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Research Article

Automatic mapping and localization in large-scale cyclic using K-nearest neighbours

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Abstract
Simultaneous localization and mapping (SLAM) is a process or technique used by autonomous mobile robots to identify the location and regenerate a map for the surrounding environments where the robot moves. One of the preconditions for autonomous mobile robots is the ability to learn a regular environment model. Closed loops are considered one of the most effective issues in SLAM research areas. One of the main challenging problems in generating the environment map of closed loop is the data association problem, where loops in the surrounding will activate data association problem. The difficulty of a particular surrounding with closed loop is based on the value of uncertainty in local mapping and the productivity of the local map representation. Uncertainty management is a core challenge in SLAM. False matching due to unclear structure in the environment represent one of the most substantial difficulties to suitably closing large loops. In this paper, combination of scanning laser, distance meter, compass and k-nearest neighbourhood (KNN) were discussed to construct an absolute localization system. The KNN and distance equation as similarity measurement with specified threshold are used to solve the uncertainty problem and to specify the node that is closest to robot location. The results showed that the cosine method had the least error value with execution time (0.000405 s) while the Chebyshev method had the least execution time (0.000360 s) and error value of (2). The results indicate the cosine method with KNN has the minimum error and less execution time.

Keywords
Localization, K-Nearest neighbourhood, Robot path planning, Large-scale cycle.

1.Introduction
Localization is considered one of the essential topics in autonomous mobile robots. With the improvements of the robotic industry in the past decades, robot localization has become more interesting: from unknown to known environments, from complex to simple environments, from dynamic to static environments [1], and from long-term to short-term localization [2]. In traditional approaches, robots' locations can be acquired using a fixed router in a predefined area, and the location of a particular robot can be evaluated depending on the distance of the robot from several routers, ultra-wide band (UWB) [3] and Wi-Fi localization [4] are used. However, these approaches depend on external setup and they are essentially used in small-scale environments.

To overcome the limitations of conventional localization approaches, simultaneous localization and mapping (SLAM) are presented to estimate the robot position using on-board sensors [5].

SLAM is independent of external setup like routers, which makes it the promising future in robotic applications, because mapping using SLAM technique comprises both, estimating the location of the robot compared to the map and recreate the map using the sensory input, and the estimations about the robot's position.

Utilizing of SLAM with moving robots has implemented successfully in numerous areas, namely home applications [6], military [7], exploration [8], [9], and rescue [10, 11]. The effort on localisation algorithm development usually has categories of algorithm-based which are scan matching [12, 13], probability method [14] and Kalman filter [15]. These kinds algorithms are used to compute and

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predict the position of the moving robot based on the information of the surrounding environment that gained from range detector sensor [16]. Scan matching process divided into two methods, point-to-point and feature-to-feature. The point-to-point method (e.g. iteration closest point (ICP) [13] and cluster method [17]) needs two scans compared directly, and it applied usually in a static environment. However, there are two problems of applying the point-to-point method which are: the results of scanning the input are not close to reference scans which leads to higher probability that a certain point of scanning outcomes can be misplaced. Because of these problems, point-to-point method is not appropriate for certain range discoverer sensor. In order to resolve this drawback, the laser has been used, since it gives additional scanning points, or multiple sensors [18] and multiple types of sensors [19]. Feature-to-feature method has been applied to implement scan matching. It is appropriate for both dynamic and static environments. The computational complexity of feature-to-feature method is higher compared to point-to-point method. Besides, the matching quality relies on the features reliability [20]. Both of these methods apply iteration process so as to make the matching between the input and the references scans. The iteration will stop as soon as the input sample is matched with any of reference samples and is exceeded or equalled to threshold. This work used the feature-to-feature method since the combination of scanning laser, distance meter; compass where this combination forms an absolute localization system. This paper discusses and compares among different similarity measurements (Jaccard, Euclidean, Cityblock, Chebyshev, Cosine, Correlation and Variation) with K-Nearest Neighbourhood (KNN) to solve the uncertainty problem and to specify the node that is closed to the robot location in large-scale loop. Large-scale loop considered one of the most difficulties in robotic mapping. As a robot try to conduct a large cycle in the surrounding environment, it faces a strong data association of appropriately linking to its own map but with large location errors. This problem has long been recognized for its rigidity. A number of methodologies [21] have addressed false matching according to the unknown structure of the environment which become one of the most substantial difficulties to suitably closing large loops. When the environment has repetitive structure, a non-unique map-match appears. Besides, the former uncertainty of the mapping robot may be too large to clarify the correct match before closing the loop. Even when there is only one visible match, it is probably that the correct match cannot been recognized; thus, the single match is uncertain.

