



Quantitative Performance Review of Wheeled Mobile Robot Path Planning Algorithms

Oluwaseun Opeyemi MARTINS^{1,*} , Adefemi Adeyemi ADEKUNLE¹ ,
Samuel Babatope ADEJUIGBE¹ , Oluwole Hezekiah ADEYEMI² 

¹Federal University Oye-Ekiti, Department of Mechatronics Engineering, Ekiti State, Nigeria

²Olabisi Onabanjo University, Department of Agricultural and Mechanical Engineering, Ogun State, Nigeria

Highlights

- This paper focus on review of mobile robot path planning algorithms.
- Quantitative performance approach is proposed for evaluation of these algorithms in the study.
- Objective conclusions are made on the performance of the path planning algorithms.

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Abstract

Path planning evaluates and identifies an obstacle free path for a wheeled mobile robot (WMR) to traverse within its workspace. It emphasizes metric like, start and goal coordinate, static or dynamic workspace, static or dynamic obstacles, computational time and local minimum problem. Path planning play a significant role toward WMR effective traverse within it workspace like industrial, military, hospital, school and office. In this workspace, path planning is an optimal method to increase the productivity of WMR to achieve it specific task. Hence, in this paper, we present a review of path planning algorithms (classical algorithms, heuristics and intelligent algorithms, and machine learning algorithm) for mobile robot using statistical method. Regarding our objective, we use this statistical method to evaluate the success of these algorithms base on the following metrics: architecture (hybrid or standalone), algorithm sub-category (global or local or combine), workspace (static or dynamic), obstacle type (static or dynamic), number of obstacle (≤ 2 , ≤ 5 , > 5) and test workspace (virtual or real-world). Research materials are sourced from recognized databases where relevant research articles are obtained and analyzed. Result shows hybrid of machine learning approach with heuristic and intelligent algorithm has superior performance where they are applied compare to other hybrid. Also, in complex workspace Q-learning algorithm outperforms other algorithms. To conclude future research is discussed to provide reference for hybrid of Q-learning algorithm with Cuckoo Search, Shuffled Frog Leaping and Artificial Bee Colony algorithm to improve its performance in complex workspace.

1. INTRODUCTION

Wheel Mobile Robots (WMRs) are identified with industrial workspace designed for them to collaborate in manufacturing task. However, in recent time technology has made it possible to apply this class of robots in other workspaces such as military, hospital, school, office among other examples [1-3]. These workspaces are largely complicated for the WMR to traverse due to uncertainty and obstacle presence without laid track for the WMR to traverse. Hence, it has become one of the most researched area of engineering recently. The WMR is required to undertake a specific task within it workspace while moving from the start coordinate to the goal coordinate evading static and dynamic obstacle [4]. The WMR workspace or obstacle type can be static or dynamic [5, 6]. Researchers have developed and applied path planning algorithms to assist WMR traverse from it start coordinate to the goal coordinate, evade static and dynamic obstacles [6]. To achieve this the WMR must possess some level of intelligence to perceive it workspace through sensors and take appropriate action [4].

Path planning algorithms determines an obstacle free path for a WMR to traverse within its workspace [7]. It emphasizes metric like, start and goal coordinate, static or dynamic workspace, static or dynamic

*Corresponding author, e-mail: oluwaseun.martins@fuoye.edu.ng

obstacles, computational time and local minimum problem. In [7, 8], path planning algorithms are sub-categorized as global and local. Global path planning algorithms are frequently applied to static workspace having static obstacles and robot has comprehensive knowledge of this workspace. This algorithm generates the traverse path off-line before the movement of the robot within the workspace [8, 9]. However, these algorithms are very ineffective in real-world workspace, where the workspace is unpredictable and clustered with static and dynamic obstacles. Local path planning algorithms such as discussed in [10-12] generate path in real-time for the WMR in response to onboard sensor data [13]. This enable the robot traverse safely in unpredictable and clustered workspace [4]. Researchers have proposed and reported several path planning algorithms in literature in this category; classical algorithms, heuristics and intelligent algorithms, and machine learning algorithm. The classical algorithms are effective as global algorithms because they lack the intelligence to succeed in unpredictable and clustered workspace. The heuristics and intelligent algorithms, and machine learning algorithm have the requisite intelligence to succeed in unpredictable and clustered workspace where an exact mathematical model may not be available.

