

Design and Implementation an Indoor Robot Localization System Using Minimum Bounded Circle Algorithm

Israa Sabri Abdulameer AL-Forati
Electrical Engineering Department
University of Basrah
 Basrah Iraq
 israa.subri.1@email.com

Abdumuttalib Rashid
Electrical Engineering Department
University of Basrah
 Basrah Iraq
 abdturky@email.com

Abstract— a new positioning system for indoor robot localization is proposed. This system solves the problem of localization by using an array of Light Emitting Diodes (LEDs) distributed uniformly in the environment. The localization is achieved by collecting the information from a group of Light Dependent Resistor (LDR) sensors with which the robot is equipped. The binary search algorithm is used to reduce the time of the localization process by controlling the lights of the LED array. The minimum bounded circle algorithm is used to draw a virtual circle from the information collected by the LDRs sensors and the center of this circle represents the robot's location. The suggested system is simulated on an environment with (32*32) LEDs arrays. The simulation results of this system show good performance in the localization process.

Keywords— *Localization system, Binary search algorithm, Minimum bounded circle algorithm.*

I. INTRODUCTION

In recent years, the localization of mobile robots has proved a difficult task due to many physical limitations. In the mobile robot's field, the robot localization systems and formation have been of particular interest [1]. Multi-robot teams can be used for various tasks, such as inspection, surveillance and formation. In these scenarios, robots may be required to navigate information or to improve their path planning [2-4]. The most famous localization method is the global positioning system (GPS), but there are some constraints such as its high cost, power consumption and large size, that make this method difficult to use regularly. [5]. In addition, for indoor environments GPS cannot be used, this fact has attracted growing attention to propose more algorithms that deal with the needs of indoor localization [6, 7]. A Network of Wireless Sensor consists of multiple nodes of sensors divided separately to cooperatively monitor environmental circumstances and has different applications such as traffic monitoring, object tracking, navigation of ships, measuring radiation levels from nuclear reactors, and

monitoring volcanic eruptions [8]. A sensor is a small instrument that is used to measure or sense some natural quantity and then converts it via some relationship to a new signal that can then be read by men for display or for further processing. Also, they are used for different kinds of gauge, for example: distance, sound, motion, pressure, temperature, light levels.etc. [9,10]. With the rapid increase in smart technology, we are looking for a sensor that provides precise distance detection; also, it should be low in cost. The accuracy and inexpensiveness of light emitting diode (LED) sensors, along with their extended life expectancy, is valuable: lights are expected to continue for many years; moreover, the light is harmless to humans, unlike IR and lasers, and it does not overlap with the effects of electronic devices in the same environment. The foregoing features makes LEDs a very suitable choice for use in localization scenarios. Practical experiments can test the light sensors with low-cost LEDs & LDRs. Many techniques are used for indoor localization such as the system based on ultra-wideband, radio frequency identification (RFID, Bluetooth, Wi-Fi, infrared and ultrasound [11, 12]. In all these technologies used in positioning systems, the complexity varies significantly in price and precision. All the localization systems mentioned above fall into two categories: the first one uses only one photodiode (LDR) in the receiver; the second employs more than one, such as the receiver presented in [13] that employs a lens and an image sensor and calculates the direction of arrival of light collected from different visible LEDs. In the proposed new system there is an advantage of lower hardware complexity but with more accurate and realistic results, along with high speed to find the required position. Within the first category, some receivers such as those reported in [14, 15] rely on the received signal strength to calculate their distance from the beacons, while others such as those in [16, 17] exploit the variation in the propagation delays from different beacons.

Synchronization through the transmitter is an essential element in all the solutions cited, and this is expensive for implementation, while the proposed system does not need any synchronization. The new algorithm is a binary procedure, returning a number of available node receivers on the environment, then approximating the result using minimum bounded circle algorithm to include all these nodes, then the center of these circle is assumed to be the robot's position. In this paper, a new localization algorithm is proposed to overcome all the restrictions in implementation of the above algorithms. In this algorithm, the localization is based on designing a system with a pair of sensors: the first one (group of LDRs) is fixed on the robot as receiver sensor and the other (matrix of white LEDs) works as the transmitter sensor, distributed uniformly in the system. For a number of receivers (LDRs), the minimum bounded circle algorithm is used to draw a minimum circle that contains all of the points; as a result, the center of this circle is assumed to be the robot's position.