There are several approaches to determine and to accept a map-match. For instance, multiple assumptions can be used to track each possible decision branch as in Austin and Jensfelt [22]. Otherwise, one can use a technique that represents multi-modal probability distributions, such as the sum of Gaussians models [23] or Monte-Carlo localization [24]. Another approach to determine and to accept a map-match is to temporarily take the maximum likelihood decision, and then identify x errors by rolling back the computation. This procedure is used in Thrun et al. [25], where misleadingly matched links can be corrected recursively when large errors are identified.

This work discusses the combination of scanning laser, distance meter, compass and KNN, where this combination forms an absolute localization system to solve the uncertainty problem and to specify the node that is closest to the robot location. This paper is organized as follows. Section 2 involves a survey of the related works. Then, the material and methods are illustrated in section 3. While, section 4 and 5 contains the results and discussion. Finally, the conclusion of this research paper is included in section 6.

2.Literature review

A comprehensive survey for the first two decades of the problems of SLAM is highlighted by Durrant-Whyte and Bailey in a couple of studies [26, 27]. These two studies include what called the classical age (1986-2004); where the first era witnessed the presentation of the major likelihood-based interpretations for SLAM, involving methods based on lengthy Kalman filters, Rao-Blackwell fragment filters, and maximum likelihood estimate. Two other outstanding mentions characterizing the three most important SLAM concepts of the first era are the book of Thrun, Fox, and Burgard [28] and the chapter of Stachniss et al. [29]. The next era called the algorithms-analysis age (2004-2015) and is partially covered by Dissanayake et al. in [30]. The next stage is the algorithm assessment period, where a study of the basic characteristics of SLAM, comprising the monitoring, coming together, and regularity, is conducted. Recently, most of researches are lied about the visual SLAM. Visual SLAM is the technique that uses cameras to construct the surrounding environment of the robot [31]. To conduct visual SLAM, visual sensors and efficient microprocessors should be used to accomplish the mission of the robot [32]. Thus, applications that need cost effective robots will not meet visual SLAM robot.

Several literatures have discussed the use of KNN algorithm with supervised learning method to perform the searching process [33–35]. Experiments showed that supervised machine learning methods have the lead on unsupervised learning methods and in the vast majority of the outlier detection techniques, KNN algorithm can accomplish greater accuracy.

Spearman remoteness with received signal strength indicator (RSSI) during the period from the Access Points (AP's), is used by Xie et al. [36] to enhance the localization stability. In accordance with [36], even though pure readings related to RSSI for a group of fixed APs that have a fixed positions could be completely different, but the RSSI values are much more expectedly to be the same, which gives the ability to recognize the RSSI values pattern for each location. The disadvantage of this algorithm is the restriction of how many APs are accessible. In [36], computer simulation shows that there exist 400 reference locations remained with the use of just 4 AP's. Therefore, many sites have a similar identification, leads to make localization mistakes during the phase of testing.

For the purpose of considering the appliance heterogeneous nature, Zou et al. [37] suggested signal tendency index - weighted KNN (STI-WKNN) via implementing the resemblance index STI among RSSI bend shapes to enhance the localization precision. STI-WKNN, has been used in place of received signal strength (RSS) raw values, where STI-WKNN makes a comparison between the shapes of RSS vectors on one hand and RSS readings of mobile devices and online RSS fingerprint database on the other hand. The signal tendency index (STI) is calculated in accordance with Euclidean distances between the actual time of Procrustes analysis item and items that are saved on the thumbprint database. The ultimate location shall be specified via the weight between KNN that offer the least number of STI. The research reveals that STI-WKNN enhances the localization precision via 23.95% over the initial WKNN across diverse portable devices.

