quite promising in tracking the rectilinear-desired trajectories of various complexities defined by several RFID tags mounted at unknown locations in 3-D space. It is worth mentioning that although these results are based on computer simulations, the RFID model used in the simulations is built from real-world data sampled from a real RFID system. To the best of the authors' knowledge, this is the first algorithm of its kind where both a target position and a desired trajectory are tracked solely through an RFID system. This paper opens the doors for a new class of robot navigation techniques that are simple, computationally cost effective, and modular in the sense that they are independent of any specific robot architecture. Having said that, it important to articulate the fact that this technique is not meant to substitute vision-based navigation algorithms. Rather, it might be regarded as an alternative navigation solution for many robotic applications where vision might not be absolutely necessary. Although the suggested algorithm was applied here to the navigation of mobile robots, it can be easily extended to unmanned vehicles as well. A potential future research avenue to extend this paper is to append the algorithm with a real-time path-planning module to which the RFID tag locations in the 3-D space would be *a priori* known (but not to the navigation module, however). It would also be important to extend the capabilities of the proposed navigation system to be able to track curvilinear and circular paths.

References

[1] L. Peters, M. Pauly, and K. Beck, "Servicebots—Mobile robots in cooperative environments," *ERCIM News*, no. 42, pp. 30–31, Jul. 2000.

[2] J. Borenstein, H. R. Everett, L. Feng, and D. Wehe, "Mobile robot positioning: Sensors and techniques," *J. Robot. Syst.*, vol. 14, no. 4, pp. 231–249, Apr. 1997.

[3] L. R. Ojeda, G. D. Cruz, and J. Borenstein, "Current-based slippage detection and odometry correction for mobile robots and planetary rovers," *IEEE Trans. Robot.*, vol. 22, no. 2, pp. 366–378, Apr. 2006.

[4] G. N. DeSouza and A. C. Kak, "Vision for mobile robot navigation: A survey," *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 24, no. 2, pp. 237–267, Feb. 2002.

[5] C. Gharpure and V. Kulyukin, "A robotic shopping assistant for the blind: A pilot study in a supermarket," Comput. Sci. Dept., Utah State Univ., Logan, UT, Tech. Rep. USU-CSATL-1-01-06, 2006.

[6] S.-Y. Yi and B.-W. Choi, "Autonomous navigation of indoor mobile robots using a global ultrasonic system," *Robotica Archive*, vol. 22, no. 4, pp. 369–374, Aug. 2004.

[7] I. Hallmann and B. Siemiatkowska, "Artificial landmark navigation system," in *Proc. Int. Symp. Intell. Robot. Syst.*, Jul. 2001, pp. 219–228.

[8] S. Betge-Brezetz, R. Chatila, and M. Devy, "Control and localization of a post distributing mobile robot," in *Proc. IEEE Int. Conf. Robot. Autom.*, 1994, pp. 150–156.

[9] O. Wijk and H. I. Christensen, "Localization and navigation of a mobile robot using natural point landmarks extracted from sonar data," *Robot. Auton. Syst.*, vol. 31, no. 1/2, pp. 31–42, Apr. 2000.

[10] H. Makela and K. Koskinen, "Navigation of outdoor mobile robots using dead reckoning and visually detected landmarks," in *Proc. 5th Int. Conf. Advanced Robot.*, 1991, pp. 1051–1056.

[11] T. D'Orazio, M. Ianigro, E. Stella, F. P. Lovergine, and A. Distante, "Mobile robot navigation by multi-sensory integration," in *Proc. IEEE Int. Conf. Robot. Autom.*, May 1993, vol. 2, pp. 373–379.

[12] E. Stella, F. Lovergine, L. Caponetti, and A. Distante, "Mobile robot navigation using vision and odometry," in *Proc. Intell. Vehicles Symp.*, Oct. 1994, pp. 417–422.

[13] K. Park, D. Chung, H. Chung, and J. G. Lee, "Dead reckoning navigation of a mobile robot using an indirect Kalman filter," in *Proc. IEEE Int. Conf. Multisensor Fusion Integration Intell. Syst.*, 1996, pp. 132–138.