II. THE INDOOR ROBOT LOCALIZATION SYSTEM

A new algorithm for indoor robot localization is introduced. It relies on estimating the position of the robot depending on the indoor environment. The localization is achieved using pairs of sensors: a group of LDRs fixed on the robot represents the first part and the other is represented by matrix of white LEDs distributed uniformly in the environment. The binary search algorithm is used to control the lighting on the matrix of LEDs and the information collected from the LDR sensors is sent to the central unit. The robot position is estimated by applying the minimum bounded circle algorithm to the collected information.

A. The LEDs Array Environment

The indoor environment used in this paper consists of two dimensional holes distributed uniformly as shown in Fig.1. These holes are used to fix LEDs in an array (M*M LEDs). These LEDs work as the transmitter portion of the localization sensor pairs. The receiver part is represented by the LDR group fixed on the robot. The coordinate axis and the connection of each LED depends on its location in the LED array. The anode of each LED is connected to one of the matrix columns and the cathode of each LED is connected to one of the rows in the matrix as shown in Fig.2. The principle of the LED turn on and turn off depends on the binary search algorithm that used to help in robot localization. This algorithm is designed to minimize the required time for searching the rows and the columns of the LED matrix. If any robot detects the light of any LED that means the robot has the same coordinate axis as that LED.

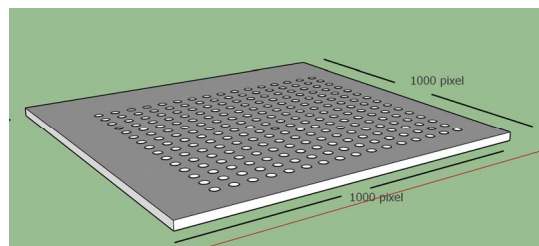


Fig. 1. The M*M holes indoor environment.

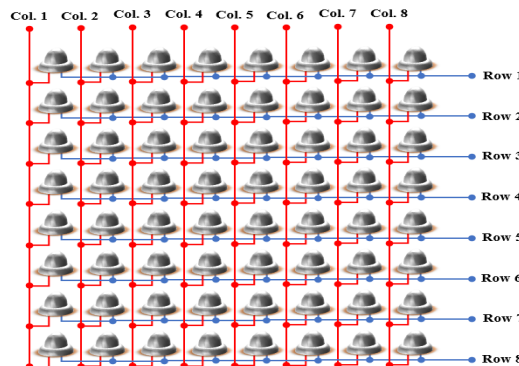


Fig. 2. The 8*8 LED matrix.

B. The Binary Search Algorithm

In fact, the binary search algorithm is applied to search for any number among any sorted array of numbers. It is a very simple algorithm and can be improved to work in logarithmic time. The searching process is achieved by repeatedly dividing the array in half. If the value of the search number is less than the item in the middle of the array, narrow the array to the lower half. Otherwise, narrow it to the upper half. Repeatedly check until the number sought is found or the array is empty. At every step of the algorithm, we should remember the beginning and the end of the remaining part of the array. The benefit of this algorithm is that its complexity depends on logarithm of the array size [18]. The steps for the binary search algorithm are shown in Fig. 3.

Binary Search Algorithm

1. Def. binary Search (A, x):
2. $n = \text{len}(A)$
3. $\text{beg} = 0$
4. $\text{end} = n - 1$
5. $\text{result} = -1$
6. While ($\text{beg} \leq \text{end}$):
7. $\text{mid} = (\text{beg} + \text{end}) / 2$
8. If ($A[\text{mid}] \leq x$):
9. $\text{beg} = \text{mid} + 1$
10. $\text{result} = \text{mid}$
11. Else:
12. $\text{end} = \text{mid} - 1$
13. Return result

Fig.3. Binary Search Algorithm

The introduced algorithm is modified to be compatible with the suggested system. In this paper, more than one LDR sensor equips the robot. Each LED in the matrix has a binary value (one or zero) and these LEDs are distributed in the two-dimensional array. According to these parameters, the modification in the binary search algorithm indicates the following steps:

1) The array elements in the binary search algorithm are represented by the decimal digits, so that the sorting process is implemented at the first step in this algorithm. In the suggested system, each element is replaced by the reading of the LDR sensor, which has one of two logical values (one or zero). In this case, no sorting process is required.

2) The LED matrix is distributed in the two-dimensional array; thus, the binary search algorithm applies to the rows and the columns of this matrix.

