



ORIGINAL ARTICLE

Autonomous mobile robot localization based on RSSI measurements using an RFID sensor and neural network BPANN

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Abstract Radio Frequency Identification (RFID) technology is broadly deployed for improving trade and transactions. An RFID tag can identify the region (position) where it resides; thus, a popular trend among researchers is to deploy RFID technology for mobile robot localization. Because the intensities of signals at adjacent regions are similar to each other, it is a challenge to employ an RFID system as a sensor. In this proposed system, tags are scattered throughout a mobile robot's environment in a constrained random pattern and are treated as landmarks. An RFID receiver is mounted on a mobile robot that can navigate such an environment. The robot senses all landmarks in the vicinity to acquire the IDs and *received signal strength indicator* (RSSI) measurements of the scattered tags. The robot can locate itself depending on the classification result provided by a *feed-forward back-propagation artificial neural network* (BPANN) supplied with a set of all RSSI measurements read by this robot at a specific location. To be acceptable, this set should only have one high RSSI measurement. The robot senses the location information from a high-valued RSSI tag and adds it to a list of tag IDs along with the corresponding location information. The robot can use this information to travel between any two identified locations. The experimental results demonstrate the efficiency of this proposed system.

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1. Introduction

1.1. Overview

Learning is based on no prior knowledge, but on the perceived states of an environment. The representation of objects within an environment that a mobile robot uses is based on the interaction between the mobile robot and its environment (Brooks, 1991). To be autonomous, the robot must learn, and an

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autonomous robot can locate itself and navigate its environment, specifically, it can determine a path to a specific target using localization and orientation information. The mobile robot may use one of several methods for data classification to divide its environment into regions that may be called, by different researchers, locations or partitions. To locate itself, the mobile robot must be informed regarding the region in which it lies.

To avoid errors, redundant sensors are used, especially to avoid the errors that emerge from computing the robot's position. Information is gathered by fusing the sensor observations with prior knowledge about the environment (Pauly et al., 1998).

Most work using RFID systems for localization purposes in mobile robotic applications uses *rewritable* tags to store the prior knowledge of location information in them (Pauly et al., 1998). In this work, to enhance the autonomous mobile robot navigation and to distribute tags randomly, we consider storing distance information and the initial heading angle of the mobile robot in the robot brain. This information has been gathered as the robot explores the environment using its sensors.

In this work, a supervised form of a feed-forward *back-propagation artificial neural network* (BPANN) is used to classify the signals received from all the sensors for the purpose of localizing the mobile robot.

This paper is organized as follows: the Problem Statement is provided in Section 2. In Section 3, the related works are discussed. Section 4 is dedicated to the implementation details and investigations. Section 5 presents concluding remarks.

1.2. Problem statement

The problem of mobile robot localization has been widely addressed in the literature in recent years. An accurate localization technique will produce coordinates of the mobile robot's position so it can travel from one location to another. Tags, which play the role of landmarks, emit signals to identify environmental regions. To localize itself, the mobile robot should learn how to classify these signals, which requires the use of an RFID system to provide the *received signal strength indicator* (RSSI) measurement throughout the navigation arena.

To perform autonomous navigation, the mobile robot initially gets its heading angle, then explores its environment to find low-cost write-once tags, which provide their IDs. The robot measures their RSSI values by RFID sensor. As a result, the mobile robot stores the location information of these tags on the permanent storage of a server PC. Because the tags have a constrained random distribution, the mobile robot motion should be a systematic motion to ensure that the mobile robot reaches all regions in its environment.