Although review paper on path planning algorithms for mobile robot have been done [4, 14], these reviews do not present how these path planning algorithm has been applied; neither is machine learning algorithm compared with other approach. In this paper, we present a review of path planning algorithms (classical algorithms, heuristics and intelligent algorithms, and machine learning algorithm) for mobile robot using statistical method. This is one of the contributions of this work. Regarding our objective, this statistical method evaluates the success of these algorithms base on the following metrics: architecture (hybrid or standalone), algorithm sub-category (global or local or combine), workspace (static or dynamic), obstacle type (static or dynamic), number of obstacle (≤ 2 , ≤ 5 , > 5) and test workspace (virtual or real-world). These metrics are selected base on how researchers have used their proposed algorithms to solve path planning problem for mobile robot. For us to use the statistical method, different weights are assigned to these metrics. Also we review the performance of Q-learning a machine learning algorithm for path planning for mobile robot using these metrics and compare it success with other approach. This is another contribution of our work since many previous works do not present this information. Hence, the path planning algorithms are discussed in section 2 under three category (classical, heuristics and intelligent, and machine learning). Section 3 describe the method used, then result and discussion in section 4 and finally conclusion in section 5.

2. PATH PLANNING ALGORITHMS

2.1. Classical Algorithms

The classical algorithms such as cell decomposition, roadmap approach and potential field are the foremost path planning algorithms. This classical algorithm lack intelligence hence they require a comprehensive model of the workspace and also surfer some drawbacks like local minimum problem and excessive computational time [15].

Cell Decomposition

The principle for this algorithm is to partition the workspace map into number of cells. These cells form a connected graph and free path is searched from the start coordinate to the goal coordinate, but it approach does not find the shortest path in most cases [16]. This approach is of the exact cell decomposition and approximate cell decomposition type. Cell can be occupied with obstacle or free of obstacle. The free cells are considered for path planning from start coordinate to goal coordinate. Cell with obstacle is further split into new cells to get free cell. Then this free cell is added to the existing free cell and is considered to determine the optimal path from start coordinate to goal coordinate [17].

Roadmap Approach

In this approach traverse from one coordinate to another is through free cell represented by a set of one-dimensional curves [18]. Voronoi graph and Visibility graph are methods used to build up the roadmap.

The cell nodes are crucial to get desired path for robot. The roadmap can search to find the shortest path from the robot's successive nodes [19].

Potential Field

The idea of the potential field approach is to apply attractive force to the goal coordinate and repulsive force about the obstacles within the mobile robot workspace. This creates imaginary force on the mobile robot that guide it robot toward the goal and repel it from obstacles [20-21]. The summation of these imaginary forces is the total potential field called Artificial Potential Field [22]. However, this approach suffer a problem where the goal is non-reachable due to obstacles in close proximity, here the repulsive force from obstacle close to the goal is negate the attractive force, hence, the goal non-reachable [23].

2.2. Heuristics and Intelligent Algorithms

The workspace of mobile robot has substantial level of uncertainty such as sudden obstacle which the classical algorithms has not been able to handle effectively. Also, they require comprehensive model of the workspace [15] that increase with the size of the workspace. Hence, researchers develop heuristics and intelligent algorithms to handle this uncertainty.

Artificial Bee Colony

This algorithm model the procedure for food search behavior of honey bee colony. This algorithm is a stochastic search approach that consist of a population of food sources and artificial bees (50 % employed bees and 50 % onlooker bees). The ratio of the colony size to food sources is 2:1. Employed bees modify these food sources over time. Where a food source cannot be improved by an employed bee after a number of specified trials it become a scout bee. This scout bee find another random food source. The employed bees exploit food sources and give information about it nectar quality to the onlooker bees. Onlooker bees select food sources base on the nectar quality information from the employed bees and exploit these food sources. Some of the merit of this algorithm is simplicity, fast processing [24-25].

Cuckoo Search Algorithm

Cuckoo are a specie of bird with parasitic behavior. Cuckoo search algorithm is a meta-heuristic algorithm able to solve optimization problems. The algorithm model the reproductive behavior of female cuckoo's. This bird lay their fertilized eggs in the nests of other host bird to hatch and brood the young cuckoo chicks. If the host bird identifies these unfamiliar eggs it either destroy it or abandon the nest to nest elsewhere. However, for simplicity of this algorithm Yang and Deb in 2009 establish three rule which states: Each cuckoo lay at most one egg at a time in a random chosen nest; The best nest with high-quality eggs will be carried over to the next generation; The number of available host nests is fixed, and the egg laid by a cuckoo may be discovered by the host bird with a probability $p \in (0,1)$ [26-27].