Ying et al. [38] uses image covariance matrix matching to resolve the problem of loop closure in mobile robots. In this study, three different methods have been studied. This study has shown that accuracy and recall rate are not effective like the proposed method. However, this study is related to visual SLAM and does not solve the problem in SLAM. In another study, Duan et al. [39] has studied the loop closure issue. In this study, a deep feature matching-based keyframe retrieval approach is proposed. Many other studies [40–42] has studied how to solve the problem of loop closure in visual simultaneous localization and mapping (VSLAM). But, according to [43] VSLAM is susceptible to the environment conditions like low-visibility condition. As a summary, the algorithms mentioned above apply the iteration process in order to match the input to the reference scans, and this process may affect on the execution time. Also, the Euclidean equation is a default equation that is applied with KNN algorithm. In this paper, localization in large-scale cyclic using KNN has been discussed. KNN algorithm has been applied to perform the searching process among the properties' tables.

3.Methodology

Autonomous robots perform many duties such as exploration, monitoring, and surveillance; while doing so, autonomous robots suffer from uncertainty problems which should not to be ignored for fully ensuring the feasibility of the path and safety of the robot. In this paper, an autonomous mobile robot has been simulated with MATLAB framework to navigate an unknown indoor environment using Massachusetts Institute of Technology 's Killian Court map as illustrated in *Figure 1* [44]. This robot used a laser sensor to detect external objects or surrounding structure in this environment such as doors, walls, windows, etc. Our work concentrates on evolving a simple, cost-effective, precise and adequate method of mobile robot localization using a multisensory. The novelty and contribution of this method lies in using a combination of techniques, like scanning laser, distance meter, and a compass. Then, the map is divided into sub maps or groups of matrices in order to reduce the execution time. Lastly, the suitable similarity measurement method used with KNN with specified threshold to establish an absolute localization system and to solve the uncertainty problem. The laser sensor is used to scan the obstacles, walls, etc. and the distance meter and compass are used to calculate the robot position in X and Y coordinator by increase the meter when the compass mentions a direction to the north or east and decrease the meter when the compass mentions a direction to the south or west.

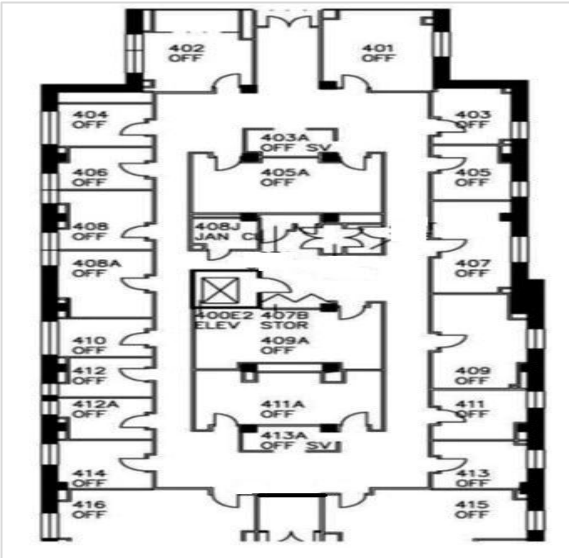

Figure 1 Indoor environment map

3.1KNN Classifier

KNN considered as powerful classification algorithm of non-parametric analysis [45]. Three main elements are there in KNN classifier: (1) a set of objects with their labels, (2) a metric for measuring the distance among objects called similarity or distance metric, and (3) a k value, which represents the value of nearest neighbour. A classification procedure is carried out to classify unlabelled object. This procedure starts by measuring the distance from unlabelled object to all labelled objects. Then, the KNN neighbours are distinguished from other neighbours; where the list of nearest neighbours is obtained based on previously mentioned procedure. After, the unlabelled object is then classified based on the majority class of its nearest neighbours [12–14].