The regular classification process using a supervised form of a feed-forward back-propagation artificial neural network, which classifies the RSSI measurements into groups, results in dilation because the RSSI measurement of each tag should be read several times to be provided to the classifier algorithm for error reduction. Therefore, an alternative classification method for this purpose is applied, also using a supervised BPANN. All environmental features contribute to the decision making; namely, all the RSSI measurements are treated as one input set and processed to produce one output result whose value is either approximately 1 or approximately 0 depending on

the input set. Regardless of the number of tags in the mobile robot's environment, whenever the RSSI measurement received from any one of the tags reaches the *detection-RSSI-threshold* value, the tag ID is added to the input set of the BPANN. The *detection-threshold-value* is constantly updated and depends on the difference between the maximum and minimum RSSI measurement received from tags in the mobile robot's sensible environmental space. As the mobile robot moves to explore its environment, just before leaving the immediate vicinity of a tag, the tag's RSSI measurement starts to drop. If the RSSI measurements of two or more tags end up being the maximum RSSI measurement and at the same time equal to each other, the robot will continue the exploration and stop considering any RSSI measurements until one of the maximum values starts to reduce. Using this approach for signal classification guarantees the unique association of the robot with a single tag at any given time.

The constrained random distribution used to scatter the tags ensures that the tags are "randomly" distributed with an acceptable minimum distance between them. The mobile robot is established to be localized at a specific location (or node, in grid-based localization literature) marked by the positive output of the BPANN given an acceptable *input-RSSI-set*. The acceptable *input-RSSI-set* is defined as a set containing all RSSI measurement values greater than the *detection-RSSI-threshold*.

The location information of any tag is determined by its absolute x and y coordinates. The square 2D space on the floor is considered to be the experiment arena. The south-west corner of the square space is the start point. The robot also has a sonar-based localization capability, i.e., the two sonars return the distance of the robot from the 0.5 m high walls along the perimeter of the square space arena. The robot also has a compass sensor to determine its direction (theta). With the coordinates of two locations, the mobile robot can navigate from one location to another by adjusting its heading using an angle computed by a trigonometric function to face the first destination and computing the required traveling distance between these locations.

2. Related works

Several approaches have been proposed for mobile robot localization using environmental features called landmarks (Jang et al., 2002; Saotti and Wasik, 2000; Loevsky and Shimshoni, 2010). Given the logical foundations of RSSI signal strength behavior and the classical machine learning algorithm-based classification, a combination of approaches can solve a typical localization problem. In Tanaka et al. (2007), Tanaka et al. considers short-range RFID sensors and uses a *support vector machine* (SVM) binary classifier, which is trained using the features of signals received at a selected location and of signals received at each nearby location, to distinguish the selected location from the rest. This problem is solved using Fuzzy Logic in Gueaieb and Miah (2009). Gueaieb and Miah propose applying Fuzzy Logic to the phase difference of the two phase angles of the signals received by two receiving RFID-reader antennas. The mobile robot is supposed to turn to the left or to the right if the target tag is on the left or on the right of the receiving antennas, namely if the phase difference is negative or positive, respectively (Gueaieb and Miah, 2009).

Similarly, the authors of Hekimian-Williams (2010) propose exploiting the phase difference to estimate the location of a specific tag. A signal transmitted by a tag and received at the antenna of a receiver is transformed to a baseband signal, and the phase is calculated using the inphase and quadrature components of this baseband signal. The phase depends on the distance between a tag and a receiver. By considering two phases, the phase difference between them can be defined as the difference of the two distances separating the two signal receivers from the tag (Hekimian-Williams, 2010).

Other current work considers offering the geographic coordinates of the distributed tags as prior knowledge for the mobile robot. Mehmood et al. (2008) propose distributing passive tags at the vertices of equilateral triangles to ensure the optimal coverage of the read-ranges of the tags, which form circular disks. The triangular coordinates of each tag, namely the number of vertices from the origin on both axes, are stored in its memory. The partitions may be identified by more than one tag, and the mobile robot locates itself using the mean location of the read-ranges of these tags. To reach the destination, the mobile robot moves in a straight line between adjacent partitions to bound the mobile robot's orientation angle measured with respect to the x axis to face the destination (Mehmood et al., 2008). In Park and Hashimoto (2008), Park and Hashimoto propose a system using a read-time model, which is defined by how long the RFID reader can recognize a specific tag when the mobile robot crosses its circular region, to reduce the mobile robot localization error. Unlike our proposed system, their system considers only a single tag among the distributed tags in a grid pattern to be read at a time. Based on the tag's absolute coordinates stored in a database in the mobile robot's memory, the orientation angle is calculated in each circular region reached by the mobile robot during the navigation process. Based on the previous position of the mobile robot, the proper read-time is chosen, and the deviations in the heading angle, with reference to its actual direction and the calculated one, are used to correct the mobile robot's direction toward the ultimate goal (Park and Hashimoto, 2008).