Genetic Algorithm

This is a search-based optimization algorithm which simulate the principle of natural selection and natural genetics. It is based on the principle of Darwinian evolution that consist an initialization method, fitness function to evaluate each chromosome, natural selection, crossover, and mutation operators. It optimize difficult problems where an objective function must be maximized or minimized under given constraints. The procedure is as follows: Population of individuals is generated randomly to represent feasible solutions (chromosomes) to the problem. Every solution is then evaluated by a fitness value depending on the objective function to determine the quality of every potential solution. Individuals are selected based on their fitness value and allowed to pass their genes to a new progeny by crossover. Mutation guarantee diversity in the population and prevent premature convergence. Finally, the algorithm is stopped if the population has converged [28-29].

Dijkstra's Algorithm

The Dijkstra algorithm is a long-familiar shortest path algorithm use to search the shortest path in a directed graph [5]. Hence it is use to solve mobile robot path planning problem. It principle is to expand outward from the start coordinate s to the goal coordinate g , calculate the optimal path costs from s to g through all the free states, and store optimal path from s to g until all states between s to g have been traversed [8].

Theta* Algorithm

Unlike A* algorithm, that finds grid paths and constraints the mobile robot heading to multiples of 45 degrees and result in non-shortest paths, the Theta* algorithm is a any-angle path-planning algorithm that find paths without constraints on the mobile robot headings on the paths [30]. The only difference in the procedure of A* and Theta* is the update vertex function. Compared to A*, the parent of a node in Theta* is an unexpected node as long as there is a line-of-sight between the two nodes.

Shuffled Frog Leaping Algorithm

The shuffled frog leaping algorithm is a bioinspired intelligent optimization algorithm based on frogs' behavior in nature in search of food [31]. It principle consist of initialization, partition, update and shuffle. The procedure is as follows: Generate a random initial frog population within the feasible solution space (frog) and sort the frogs in a descending order according to their fitness. Partition frogs into m memeplexes and each memeplex contains n number of frogs. Update the position of the worst frog with the worst fitness in each memeplex. Re-shuffle all frogs in the population and repeat the partition and update process until the convergence condition is attained [32].

A* Algorithm

The A* algorithm is developed on the basis of the Dijkstra algorithm. But unlike the Dijkstra algorithm the A* algorithm include heuristic information into the path cost function to define a new function; the estimated path cost function. This focus the expansion on the direction of the start coordinate and ring down the total number of state expansions. The estimated path cost function of A* is $f(u) = g(u) + h(u)$ [33]. Where $f(u)$ estimated path cost from start coordinate through free cells to goal coordinate, $h(u)$ is the heuristic function which denotes the estimated path cost from start coordinate to a free cell and $g(u)$ denotes the actual path cost from a free cell to goal coordinate. The heuristic function is expressed as Manhattan, diagonal, or Euclidean distances [5].

Neural Network

Neural network is an intelligent system which compose of a number of interconnected neurons. These neurons receive inputs parameters (signals) from the environment and transfer the signal by their capability of dynamic state response. After the signal is transferred, calculations are performed using an activation function to obtain the output. The neural network architecture consist of the input layer, hidden layers and the output layer of interconnected nodes. The input layer recognize the input signal and communicate to hidden layers for actual processing and the required response is given to the output layer [34-35]. This approach is very useful for mobile robot real-time navigation [36-37].

Firefly Algorithm

It is a nature base swarm intelligence metaheuristics algorithm motivated by the flashing behavior of fireflies [38]. The firefly is a winged beetle; by nature, it has the ability to produce light so it is sometimes called a lightning bug [39]. This process of producing light is known as bioluminescence and the bug use this light to select a mate, communicate a message and sometimes to scare off predator. The principle of firefly comprise of random states and general identification as trial and error of fireflies exist randomly in

nature. Firefly concept is based on attraction between fireflies as a result of difference in light intensity. Hence, fireflies with higher intensity attract the one with lower intensity in a probabilistic manner [40-41]. The movement and light intensity of this bugs are updated and the algorithm can converge to a solution.

Bacterial Foraging Optimization

This is a nature-inspired optimization algorithm which mimics the foraging behavior of *E. coli* bacteria and *M. Xanthus* bacteria. Based on the forage strategy it is applied for mobile robot path planning [42]. Its principle consists of chemotaxis, reproduction, elimination and dispersal [43]. Chemotaxis is the movement (tumble or runs) of these bacterium in reaction to a chemical stimulus and the new position is updated. Reproduction step is taken on the bacteria population for every chemotactic step. Bacteria are sorted in descending order by their nutrient obtained in the previous chemotactic processes. Eliminate-dispersal event happens after reproduction step based on change in temperature or concentration of nutrient [44].