3) More than one LDR is used on each robot, so that the searching process is applied to more than one value at each time.

Since the location of each LED in the matrix is assumed to be known, the information collected from reading the robot LDR sensors can be used to estimate its location. The process of localization starts by using the reverse binary search algorithm across the rows of the LED matrix. The LDR sensors are used to label the columns within their sensing range with the value of one and the other columns with the value of zero as shown in Fig. 4.a. This process repeats for the columns of the matrix to label LEDs within the sensing range of the LDR sensors with the value of one Fig. 4.b. The information from the chosen LEDs is sent to the main control unit to estimate the robot's location.

C. Minimum Bounded Circle of 2D Convex Hull

This section explains the procedure used to estimate the location of the robot using information collected from the reverse binary search algorithm. For this purpose, it is a good idea if the LED information is represented by a virtual circle, and the center of this circle represents the location of the robot. To solve the problem the algorithm of a minimum bounded circle with 2D convex hull is introduced. The calculation for a set of points to obtain the minimum bounded circle is started by building the polygon convex hull from computing a circle with minimum boundary, then, by using Chan's approach, the circle with minimum bounding is computed [19].

- Convex Hull via Chan's Algorithm

The convex hull is the smallest subset of points in the two-dimensional environment which does not include any of the inner set points. Chan's algorithm is one of the

best known algorithms used to build the convex hull of set points in a 2- or 3-dimensional environment [20]. Chan's algorithm is based on the divide and conquer concept using a combination of the Jarvis March algorithms and Graham's scan. The divide stage starts by applying the Graham's scan algorithm to fragment a collection of points into groups, (each one ranging from 4-16-32-256-512...) then the sub-hull is computed for each subset. In the conquer stage Jarvis's march is used to find the smallest point of p_0 , then sequentially to find the convex hull vertex starting from p_0 and using binary search to reach point p_0 again, as shown in Fig. 5.

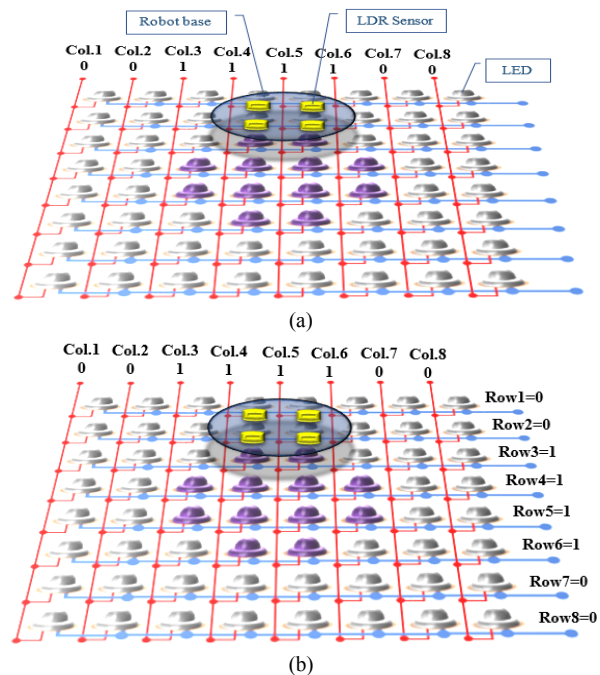


Fig. 4. The modified binary search algorithm. (a) Label the columns. (b) Label the rows.

Chan's Algorithm (p)

1. For $t = 1; 2; \dots$
2. Let $m = \min(2^{\wedge}(2^{\wedge}t), n)$
3. Let $r = \text{ceil}(n/m)$
4. Divide stage
5. For $k = 1$ to r do
6. For $i = 1$ to m do
7. Compute sub hull $P(m)$ using Graham's scan and store the vertices in an ordered array S in CCW oriented.
8. End
9. Jarvis stage
10. Find leftmost vertex S_0 from all sub hulls that resulted from Graham scan algorithm
11. Compute final convex hull $ch(h)$ using Jarvis March algorithm
12. End

Fig. 5. Chan's Algorithm for convex hull construction.