Although the authors of Mehmood et al. (2008) consider the optimality of covering passive tags and circular read ranges by locating tags at the vertices of equilateral triangles, the passive tags and their circular read ranges do not cover the whole area of the environment. In Kutiyawala and Kulyukin (2007), Kutiyawala and Kulyukin consider the optimality of covering the whole area of a surface embedded with passive tags without consideration of a regular distribution of many passive tags. By using a Cartesian robot, they consider the optimality of the mobile robot localization process based on the number of straight traveled paths, which cross the circular ranges of passive tags that are initially distributed randomly, but whose positions are randomly adjusted to enhance the localization probability. The experiment conducted using the Cartesian robot shows that the position and the orientation of a passive tag with respect to the RFID reader are factors that affect the detection of the tag, and its range is an imperfect circle but can be approximated as a circle (Kutiyawala and Kulyukin, 2007).

3. Proposed system

3.1. Experimental setup

The brain of our RFID receiver-mounted experimental robot is a Parallax Basic Stamp 2px BS2PX microcontroller. As

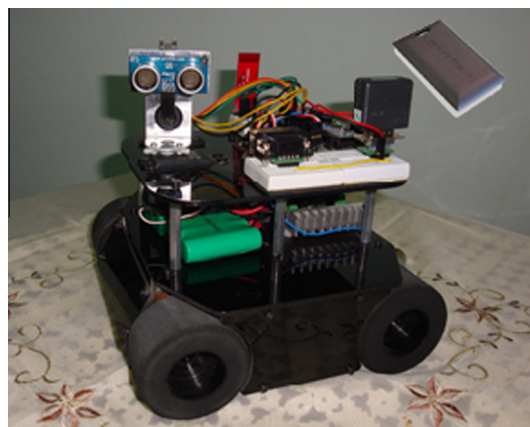


Figure 1 The robot hardware.

mentioned in its description manual, the baud rate of the BS2PX is 125,000 bps as a maximum serial communication rate. The BS2PX establishes serial communication with the PC through an available Bluetooth serial communication port to control decisions and store data. During its exploration phase, the robot employs three sensors. The RFID system is a 433-MHz Wavetrend L-RX300 receiver, whose baud rate equals 57,600 bps, and Wavetrend TG501 Personnel Tags, each of which has its own battery and transmits its data every 1.5 s. A sonar sensor (for distance measurements by PING) and a dual-axis compass sensor (for direction measurements by Parallax Hitachi) are also used in this robot. Fig. 1 shows the robot hardware.

The compass sensor points to the earth's magnetic north and therefore provides a specific angle in *binary radians*, which is corrected to give the value of the geographical North Pole. The true north represents the positive y axis, and thus the angle of the deviation is measured from the positive y axis in the *clockwise* direction when the compass sensor heading is rotated. During its exploring phase, the mobile robot is aligned to face the front partition of the testing environment. The remote PC waits to be informed that the robot's microcontroller is ready to accept data sent to it. In the meantime, the microcontroller instructs the motor controller to stop the driving motors of the robot. After the remote PC receives acknowledgment from the microcontroller onboard the mobile robot, the PC requests RFID sensor readings, which are provided to the proposed classifier in normalized form.

When the output of the BPANN crosses above a configurable threshold, the robot is considered to be localized at the position represented by the tag with the maximum normalized RSSI measurement among all of the available measurements in the acceptable *input-RSSI-set*. Because the robot is considered to be at the location of this tag, the PC requests the current perpendicular distances with respect to the front wall of the lab testing partition and with respect to the right wall of its environment to be stored in a lookup, along with the ID of this considered tag for future calculation of coordinates. The remote PC thus localizes the robot by looking up the tag ID in S to achieve x and y coordinates for the robot's centroid. The previously stored tag IDs and coordinates are updated whenever the proposed classifier results in a better positive response. A pair of these coordinates from the lookup, namely v_{current} and v_{goal} , are used to determine a new heading,

toward which the mobile robot should face, if we want the robot to move to v_{goal} from v_{current} . The distance the mobile robot should travel to navigate from v_{current} to v_{goal} is also calculated at this stage using the distance formula.