Fuzzy Logic

Fuzzy logic is an intelligent based algorithm with ability to deal with uncertain, complex, and nonlinear data. Its principle is based on human ability to process perception-based information. It uses the human-supplied rules (If-Then) and convert these rules to its mathematical equivalent. Hence, the person who design and the computer get more correct information on how the system perform in the real-world. Fuzzification, Inference engine and Defuzzification are the three steps involve to design a fuzzy system [45]. Fuzzification; a real-valued variable x is map to a fuzzy set form by membership function. All input and output values variables of the system are fuzzified. Inference engine is used to design the rule-base constituted with IF-THEN rules to convert the inputs into output membership functions. Defuzzification; here the fuzzy output variables are converted into a real valued variable, the actual output for the process [45-46].

Ant Colony Optimization

This is a swarm intelligence algorithm inspired by ants' behavior to find shortest path from their colony to a food source [47]. The principle of the approach is that each ant release pheromone on the path it walked as a reference and also perceive pheromone released by other ants while it search for food. This enable the ants to communicate with each other and choose paths. The ant colony will spontaneously move to the path with more pheromone and release more pheromone hence, increase the concentration of pheromone on the shorter path. With increase in pheromone concentrate on the shorter path, more ant choose this shorter path and the pheromone on the other path disappear over time because it abandoned [47-48].

Particle Swarm Optimization

This is a stochastic population based, bio-inspired evolutionary optimization algorithm, based on intelligent social behavior of fish school or bird flocks but does not require a leader within the group to reach the goal [49]. The algorithm consists of a group of particles in a D -dimensional search where each particle represents a potential solution to an optimization problem. This particle is associated with a velocity that adjust dynamically according to its own flight experience, as well as those of its companions. Each particle has memory that allow it keep track of its previous best positions and global best position [50-51].

Machine Learning

Machine learning become a necessity when a machine need to learn and improve its behavior based on its experience within its workspace. Reinforcement learning is an important machine learning method and Q-learning algorithm is the most basic learning algorithm in reinforcement learning [52]. It combines dynamic programming with the knowledge of animal psychology [53]. Q-learning principle is a reward and punishment technique, and also the interaction of the robot with the environment. The robot performs an action in an environment and receives an immediate reward or punishment for the action taken. The Q-value is updated continuously based on the received reward or punishment, hence the states with the highest Q-value are considered as the optimal path for the mobile robot [54-55].

3. MATERIAL METHOD

Research materials on the path planning algorithms discussed in section 2 are sourced from recognize databases beginning from year 2010 on this subject. To retrieve relevant materials from these databases some key words such as: wheel mobile robot, path planning algorithms, mobile robotics, optimization algorithm approach to path planning in WMR and Machine Learning approach to mobile robot path planning are used with Boolean operators in advance search fields. Results are refined to include only research materials that present information on how the proposed algorithm relate to the metrics of interest in this work; these are: architecture (hybrid or standalone), algorithm sub-category (global or local or combine), workspace (static or dynamic), obstacle type (static or dynamic or combine), number of obstacle (≤ 2 , ≤ 5 , > 5) and test workspace (virtual or real-world). In order to do a fair comparison with our statistical method we assigned weight to this metric to create a generic basis for quantitative performance comparison for these algorithms and for further statistical analysis. Table 1 present the weight assigned to these performance metrics.

Table 1. Metrics assigned performance weight

S/N	Metrics	Assigned weight	
1	Architecture	hybrid	1
		standalone	0
2	Algorithm sub-category	global	3
		local	5
3	Workspace	static	3
		dynamic	5
4	Obstacle type	static	3
		dynamic	5
		combine	7
5	Number of obstacle	≤ 2	1
		≤ 5	2
		> 5	5
6	Test workspace	virtual	3
		real-world	7

These metrics are selected base on how researchers have used their proposed algorithms to solve path planning problem for mobile robot and how they present it performance in literature. The materials selected based on the aforementioned metrics from search databases for the path planning algorithms under the three category discussed in section 2 is 114 articles where researchers have applied these algorithms to solve path planning problems for WMR.

4. RESULT AND DISCUSSION

4.1. Result

Table 2 present a categorical data to show quantitative performance of the proposed algorithms based on: architecture, algorithm sub-category, workspace, obstacle type, number of obstacle and test workspace.