KNN is a lazy learner algorithm because it does not learn from the training set immediately instead it stores the dataset and at the time of classification, it performs an action on the dataset. At the training phase, it just stores the dataset and when it gets new data, and then it classifies that data into a category that is much similar to the new data. In this work, KNN classifier was used to determine if an area has been visited or not based on the following steps:

- Identifying the KNN neighbours out of N training vectors, regardless of the label of the class.
- Determining the number of vectors, k_i from the identified k samples, that is a part of region class (α_i).
- Setting the input sample x to a region class with the maximum number, k_i of samples.

Identifying KNN neighbours can be achieved by utilizing different distance measurement methods like Euclidean distance, correlation measure or sum of absolute differences. In this work, the distance is computed using several distance equations to specify the best equation that would give the best result or measurement and as illustrated below.

3.2Variance measurement

A vector X of a random variable, compose of Z scaler observations, has a variance V defined by (Equation 1):

$$V = \frac{1}{Z-1}\sum_{i=1}^{Z}|X_i - \mu|^2 \qquad (1)$$

Where μ= mean of X (Equation 2),

and $\mu = \frac{1}{Z}\sum_{i=1}^{Z} X_i$ (2)

3.3Some of pairwise distance measurements

3.3.1Euclidean distance

Is a measurement used to represent the displacement between any two feature vectors a and b (Equation 3):

$$\text{distance}_{\text{Euclidean}} = \left(\sum_{i=1}^{n}(a_i - b_i)^2\right)^{\frac{1}{2}} \qquad (3)$$

3.3.2City block distance (Manhattan distance)

Is a measurement that represents the distance between any two feature vectors a and b (Equation 4) [20]:

$$\text{distance}_{\text{Cityblock}} = \left(\sum_{i=1}^{n} |a_i - b_i|\right) \qquad (4)$$

3.3.3Chebychev distance

Also known as a chessboard distance (Equation 5), which is the maximum difference along any coordinate dimension between two points a and b:

$$distance_{Chebychev} = MAX\{|a_i - b_i|\} \qquad (5)$$

3.3.4Correlation coefficient measurement

The correlation coefficient (Equation 6) is a measure of the relationship strength between two variable vectors, the value of this coefficient ranges from [-1,1], where the negative value shows uncorrelated variables while positive value shows the strength of correlation as it goes to positive 1. If vector x and vector y have N scalar observations, then the correlation coefficient is defined as Equation 6:

$$\text{Correlation}(x, y) = \frac{covariance(x,y)}{\sigma_x \sigma_y} \qquad (6)$$

Where, Equation 7 denotes the covariance:

$$covariance(x, y) = E((x - \mu_x)(y - \mu_y)) \qquad (7)$$

E: represents the average value.

μ_x (Equation 8) and μ_y (Equation 9) are the mean value of vector x and vector y respectively which are defined as:

$$\mu_x = \frac{1}{N}\sum_{i=1}^{N} x_i \quad (8)$$

and $$\mu_y = \frac{1}{N}\sum_{i=1}^{N} y_i \quad (9)$$

σ_x (Equation 10) and σ_y (Equation 11) represent the standard deviation for vector x and vector y respectively, so that:

$$\sigma_x = \sqrt{\frac{1}{N}\sum_{i=1}^{N} |x_i - \mu_x|^2} \quad (10)$$

and $$\sigma_y = \sqrt{\frac{1}{N}\sum_{i=1}^{N} |y_i - \mu_y|^2} \quad (11)$$

3.3.5Cosine distance

The cosine of the angle between two vectors describes the cosine similarity, while the cosine distance defines the angular distance between the two cosines. The cosine distance between two vectors a and b of n length (Equation 12) is written as follow:

$$\mathrm{distance_{cosine}} = 1 - \frac{\sum_{i=1}^{n} a_i \times b_i}{\sqrt{\sum_{i=1}^{n} (a_i)^2} \times \sqrt{\sum_{i=1}^{n} (b_i)^2}} \quad (12)$$

3.3.6Spearman distance:

The Spearman rank correlation coefficient (Equation 13 or Equation 14) is a method that is developed in order to evaluate the linear association degree or correlation between two independent variables. The Spearman rank correlation coefficient (r_s) is computed according to the following formula:

$$r_s = \frac{6\sum_{i=1}^{n} {d_i}^2}{n^3 - n} \quad (13)$$

Or:

$$\mathrm{distance_{spearman}} = 1 - \frac{\sum_{i=1}^{n} (a_i - \mu_{a_i}) \times (b_i - \mu_{b_i})}{\sqrt{\sum_{i=1}^{n} (a_i - \mu_{a_i})^2} \times \sqrt{\sum_{i=1}^{n} (b_i - \mu_{b_i})^2}} \quad (14)$$

Where:

r_s is restricted as follows: $-1 \le r_s \le +1$.

di: describes the difference between the ranks for every a and b data pair.

μ_a (Equation 15) and μ_b (Equation 16) give the mean value of both vectors a and b:

$$\mu_a = \frac{1}{n}\sum_{i=1}^{n} a_i \quad (15)$$

$$\mu_b = \frac{1}{n}\sum_{i=1}^{n} b_i \quad (16)$$

3.3.7Jaccard distance:

The ratio of the size value of the intersection of two vectors to the size value of their union refers to the Jaccard similarity of these vectors. For both a, and b vectors the Jaccard distance (Equation 17) value of them is one minus the value of Jaccard similarity and will be displayed as J (a, b) and is computed by an equation:

$$J(a,b) = 1 - \frac{a \cap b}{a \cup b} \quad (17)$$

3.4The proposed algorithm

In mobile robot self-localization, there are cases that need reference to show and illustrate the mobile robot location. The reference can be the previous or initial map, location of corner and specific landmark. In this study, the reference is consisted of initial local map. The proposed algorithm is based on using the compass and the KNN algorithm in order to reduce the execution time. The initial map can be obtained by creating groups of matrices that include the direction of compass (N, E, W, S) and an indicator for each direction (which is called the direction indicator in this paper (NI, EI, WI, SI)). This indicator would help in reducing the searching process. As a brief, if we assume that the robot is directed to move to the north, then the indicator (NI) will equal to 1, and continue to discover the surrounded area and recording the properties of this area in a table related to NI. Once the robot changes its direction to any other direction, to the west for example, then the (WI) indicator will equal to 1 (WI=1). If the robot back to the north again, then the (NI) indicator will increased by 1 (it means NI=2) and a comparison with a generated table for all previous NI values will is carried out to check if this region is visited or not. *Figure 2* illustrates the block diagram of the proposed algorithm.

Below are the steps for the proposed algorithm:

Step 1: Create the groups that include the properties of the surrounding visited areas, collected by the laser and compass direction sensors (N, E, W, and E) and also the direction indicator (NI, SI, WI, and EI). In case of there is no wall, a new way will be identified as a branch with a different direction than the current direction. These branches are an open area whereas there are no walls at the end of their paths can be detected and this area would be registered in a list (we identify it in this paper as “open areas’ list”).

Step 2: Increase the direction indicator by 1 (NI, EI, WI, or SI) according to the current direction. The direction indicator will not increase in case the robot moved straight in the same direction and did not change its direction to a new different one.

Step 3: If the robot changed the previous direction, then go to step 2. Else, go to step 4

Step 4: Check if direction indicator (NI, EI, WI, or SI) for the current direction is more than the previous value by 1, then go to step 5. Else, go to step 2.

Step 5: If direction indicator (NI, EI, WI, or SI) is more than the previous value by 1 then check the surrounding environment properties of the entire previous direction indicator according to the current direction using KNN (Here, K–parameter uses is 4) and similarity measurements (μ (the similarity measurement value) > th (threshold)) to check if the region has been visited before or not.

Step 6: If the region has been visited, then go back to visit the other regions that are not visited as mentioned in step 1. Else, continue to discover the new region as mentioned in steps 2-5.