By choosing any goal location from the available list, the orientation to face the destination and the distance to reach it are provided to the mobile robot's microcontroller, which in turn informs the PC when the robot reaches the goal. Now, the PC updates the source location coordinates of the current location to the goal location for future path generation. Eq. (3) calculates the new heading angle by which the mobile robot should rotate for the new movement. This angle is an absolute angle, and the onboard sensors are used to verify this angle.

$$\text{New heading} = \left[\tan^{-1} \left(\frac{y_{\text{goal}} - y_{\text{current}}}{x_{\text{goal}} - x_{\text{current}}} \right) \right]_{\text{Cartesian} \rightarrow \text{Compass}} \quad (3)$$

3.2. BPANN framework

In this work, we propose to use a supervised form of the BPANN to learn how to classify the received signals at any location using the RSSI measurements emitted by all tags. As mentioned in Section 2, at a specific location, all the RSSI measurements are provided to the classifier as one input RSSI set. An acceptable input RSSI set, in which one of the RSSI measurements reaches the maximum value and the remaining RSSI measurements reach the minimum value, results in approximately 1 as an output value; otherwise the output is approximately 0 based on a chosen error value.

The proposed BPANN consists of neurons organized into an input, a hidden and an output layer that are connected by weighted links. Because the proposed BPANN is a supervised form of an ANN, the desired output of each possible input pattern is provided to calculate the error at each output neuron. Using the errors at the output neurons, the BPANN starts learning by calculating the error gradient for each neuron in the output layer. The corresponding weights at the output layer are updated with a threshold level, and the error gradients are then back-propagated to the preceding layer, where the neuron error gradients are also calculated. This process is reiterated to produce the appropriate outputs. In other words, BPANN learns by adjusting the weights and the threshold levels till the Root Mean Squared Error RMSE at the output layer reaches an acceptable value.

The mobile robot explores its environment systematically while ensuring that all RFID tags are visited, to measure the tag RSSI measurements using its RFID receiver and form the acceptable *input-RSSI-set* for each tag location. The adjusted weights and threshold levels are used to classify the set of normalized RSSI measurements provided by the normalized RSSI measurements of all available tags n . The set is defined as follows:

$$\{RSSI_{\text{tag}i} | RSSI_{\text{tag}i} \in [0, 1]; i \text{ is an interger; and } i \in [1, n]\} \quad (1)$$

The proposed BPANN classifier results in a positive response when it receives a set of the normalized RSSI measurements defined as follows:

$$\{RSSI_{\text{tag}i} | RSSI_{\text{tag}i} \in [0, 1]; i \text{ is an interger } i \in [1, n]; \text{ and } \exists! RSSI_{\text{tag}i} \approx 1\} \quad (2)$$

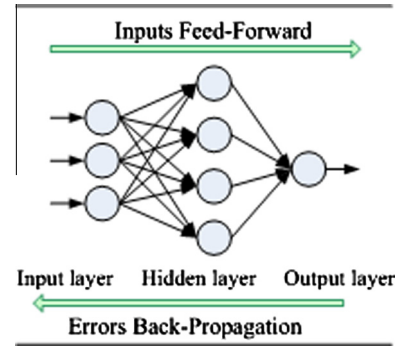


Figure 2 The architecture of the proposed BPANN.