Table 2. Performance of proposed path planning algorithms

Author	Algorithm class	Architecture	Algorithm sub-category	Work space	Obstacle Type	No. of obstacles	Test workspace
[16]	Cell Decomposition	1	3	3	3	2	3
[17]		0	5	3	3	5	3
[56]		0	5	3	3	1	7
[57]		1	5	5	5	1	3

[18]	Roadmap Approach	0	5	3	3	1	3
[19]		1	5	3	3	5	3
[58]		0	3	3	3	1	3
[59]		0	5	3	3	2	3
[20]	Potential Field	0	3	3	3	1	3
[21]		0	3	5	3	1	7
[22]		1	5	5	7	2	3
[23]		1	3	3	3	5	3
[60]		0	3	5	3	2	3
[61]		1	5	5	7	5	3
[62]		0	3	3	3	1	3
[63]		0	3	5	7	5	3
[64]	0	3	3	3	5	3	
[24]	Artificial Bee Colony	1	5	3	3	1	7
[25]		0	5	3	5	2	3
[26]	Cuckoo Search Algorithm	0	3	3	3	5	3
[27]		1	3	3	3	5	3
[9]	Genetic Algorithm	0	5	3	3	5	3
[28]		0	3	3	3	5	3
[29]		0	3	3	3	1	3
[65]		1	3	3	7	5	7
[66]		0	3	3	3	1	3
[67]		0	5	5	7	5	3
[68]		0	3	3	3	5	7
[69]		0	3	5	7	5	7
[70]		0	3	5	3	2	7
[71]		0	3	5	3	5	3
[72]		0	3	5	3	5	3
[73]		1	5	3	3	5	3
[5]		Dijkstra's Algorithm	0	3	3	3	1
[8]	1		5	5	7	5	3
[74]	1		5	5	7	5	3
[30]	Theta* Algorithm	0	3	3	3	1	3
[75]		0	3	3	3	1	3
[31]	Shuffled Frog Leaping Algorithm	0	5	3	3	2	3
[32]		0	5	5	3	5	3
[33]	A* Algorithm	0	3	3	3	1	3
[34]	Neural Network	1	3	3	3	1	3
[35]		0	5	3	3	1	7
[36]		0	3	3	3	1	7
[37]		1	3	3	3	5	7
[76]		0	3	3	3	2	3
[77]		0	3	3	3	2	3
[38]	Firefly Algorithm	0	3	5	3	5	3
[39]		0	3	3	3	5	7
[40]		0	3	5	3	1	3
[41]		0	5	5	7	5	7
[78]		0	3	5	3	2	7
[42]	Bacterial Foraging Optimization	0	3	3	3	5	3
[43]		0	3	3	3	5	3
[44]		0	5	5	7	5	3
[79]		0	5	5	7	5	3
[45]	Fuzzy Logic	0	5	3	7	2	7
[46]		1	3	3	3	1	3
[80]		0	3	3	3	5	3
[81]		0	3	3	3	1	3
[82]		1	3	5	7	5	3

[83]		1	3	5	3	5	3
[84]		1	3	3	3	2	7
[85]		0	3	3	7	5	7
[86]		0	3	5	3	2	7
[87]		0	3	5	3	5	3
[88]		0	5	5	7	2	3
[89]		1	3	3	3	2	7
[47]	Ant Colony Optimization	0	3	3	3	1	3
[48]		0	5	3	3	5	3
[90]		0	3	3	3	5	7
[91]		0	3	3	3	5	3
[92]		0	3	3	3	1	3
[93]		0	3	3	3	5	3
[94]		0	3	3	3	5	3
[95]		0	3	3	3	5	7
[96]		1	5	5	3	5	3
[97]		0	5	5	3	1	3
[98]	1	3	3	3	2	3	
[15]	Particle Swarm Optimization	0	3	3	3	2	7
[19]		1	5	3	3	5	3
[49]		0	3	3	3	5	3
[50]		0	3	3	3	5	7
[51]		1	3	3	3	5	7
[99]		0	3	3	3	5	3
[100]		1	5	5	5	5	3
[101]		1	3	5	3	2	3
[102]		0	3	3	3	5	3
[103]		0	5	5	7	2	3
[104]		0	3	3	3	5	3
[105]		0	3	3	3	2	3
[106]		1	5	3	3	5	7
[107]		1	5	3	3	5	7
[108]		1	3	3	3	5	3
[109]	0	3	5	3	5	3	
[52]	Q-Learning Algorithm	1	5	3	3	5	3
[53]		0	3	3	3	1	3
[54]		1	5	3	3	5	3
[55]		1	5	3	3	5	3
[110]		0	5	5	3	1	3
[111]		0	5	5	7	5	7
[112]		0	5	3	3	1	7
[113]		1	5	3	3	5	3
[114]		0	5	3	3	1	3
[115]		0	5	5	7	5	7
[116]		1	5	5	7	5	3
[117]		0	5	5	3	5	7
[118]		0	3	3	3	5	3
[119]		1	3	3	3	2	3
[120]		0	5	5	7	5	3
[121]		1	5	5	3	5	3
[122]		1	5	5	7	2	3
[123]	1	5	5	7	5	7	
[124]	1	5	5	7	5	7	