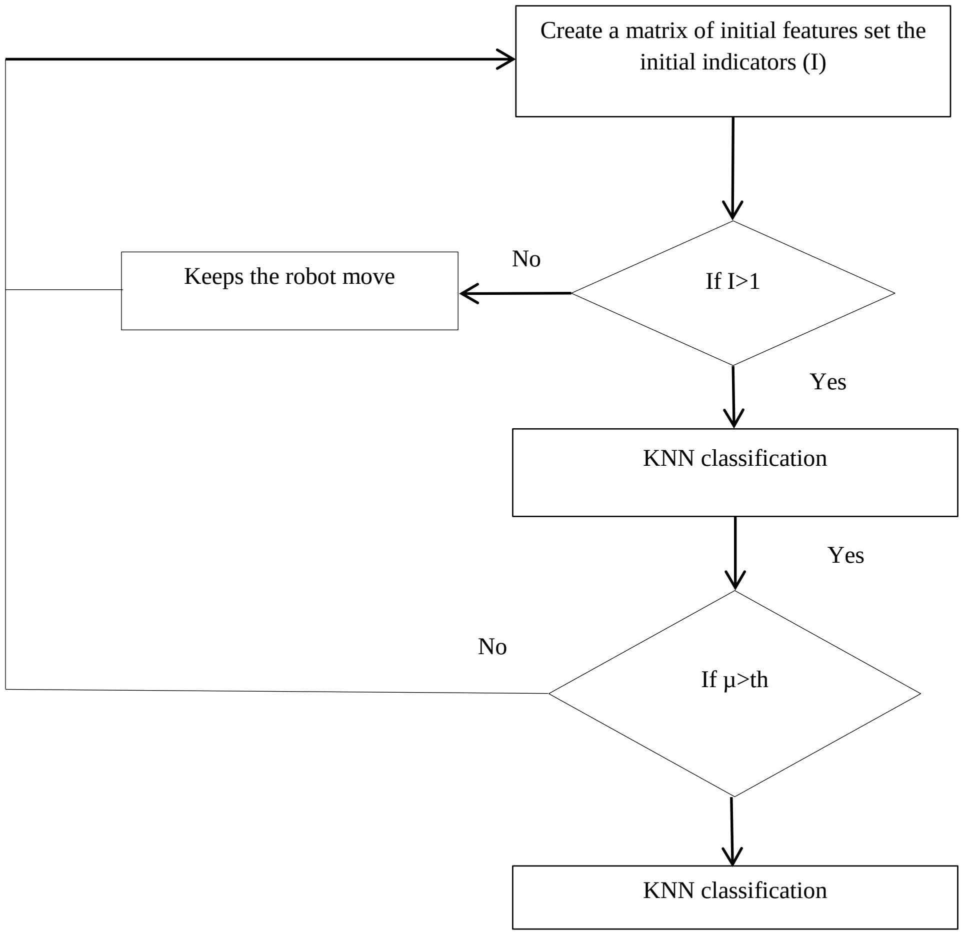

Figure 2 illustrates the block diagram of the proposed algorithm

Table 1 Illustrates the error value for each similarity measurement methods

Method	Jaccard	Euclidean	Cityblock	Chebyshev	Cosine	Spearman	Variation
Error	0.429	2.449	4	2	0.002	0.317	101.952

4.Results

In this section, the results will be shown to compare among different similarity measurements such as (Jaccard, Euclidean, Cityblock, Chebyshev, Cosine, Spearman, Correlation and Variation) with KNN to solve the uncertainty. Using the combination of sensors, the indicators, and the suitable similarity measurement method with KNN would reduce the computational time and reduce the error. *Table 1* shows the use of similarity measurement methods and error calculation for each method when it reaches a similar point (here for example the starting point).

In the case of using similarity measurement methods alone, the algorithmic methods give inaccurate results with regard to whether the place is visited or not. To illustrate this point, let us assume that the starting point is (x=104 and y=490) which is illustrated in *Figure 3*, after the robot would approximately complete the cycle reach the point e.g. (X=104 and y=490), it has been expected that the use of the similarity measurement methods that mentioned previously would give the minimum error value. The result showed that the minimum error would continue to the area point with (x=94 and y=497) as illustrated in *Figure 4*. Accordingly, this would give inaccurate position's result, as well as the process of comparing each visited point would lead to high execution time. In the case of using the combination of sensors and indicators along with dividing the map to the sub maps or group of matrices and KNN, the result would be more accurate as illustrated in *Figure 5*, and the execution time can be reduced due to comparing the regions as groups and not as individual points as indicated in *Table 2*, as well as using the group centre to determine whether the region was visited or not, which will contribute to the increasing of the accuracy to determine the visited place. Additionally, the use of the groups (which are the tables of properties) as memory points would help to return the robot to the previous path (that it moved on earlier) and consequently it would save the time in case of needing to direct the robot to any specific point.