- Minimum Bounded Circle Algorithm

This algorithm is used to draw a minimum bounded circle containing all the set points which at first represent

a convex hull polygon using Chan's algorithm. The steps for implementing the minimum bounded circle algorithm are as follows:

- 1) Use the line between the two points with maximum distance as an initial value of circle diameter and the center of the diameter as the initial circle center.
- 2) Check the distance of each point in the set from the center of the circle. If any distance is greater than the radius, then this line is extended to intersect the far side of the circle. This new line is used as the diameter for a new circle.
- 3) The process in step 2 is repeated until all the set points have distances less than the radius of the last tested circle. This circle is the minimum bounded circle.
- 4) The midpoint in the last circle diameter is chosen to be the position of the robot.

III. SIMULATION RESULTS

In this paper, a new robotic localization system is validated by simulation. Simulations are performed for the single robot with different numbers of LDR sensors (1, 2, 3 and 4). The simulations are repeated for 50 different topologies representing different robot locations, different sensing ranges for the LDR sensors and different distances between the LDR sensors. The dimensions of the environment used for these simulations are 1000*1000 Pixels with a 32*32 LED matrix distributed uniformly. The system parameters used in these simulations are:

- 1) Number of LDR sensors equipped on each robot.
- 2) Maximum sensing range of the LDR sensor.
- 3) Number of LEDs in the LED matrix.

Figs. 6, 7, 8 and 9 show the first group of simulations for the localization system on a robot with 1, 2, 3 and 4 LDR sensors respectively.