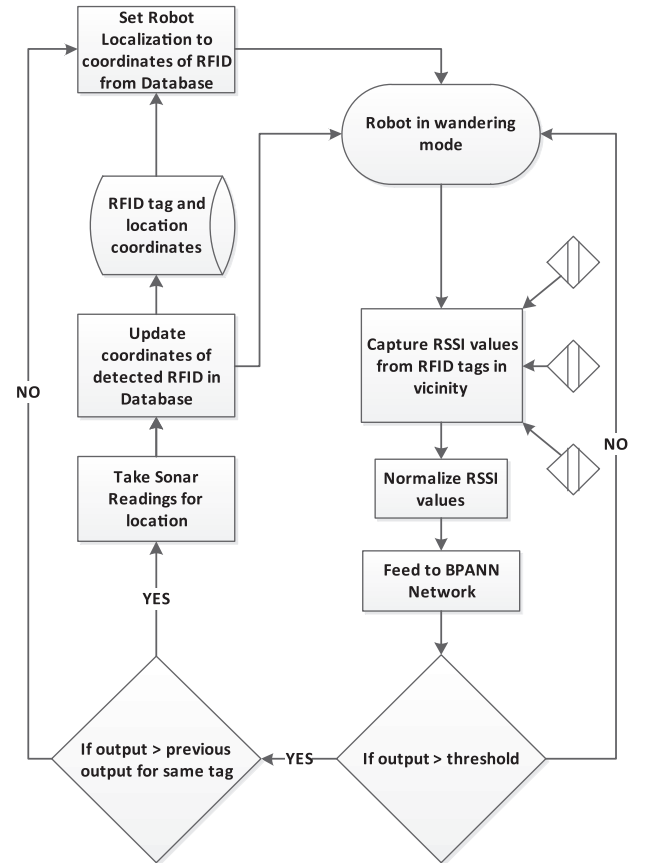


Figure 3 Flowchart of the navigation and localization algorithm.

For the purpose of learning, both the acceptable *input-RSSI-sets* and the corresponding outputs are provided to the proposed BPANN. The randomly initialized weights and threshold levels are repeatedly adjusted based on an ideal output corresponding to each probable input pattern till an acceptable RMSE is reached. Fig. 2 illustrates the architecture of the BPANN proposed in this work.

It may be highlighted here that the input layer corresponds to the minimum number of tags required for the localization, i.e., three in our case. An acceptable *input-RSSI-set* (always containing three members) with any value for any member must result in a 1 output at the output layer if only one member has the highest value. Otherwise, the output must be a 0. A

typical acceptable *input-RSSI-set* will contain the highest available RSSI values. Only one hidden layer was chosen to classify, as our experiment dealt with a very small acceptable *input-RSSI-set*. It is expected that with increasing membership in the acceptable *input-RSSI-set*, the classification accuracy will degrade. Fig. 3 illustrate the navigation and localization algorithm used for the real time control and navigating of the Robot.

4. Implementation and results

Indoor laboratory testing was carried out successfully to validate the proposed method. The methodology of the lab work is explained in the next section.

4.1. Observations

The physical characteristics of a specific type of wave determine the purpose for which these are used. There also exists an accuracy cap for each type of wave regarding distance calculation and signal strength calculation. Although radio waves, which can be used to identify regions, can penetrate objects, the penetrating waves have low accuracy, whereas ultrasonic waves are blocked by objects but tend to have higher accuracy. Thus, ultrasonic waves are better suited for distance measurements. Table 1 represents the characteristics of these types of waves.

In an indoor environment, it is well known that an RFID system offers superior performance over a Global Positioning System (GPS). Because GPS signals do not greatly penetrate concrete structures, an RFID system has better accuracy and less signal error than a GPS in an indoor/semi-indoor environment. Because the compass sensor, which measures the strength of a magnetic field, is highly sensitive to magnetic waves emitted by nearby electrical devices, our test results were more or less affected by appliance clutter throughout the building in which the arena was erected. The proposed method partially addresses this problem by ignoring sudden large deviations in the compass readings and requesting fresh readings as required.

4.2. Experimental results

The RF waves are electromagnetic waves that propagate spherically and obey the inverse-square law. As the sphere's radius expands, the RSSI falls to indicate the approach to the region's boundary.