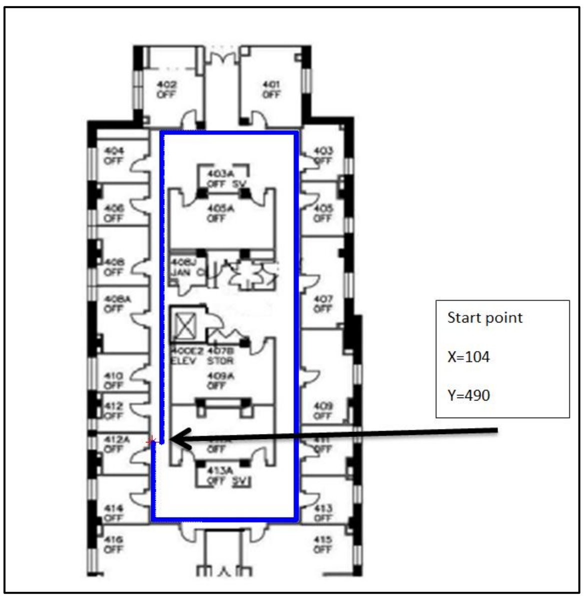

Figure 3 Illustrates the starting point

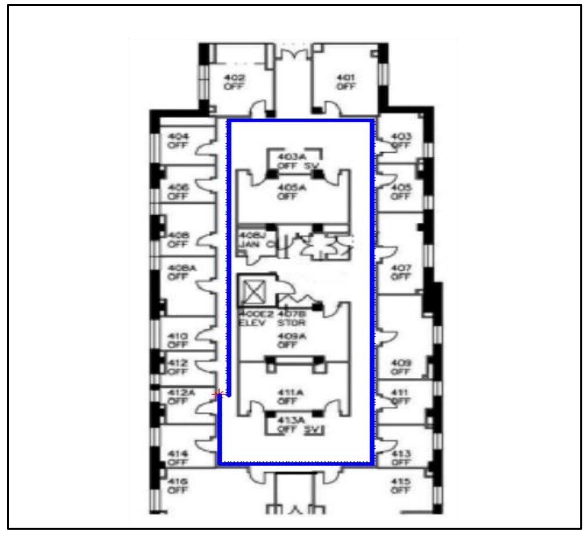

Figure 4 shows the position of robot after one large cycle using the similarity measurements only

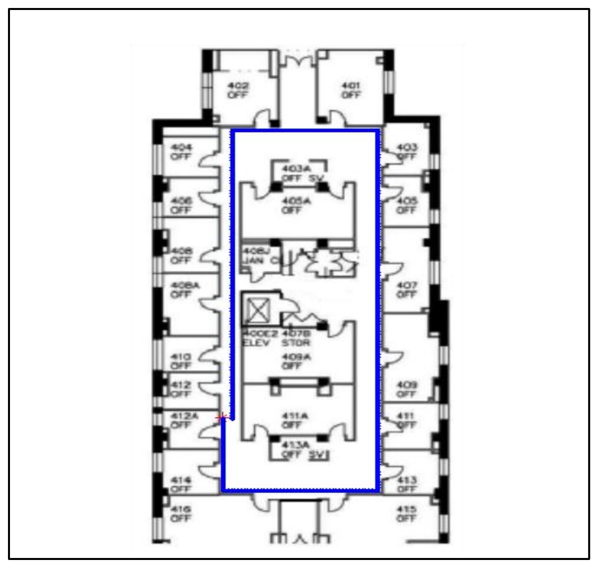

Figure 5 shows the position of robot after one large cycle using the similarity measurements with KNN