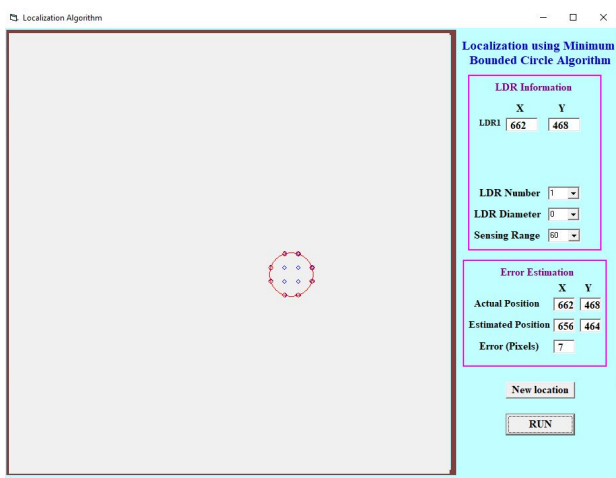


Fig. 6. Simulation for robot localization with one LDR

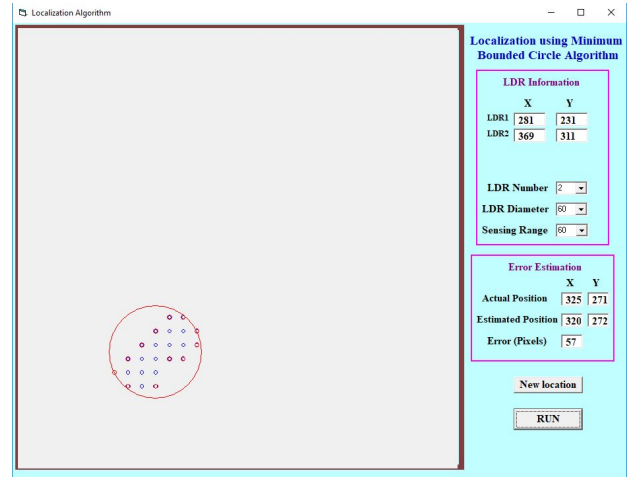


Fig. 7. Simulation for robot localization with two LDRs

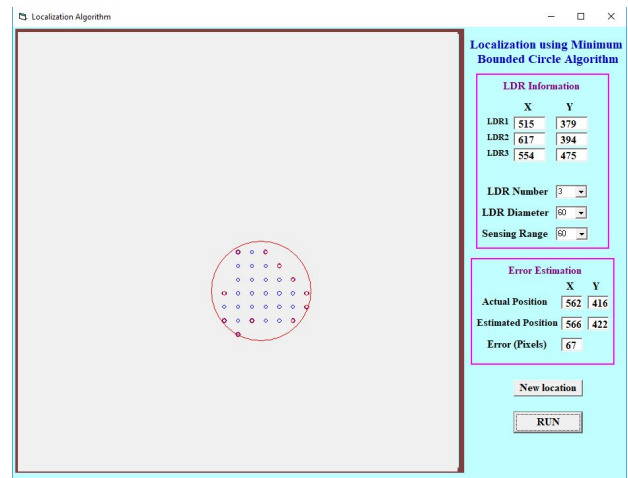


Fig. 8. Simulation for robot localization with three LDRs

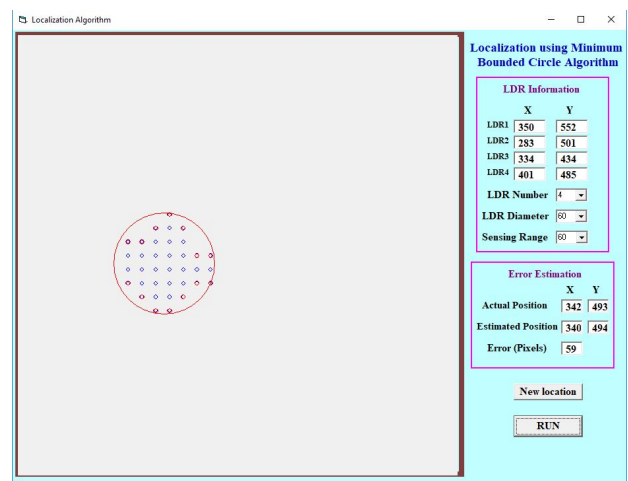


Fig. 9. Simulation for robot localization with four LDRs

The first simulation is implemented on a robot with a single LDR sensor and is repeated for different sensing ranges of this sensor. Fig. 10 shows the simulation result obtained by repeating the first simulation 50 times with random locations of the robot to obtain the relationship between the percentage of the full sensing range and the different values of the sensing range. The result shows that the best sensing range to obtain a full sensing range is 40 Pixels.

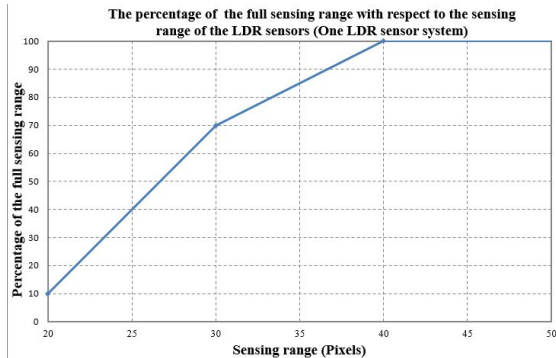


Fig. 10. The relationship between the full sensing range and the LDR sensing range with one LDR robot

The second simulation is applied to the robot with two LDR sensors and the same procedure used by the first simulation is repeated for this simulation. Fig. 11 shows the result of this simulation, which also shows that the best sensing range is 40 Pixels.

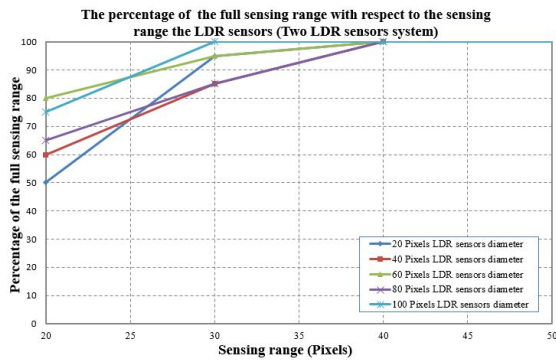


Fig. 11. The relationship between the full sensing range and the LDR sensing range with two LDR robot

The same simulation procedures used by the above simulation are repeated in the cases of robots with three and four LDR sensors. Fig. 12 and Fig. 13 show that the best sensing range is 40 Pixels.

The second group of simulations is implemented for comparison the average of the LDR sensor error occurring on robots that have a different number of LDR sensors. These comparisons are tested in the localization process for robots with different sensing range. At first, the average error in the robot localization is compared to robots with one, two, three

and four LDR sensors with respect to the distances between the LDR sensors equipped on each robot. Fig. 14 shows comparison of the results when the sensing range of each LDR is 40 Pixels. This comparison shows that the average error is reduced as the distance between LDRs are also reduced, and the smaller average error occurs when the robot has a single LDR sensor.