Architecture: Hybrid (with heuristics or intelligent algorithm) =1, Standalone = 0; Algorithm sub-category: Global = 3, Local = 5; Workspace: Static =3, Dynamic = 5; Obstacle type: Static = 3, Dynamic = 5, combine = 7; Number of obstacle: $\leq 2 = 1$, $\leq 5 = 2$, $> 5 = 5$; Test workspace: Virtual = 3, real-world =7.

4.2. Discussion

The real-world workspace is unpredictable, dynamic with many obstacles; static and dynamic. This is the characteristic of workspaces where WMR are deployed and often proposed to be deployed. Hence, a robust path planning algorithm should guide the WMR through such workspaces. Based on the evidence found in the research articles cited, presented in Table 2. Tables 3 and 4 present number of paper in the reviewed category for path planning algorithms as standalone architecture or hybrid architecture.

Table 3. Number of paper in the reviewed category for path planning algorithms as standalone

Category	Architecture: Standalone	Compare metric									
		Algorithm sub-category		Workspace		Obstacle type			No. of Obstacles		
		Global	Local	Static	Dynamic	Static	Dynamic	Combine	≤ 2	≤ 5	> 5
Classical Algorithm	11	4	7	8	3	10	0	1	6	2	3
Heuristics and Intelligent Algorithms	56	42	14	38	18	46	1	9	13	12	31
Machine Learning	9	2	7	4	5	6	0	3	4	0	5

Table 4. Number of paper in the reviewed category for path planning algorithms as hybrid

Category	Architecture: Hybrid	Compare metric									
		Algorithm sub-category		Workspace		Obstacle type			No. of Obstacles		
		Global	Local	Static	Dynamic	Static	Dynamic	Combine	≤ 2	≤ 5	> 5
Classical Algorithm	6	2	4	3	3	3	1	2	1	2	3
Heuristics and Intelligent Algorithms	22	13	9	15	7	17	1	4	3	4	15
Machine Learning	10	1	9	5	5	6	0	4	0	2	8

Equation (1) is used to determine the percentage success of paper in the reviewed category:

$$\text{Percentage Success} = \left(\frac{\text{Compare metrics Number of papers}}{\text{Algorithm category Architecture Number of papers}} \right) \% . \quad (1)$$

The result of Equation (1) with data from Tables 2 and 3 is presented in Figures 1 and 2 and Table 5. From Figures 1 and 2 Q-learning algorithm has found more success as standalone or hybrid; for local algorithm, in dynamic workspace, for combine obstacle type, and number of obstacles > 5 than classical algorithms or heuristics and intelligent algorithms.