For accurate results, we tied the suspended distributed tags with a ribbon to measure the degree to which the robot can track the actual path. The distances were measured in centimeters, and the deviation angles were measured in degrees. An

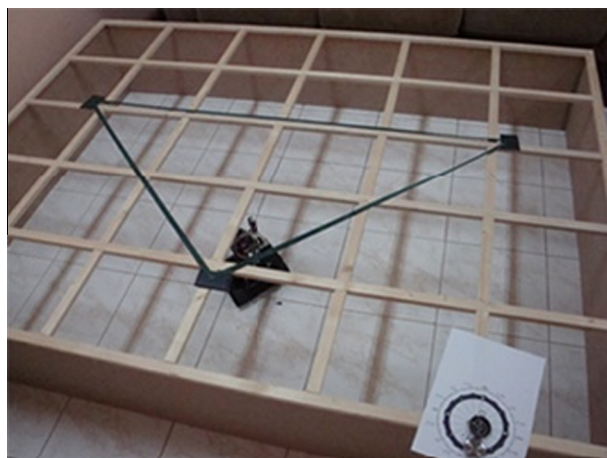


Figure 4 The testing environment.

ideal distance was measured between two projections of two tags. A tag was considered to be the center of the region identified by this tag. While the mobile robot was exploring its environment, the center of the mobile robot on the floor location was calculated whenever the proposed BPANN classifier resulted in a positive response. Consequently, the desired traveled distance and the actual traveled distance between any two allocated points were measured. The desired steering angle and the actual steering angle were calculated between the ideal and the actual traveled paths. Fig. 4 shows the testing environment. Tables 2 and 3 give the results and their RMSEs, which represent the deviation of the mobile robot from the regions' centers. The RMSE (between the ideal and actual path) acceptable range for training the BPANN was set between -0.1 and 0.1 . The calculated distance and theta in Tables 2 and 3 are different from the ideal because of the localization error induced by the inherent errors in RFID strength readings, sonar readings, wheel slippage and real time delay in the execution of the control algorithms. In this work, this error did not influence the accuracy of the navigation of the robot substantially because it is small compared to the actual steering angle. Fig. 5 shows the desired travel path and the actual travel path (distances in cm). This graph demonstrates good experimental results for the work proposed in this paper.

For obstacle avoidance, the two front ultrasonic sensors were used for obstacle avoidance with a minimum fixed distance from the obstacle (50 cm) to avoid a collision with the obstacle. A separate controller was used to decide whether to turn left or right when approaching an obstacle. The turn direction (left or right) depended upon the distance of the obstacle from the right and left sonar sensors. By comparing the distance measurement from the two front ultrasonic

Table 1 Deployed wave characteristics.

Ultrasonic wave	RF wave
Blocked by obstacles.	Can penetrate objects.
Travels in a cone transmission direction.	Extends in all directions.
Measurement principle based on measuring the time of flight between the transmission and reception of a directed short pulse.	Measurement principle based on querying RFID of a tag by an RFID receiver while inside the interrogation zone of the RFID tag.

Table 2 The RMSEs for the distance measurement.

Trial #	Ideal distance (cm)	Calculated distance (cm)	Actual distance moved (cm)	Difference error considering ideal and actual distances moved	Difference error considering calculated and actual distances moved
1	142	132	131	$0.92 - 1 = 0.08$	$0.99 - 1 = 0.01$
2	99	86	97	-0.02	0.13
3	96	91	88	-0.08	-0.03
4	96	91	90	-0.06	-0.01
5	99	86	90	-0.09	0.05
6	142	132	139	-0.03	0.05
$RMSE = \sqrt{\frac{\sum_{i=1}^n (\text{actual}_i) - (\text{ideal}_i)^2}{n}}$				0.07	0.06

Table 3 The RMSE for the angle measurements.