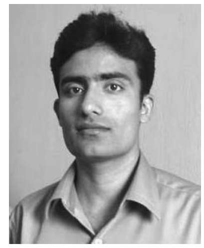
[14] K. Park, H. Chung, J. Choi, and J. G. Lee, "Dead reckoning navigation for an autonomous mobile robot using a differential encoder and a gyroscope," in *Proc. 8th ICAR*, Jul. 1997, pp. 441–446.

[15] D. Y. Ju and S. Kushida, "Intelligent control of mobile robot during autonomous inspection of welding damage based on genetic algorithm," in *Proc. 14th Int. Conf. Ind. Eng. Appl. Artif. Intell. Expert Syst.: Eng. Intell. Syst.*, Budapest, Hungary, Jun. 4–7, 2001, pp. 661–669.
[16] D. R. Parhi, "Navigation of mobile robot using a fuzzy logic controller," *J. Intell. Robot. Syst.*, vol. 42, no. 35, pp. 253–273, Mar. 2005.
[17] P. Rusu, E. M. Petriu, T. E. Whalen, A. Cornel, and H. J. W. Spoelder, "Behavior-based neuro-fuzzy controller for mobile robot navigation," *IEEE Trans. Instrum. Meas.*, vol. 52, no. 4, pp. 1335–1340, Aug. 2003.
[18] O. Khubitz, R. D. Matthias, O. Berger, and M. Perlick, "Application of radio frequency identification devices to support navigation of autonomous mobile robots," in *Proc. IEEE Veh. Technol. Conf.*, 1997, pp. 126–130.
[19] T. Tsukiyama, "Global navigation system with RFID tags," *Proc. SPIE*, vol. 4573, pp. 256–264, 2002.
[20] T. Tsukiyama, "World map based on RFID tags for indoor mobile robots," in *Proc. Photon. Crystals Photon. Crystal Fibers Sens. Appl.*, 2005, vol. 6006, pp. 412–419.
[21] H. Chae and K. Han, "Combination of RFID and vision for mobile robot localization," in *Proc. Intell. Sens., Sens. Netw. Inf. Process. Conf.*, Munich, Germany, Dec. 2005, pp. 75–80.
[22] W. Stallings, *Data and Computer Communications*, 8th ed. W. Stallings, Ed. Englewood Cliffs, NJ: Prentice-Hall, 2006.
[23] F. Karray and C. W. de Silva, *Soft Computing and Intelligent Systems Design, Theory, Tools and Applications*. Essex, U.K.: Addison-Wesley, 2004. [Online]. Available: http://pami.uwaterloo.ca/softcomp/textbook.html

Wail Gueaieb (M'04-SM'06) received the Bachelor's and Master's degrees in computer engineering and information science from Bilkent University, Ankara, Turkey, in 1995 and 1997, respectively, and the Ph.D. degree in systems design engineering from the University of Waterloo, Waterloo, ON, Canada, in 2001.

He is currently an Assistant Professor with the School of Information Technology and Engineering (SITE), University of Ottawa, Ottawa, ON, and the Founder and Director of the Machine Intelligence, Robotics, and Mechatronics Laboratory, SITE. His research interests include intelligent mechatronics, robotics, and computational intelligence. From 2001 to 2004, he was with the industry, where he worked on the design and implementation of a new generation of smart automotive safety systems.

Dr. Gueaieb is a member of the Editorial Board of the International Journal of Computational Intelligence in Control.



Md. Suruz Miah (S'07) received the B.Sc. degree in computer science and engineering from Khulna University of Engineering and Technology, Khulna, Bangladesh, in 2004, and the Master's degree in electrical and computer engineering from the University of Ottawa, Ottawa, ON, Canada, in 2007. He is currently working toward the Ph.D. degree at the School of Information Technology and Engineering, University of Ottawa, where he is a Research Member of the Machine Intelligence, Robotics, and Mechatronics Laboratory.

His research interests include mobile robotics and Radio Frequency IDentification technology.