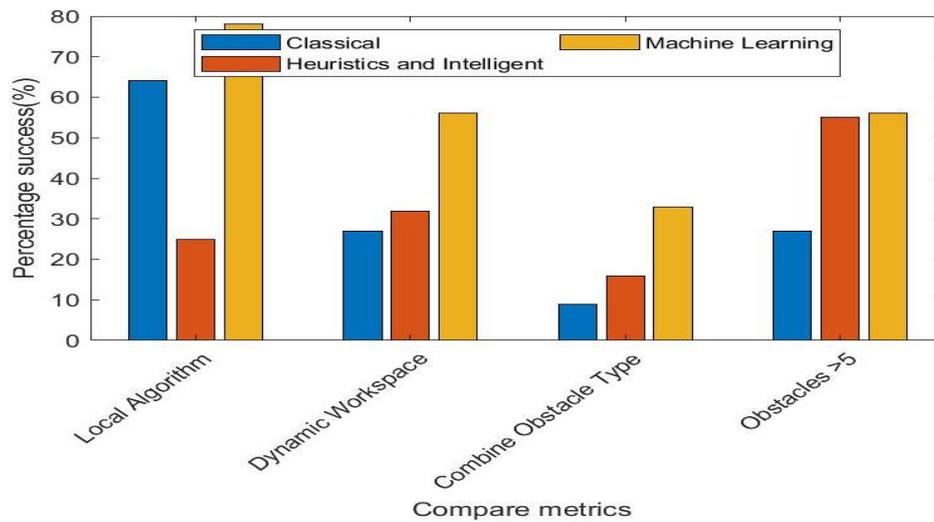


Figure 1. Algorithm percentage success on four performance metric as standalone

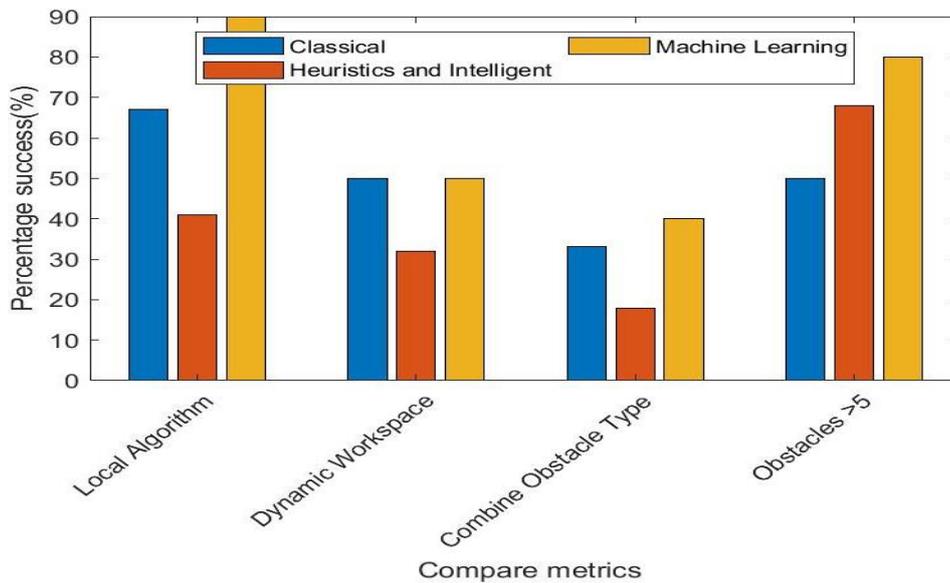


Figure 2. Algorithm percentage success on four performance metric as hybrid

Q-learning algorithm possess this advantage over other algorithms because it does not require the model of the workspace and the WMR can learn as it interacts with the workspace [55, 117]. But classical algorithms require a comprehensive model of it proposed workspace; and as reported in Table 5, as standalone in cited literature; 63.64 % paper record it success as global path planning algorithm with 72.73 % of this research successful in static workspace. This class of algorithms also surfer some drawbacks like local minimum problem and excessive computational time [15]. Although researchers had attempt to solve these problems through it hybrid architecture and this improve it record percentage success as local algorithm in dynamic workspace (see Table 5).

Table 5. Percentage success comparison of the reviewed category for path planning algorithms as hybrid and standalone

Metric		Hybrid			Standalone		
		Classical Algorithm	Heuristics and Intelligent Algorithms	Machine Learning	Classical Algorithm	Heuristics and Intelligent Algorithms	Machine Learning
Algorithm sub-category	<i>Global</i>	33.33	53.57	10.00	63.64	75.00	22.22
	<i>Local</i>	66.67	46.43	90.00	36.36	25.00	77.78
Workspace	<i>Static</i>	50.00	64.29	50.00	72.73	67.86	44.44
	<i>Dynamic</i>	50.00	35.71	50.00	27.27	32.14	55.56
Obstacle type	<i>Static</i>	50.00	71.43	60.00	90.91	82.14	66.67
	<i>Dynamic</i>	16.67	7.14	0.00	0.00	1.79	0.00
	<i>Combine</i>	33.33	21.43	40.00	9.09	16.07	33.33
No. of obstacles	≤ 2	16.67	14.29	0.00	54.55	23.21	44.44
	≤ 5	33.33	21.43	20.00	18.18	21.43	0.00
	> 5	50.00	64.29	80.00	27.27	55.36	55.56

Heuristics and intelligent algorithms possess some level of intelligence. However, from Table 5 as standalone only 25 % paper record it success as local algorithm with 32.14 % success in dynamic workspace and 55.36 % paper record it success in workspace with obstacle number > 5 . Although they are applied to unpredictable workspace because they can handle uncertainty of such workspace. However, with large workspace they are faced with challenges such as: computational time, complex design, learning phase and large memory space.

Path planning algorithm seems to improve as hybrid architecture. Hence, using Equation (2), Table 5 present percentage success difference for heuristics and intelligent and Q-learning algorithm from standalone architecture to hybrid architecture

$$P_d = \frac{[V_1 - V_2]}{\left[\frac{V_1 + V_2}{2} \right]} \times 100 \quad (2)$$

where P_d is percentage difference, V_1 and V_2 is standalone value and hybrid value (values from Table 5).