Trial #	Ideal angle (°)	Calculated angle (°)	Difference error considering ideal and calculated angles
1	150	145	$0.97 - 1 = 0.03$
2	138	122	-0.12
3	88	76	-0.14
4	180	187	0.04
5	90	70	-0.22
6	135	145	0.07
$RMSE = \sqrt{\frac{\sum_{i=1}^n (\text{actual}_i) - (\text{ideal}_i)^2}{n}}$			0.12

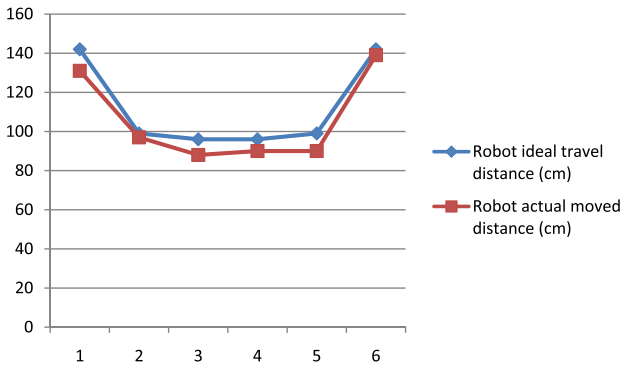


Figure 5 The robot movement conducted in the lab.

sensors, a steering angle away from the nearest obstacle was calculated. Fig. 6 shows the robot heading angle experiments conducted in the lab and the deviation of the heading angle from the calculated value.

4.3. Discussion

To compromise between using redundant sensors and depending on prior knowledge, the individual advantages of both sonar localization and RFID localization were considered. Consequently, the system does not depend completely on the RFID sensor. Moreover, we highly recommend using our BPANN RFID-based localization in conjunction with the sensor fusion framework. Such a multi-sensor approach can be very useful in patches of the map where conventional GPS,

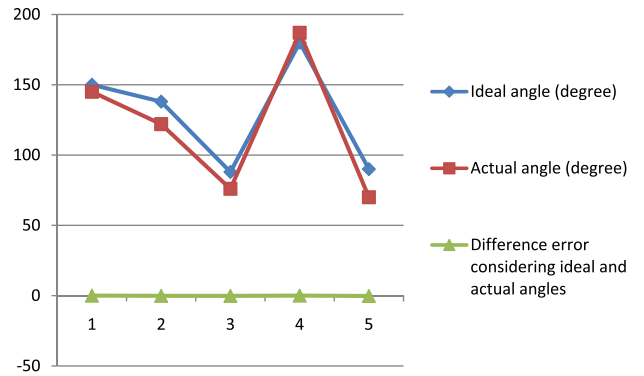


Figure 6 The robot heading angle experiments conducted in the lab.

stereo, sonar or LADAR-based sensing fails. In Mehmood et al. (2008) and Park and Hashimoto (2008), the passive tags are distributed uniformly in the environment, and the corresponding location information of each tag is stored within the tag or in a database stored on the mobile robot memory as prior knowledge. In our system, the constrained random distribution of the active or passive tags tends to reduce the chances of two equal RSSI signal strengths occurring within the same acceptable *input-RSSI-set*. We installed two RFID sensors at the extreme geometric ends of the robot to acquire the location information of a tag whenever the mobile robot was considered to be in a specific tag's region. This approach gave us a relatively unique signal strength, as the signal strength now had an added differentiation parameter for each tag, i.e., the difference in RFID sensor 1 and sensor 2 readings for two equidistant but opposite-direction RFID tags from the robot centroid. The drawback of this approach is the increased power consumption. We attempted to minimize the power drain for the mobile robot (green energy considerations), but no remarkable reduction was achieved.

In Yamano et al. (2004) and Dayekh et al. (2011), artificial neural networks (ANNs) are used to classify the sensor signature of one location from another. Such classification techniques grow in complexity and in error as the map size and resolution increases. Moreover, the resultant ANNs are huge in size, and learning requires huge datasets. Our approach is a radical escape from signature based classification. Our aim

is to home any of the RFID tags within the environment without regard for its location. The location is read once via sonar sensors and is stored for subsequent reference along with the tag ID. This approach gives us a clean classification approach and reduces the unnecessary classification load from the ANN.

5. Conclusions

There are several machine learning techniques that can be considered to be learning approaches for autonomous mobile robot localization. Using an RFID system with a partially random tag distribution, each region in the environment is uniquely identified, and the mobile robot can localize itself successfully without the need of a prior location knowledge base for the tags.