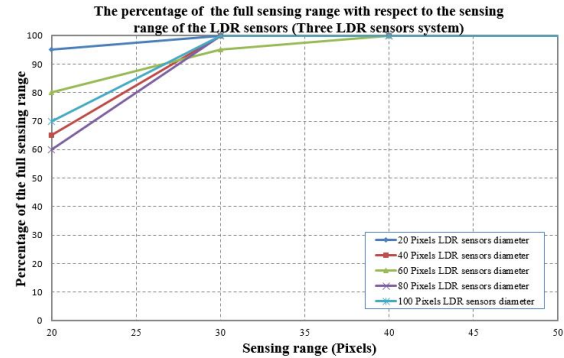


Fig.12. The relationship between the full sensing range and the LDR sensing range with three LDR robot

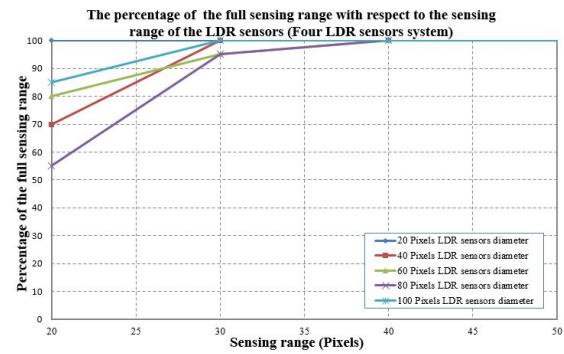


Fig.13. The relationship between the full sensing range and the LDR sensing range with four LDR robot

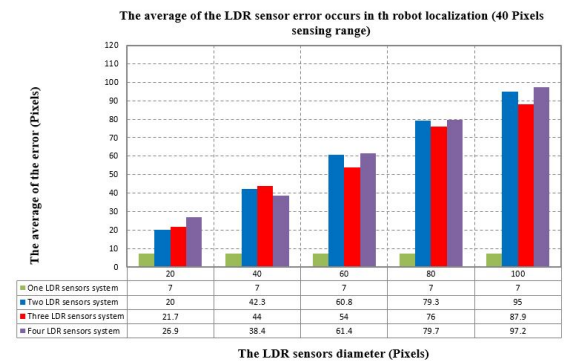


Fig. 14. The comparison of the average error in LDR sensors with respect to the distances among them (40 Pixels LDR sensing range)

The same comparison procedure in Fig. 14. is repeated for the robot with LDR sensors with 60 Pixels sensing range, as shown in Fig. 15. In addition, this comparison shows that the average error is reduced as the distance between LDRs are

also reduced; the smaller average error occurs when the robot has a single LDR sensor. The same results are obtained when using a robot with 100 Pixels sensing range, as shown in Fig. 16.

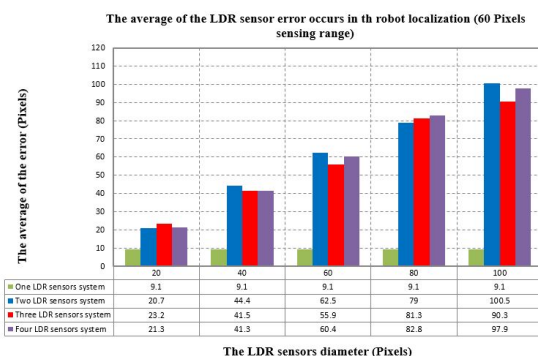


Fig. 15. The comparison of the average error in LDR sensors with respect to the distances among them (60 Pixels LDR sensing range)

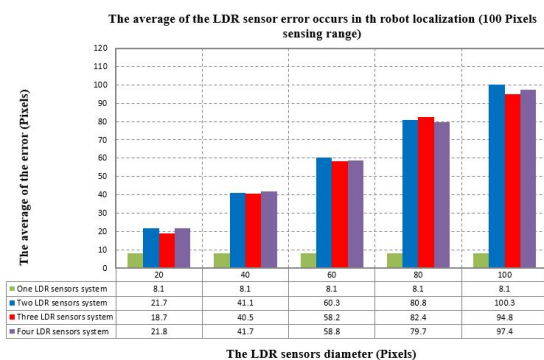


Fig. 16. The comparison of the average error in LDR sensors with respect to the distances among them (100 Pixels LDR sensing range)

IV. CONCLUSION

An indoor robot localization system is introduced. This system solves the problem of localization by using an array of LEDs distributed uniformly in the environment. The localization process is implemented and tested on robots with different numbers of LDR sensors (1, 2, 3 and 4 LDR sensors) and different sensing range (20 to 100 Pixels). The results show that the best sensing range to achieve full detection for the LED matrix is 40 Pixels; this result is suitable for any number of LDR sensors on each robot. Also, the results show that the average LDR error is reduced as the distances between the LDR sensors reduce and that the best case is obtained when the robot has only one LDR sensor.

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