Table 2 Illustrates the execution time in (sec) for each similarity measurement methods

Method	Jaccard	Euclidean	Cityblock	Chebyshev	Cosine	Spearman	Variation
Execution time (S)	0.000414	0.000528	0.000573	0.000360	0.000405	0.000661	0.000376

5.Discussion

In this section, the results are explained and discussed to show the best acquired result. According to *Table 1* and *Table 2*, the cosine method had the least error value with execution time (0.000405 s) and error value of (0.002), while the Chebyshev method had the least execution time (0.000360 s) but with error value of (2). *Figure 6* showed the final result of the proposed algorithm. As mentioned previously in section 3-4, it can be noticed that the robot has visited all the open areas' list (1, 2, 3, 4, 5 and 6) which the laser could not detect the wall or end according to its coverage distance. Also, it can be noticed that if the robot has started to discover or map one of the open areas e.g., area 2 and reached to area 3 (which they have the same path) and while it discovered the area 3 has been visited before, then the proposed algorithm would automatically cancel the mapping of the area 3 from the open areas' list. Finally, and according to the result in *Figure 6*, the robot has stopped the mapping process when it reached to the area 6 since it was the last open area in the open areas' list and all the areas around it have been visited. The limitation of the proposed algorithm is that the errors caused by rotation and shifting in the real implementation were not taken into account.

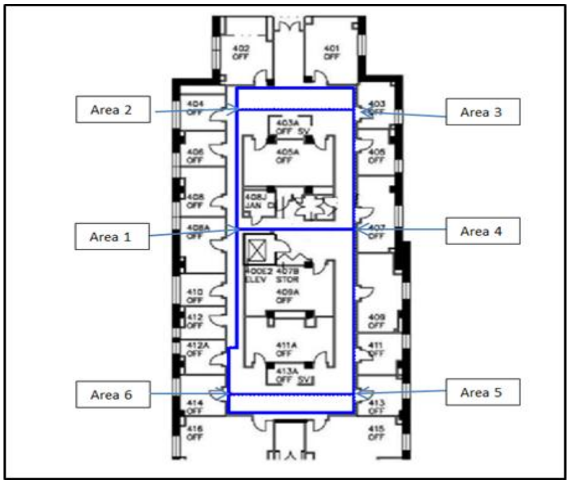

Figure 6 Position of robot after one large cycle using the similarity measurements with KNN

A complete list of abbreviations is shown in *Appendix I.*

6.Conclusion

Path detection for moving objects such as robotics is vital for project to success. In this paper, an uncertainty problem of path detection has been discussed in a large-scale cyclic environment. Eight similarity measurement techniques were used, namely Jaccard, Euclidean, Cityblock, Chebyshev, Cosine, Correlation and Variation along with KNN algorithm, and have been studied in regards of solving the uncertainty problem and to reduce the execution time. Simulation of the robot was performed using Matlab framework. The result showed that, the cosine method had the least error value with execution time (0.000405 s) while the Chebyshev method had the least execution time (0.000360 s) and error value of (2). The results indicate the cosine method with KNN has the minimum error and less execution time. As a future suggestion we will try to implement the algorithm with a real robot and to solve the problem of shifting and altering in angles during implantation with different maps.

Acknowledgment

None.

Conflicts of interest

The authors have no conflicts of interest to declare.

Author's contribution statement

Ahmed Raheem Abdulnabi: Writing original draft, review and editing, analysis and interpretation of results. **Maher Faik Esmaile:** The main idea of the proposed algorithm, data collection, conceptualization, supervision.

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Appendix I

S. No.	Abbreviation	Description
1	AP's	Access Points
2	ICP	Iteration Closest Point
3	KNN	K-Nearest Neighbourhood
4	RSS	Received Signal Strength
5	RSSI	Received Signal Strength Indicator
6	SLAM	Simultaneous Localization and Mapping
7	STI	Signal Tendency Index
8	STI-WKNN	Signal Tendency Index - Weighted KNN
9	UWB	Ultra-Wide Band
10	VSLAM	Visual Simultaneous Localization and Mapping