In this work, a solution for the mobile robot localization problem has been achieved to allow the mobile robot to travel from one location to another. A supervised form of BPANN for classifying the tag signals based on their RSSIs was implemented successfully. The proposed classifier accepts an input set formed by all available RSSI measurements, and the mobile robot is considered to be localized in the close vicinity of the tag with the normalized RSSI value that uniquely approaches the maximum limit. The laboratory-conducted experiment demonstrates the efficiency of this proposed system. Using the proposed BPANN along with a partially random distribution of tags guarantees failure-free autonomous mobile robot localization.

This work is a part of an ongoing research effort for autonomous robot navigation. Future work will involve adding a neural-fuzzy controller for robot path generation. A vision sensor will also be added to achieve a more robust (though redundant) environment mapping, thus leading to improved autonomous navigation.

References

- Brooks, Rodney. The Role of Learning in Autonomous Robots. Paper presented at the Fourth Annual Workshop on Computational Learning Theory, Santa Cruz, California, August 5–7, 1991.
- Dayekh, S., Affes, S., Kandil, N., Nerguizian, C., 2011. Radio-localization in underground narrow-vein mines using neural networks with in-built tracking and time diversity. In: Wireless Communications and Networking Conference (WCNC), 2011 IEEE, pp. 1788–1793.
- Gueaieb, Wail, Miah, Md. Suruz, 2009. A Modular Cost-Effective Mobile Robot Navigation System Using RFID Technology. *J. Commun., USA* 4 (2), 89–95.
- Hekimian-Williams, Cory, et al., 2010. Accurate Localization of RFID Tags Using Phase Difference. Paper presented at the 2010 IEEE International Conference on RFID, Orlando, FL, USA, April 14–16.
- Jang, G., Kim, S., Lee, W., Kweon, I., 2002. Color landmark based self-localization for indoor mobile robots. In: *Proceedings-IEEE International Conference on Robotics and Automation*, vol. 1, pp. 1037–1042.
- Kutiyanawala, Aliasgar, Kulyukin, Vladimir, 2007. A Cartesian Robot for RFID Signal Distribution Model Verification. Paper presented at the Fifth International Conference on Ubiquitous Intelligence and Computing, Oslo, Norway, July.
- Loevsky, I., Shimshoni, I., 2010. Reliable and efficient landmark-based localization for mobile robots. *Robotics and Autonomous Systems* 58 (5), 520–528.
- Mehmood, Muhammad Atif, Kulik, Lars, Tanin, Egemen, 2008. Autonomous navigation of mobile agents using RFID-enabled space partitions. Paper presented at the sixteenth ACM SIGSPATIAL international conference on Advances in geographic information systems, CA, USA.
- Park, Sunhong, Hashimoto, Shuji, 2009. Indoor localization for autonomous mobile robot based on passive RFID. Paper presented at the 2008 IEEE International Conference on Robotics and Biomimetics, Bangkok, Thailand, February 21–26.
- Pauly, M., Surmann, H., Finke, M., Liang, N., 1998. Real-Time Object Detection for Autonomous Robots. *Autonome Mobile Systeme*, vol. 14. Springer-Verlag, pp. 57–64.
- Saotti, P. B. A., Wasik, Z., 2000. Fuzzy Landmark-Based Localization for a Legged Robot. In: *Proceedings of IEEE/RSJ International Conference on Intelligent Robots and Systems*.
- Tanaka, Kanji et al, 2007. A supervised learning approach to robot localization using Short-range RFID sensor. *IEICE Trans. Inf. & Syst.* E90-D (11), 1762–1770.
- Yamano, K., Tanaka, K., Hirayama, M., Kondo, E., Kimuro, Y., Matsumoto, M., 2004. Self-localization of mobile robots with RFID system by using support vector machine. In: *Intelligent Robots and Systems, 2004. (IROS 2004). Proceedings. 2004 IEEE/RSJ International Conference on*, vol. 4, pp. 3756–3761.