Table 6. Percentage success difference for heuristics and intelligent and Q-learning algorithm from standalone architecture to hybrid architecture

Metric		Heuristics and Intelligent Algorithms	Q-learning algorithm
Algorithm sub-category	<i>Global</i>	33.34	75.85
	<i>Local</i>	-60.00	-14.57
Workspace	<i>Static</i>	5.41	-11.76
	<i>Dynamic</i>	-10.53	10.53
Obstacle type	<i>Static</i>	13.95	10.53
	<i>Dynamic</i>	-120.00	0.00
	<i>Combine</i>	-28.57	-18.18
No. of obstacles	≤ 2	47.62	200.00
	≤ 5	0.00	-200.00
	> 5	-14.93	-36.07

Table 6 show that Q-learning improved more on most compare metric from standalone architecture to hybrid architecture except for number of obstacle metric (≤ 5 and > 5) where hybrid heuristics and intelligent algorithms performed better. Although, the Q-learning algorithm perform better as shown, it exhibits slow convergence to the optimal solution in dynamic workspace because it is a more complex problem with several number of states. Thus with more state, to train an intelligent WMR become a challenge in real-world workspace. Therefore, at least 70 % of researcher present their test in virtual workspace as depicted in Figure 3.

To address this problem, the predominate heuristics and intelligent algorithm combined with Q-learning is PSO [54, 124], fuzzy logic [119], neural network [55, 122], artificial neural network [116] and firefly algorithm [55] to speed up it convergence rate.

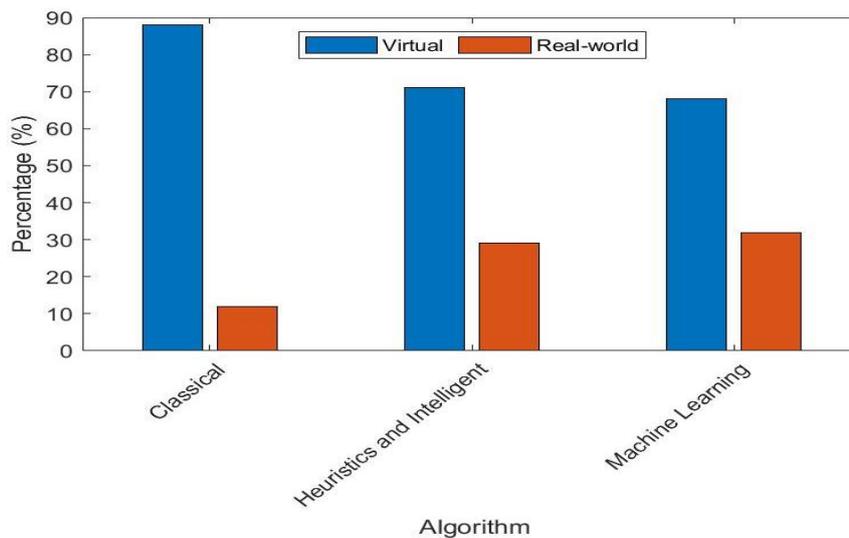


Figure 3. Comparison of Test workspace for algorithms

5. CONCLUSION

This paper present's a quantitative performance review on classical, heuristics and intelligent and machine learning category of path planning algorithms for WMR. We applied statistical method and evaluate these algorithm categories based on these metrics: architecture, algorithm sub-category, workspace, obstacle type, number of obstacle and test workspace. The following outcome are presented:

- Classical algorithms are suited as global path planning in small static workspace.
- Papers that present test on virtual workspace for the algorithm categories review within the last decade are predominant.
- The particle swarm optimization, fuzzy logic and genetic algorithm are the common applied heuristic and intelligent algorithm within the last decade.
- Algorithm performance is enhanced as hybrid compared to standalone
- Hybrid of Q-learning approach has superior performance where they are applied compare to heuristics and intelligent algorithm hybrid.
- Q-learning algorithm found more success as standalone or hybrid; for local algorithm, in dynamic workspace, for combine obstacle type, and number of obstacles > 5 than classical algorithms, heuristics and intelligent algorithms.
- PSO, fuzzy logic, neural network, artificial neural network, and firefly algorithm, are commonly used in literature as hybrid to improve the convergence to the optimal solution in dynamic workspace for Q-learning in the last decade.

- Improve heuristic and intelligent algorithms such as Artificial Bee Colony algorithm [125, 126], Cuckoo Search [127,128], Shuffled Frog Leaping [129,130] reported to have achieved good results in 3D workspace should be researched on how to develop it hybrid with Q-learning to solve WMR path planning problem in complex 2D workspace.

CONFLICTS OF INTEREST

No conflict of interest was declared by the authors.

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