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Path Planning Methods for Mobile Robots: A systematic and Bibliometric Review

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Abstract: Robots are currently replacing humans in different tasks in various sectors. Among the vital features desirable in autonomous robots is the capability of navigating safely through a given environment. Robot navigation is a process designed with the ability of avoiding any hitches or obstacles while aiming at a specific predefined position. Many studies have been proposed to find solutions to robot path-planning problems. This paper presents a survey of the heuristic and classical path-planning approaches. Focal strengths, together with the weaknesses of these approaches, were also identified to provide deep insight for future studies. As several literature studies have recommended, classical methods might not be effective in real-time applications as a result of their failure to confront the unpredictable nature of the real-world. They require a considerable amount of computation and space, while heuristic-based methods can overcome real-world problems with some modifications. To summarize the research progress and also suggest future directions of path-planning research, this study performs a bibliometric analysis of the relevant publications published from 2000 to 2020. The results show that 5385 articles were published in 1128 journals, hence indicating publication diversity. There is a steady rise in the yearly publication output, reflecting an increase in global research interest in the topic. In general, this research provides useful insight into path-planning research so that researchers in this area can better recognize the relevant research study topics and search for the appropriate research partners.

Keywords: Bibliometric, Path planning,

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INTRODUCTION

The major emphasis in the field of autonomous control is the need for path planning. There is increased attention in the scientific community to enhance the knowledge of automation systems for different applications, such as chemically polluted or harmful locations [1]. Robotic path planning is an appealing research study in the field of robotics [2]. Since mobile robotics are used in a vast array of applications, numerous researchers have been working on various approaches in order to conquer a few of the significant challenges faced in autonomous navigation. These challenges restrict its usage in many applications, including industrial and military fields [3].

1.1 Path planning

Robot path planning is the process of finding an enhanced collision-free path from a start to a predefined goal point through a certain given cluttered real world environment within the shortest possible time [4], [5]. Siegwart and Nourbakhsh [6] identified path planning as defining a trajectory through a map with which a robotic can reach a known goal point from its starting place while avoiding obstacles.

The four integral path planning components that made up the navigation problem are: Perception, localization, motion control and path planning [7]. Figure 1 below shows the four integral parts of robot navigation problem. Localization as well as path planning are necessary components in navigating of mobile robots.

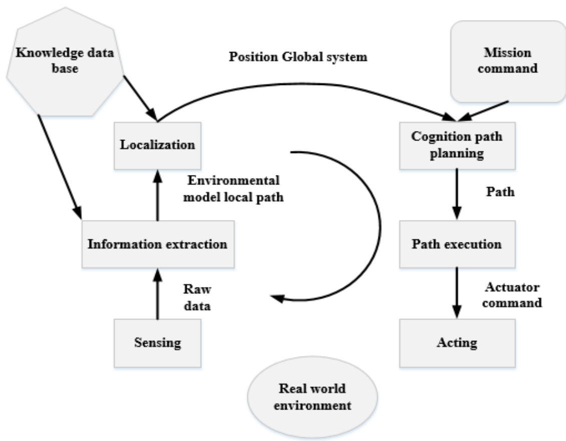

Figure 1: Parts of robot navigation problem [6]

Path planning is a major problem in robotics since its intricacy increases tremendously with the dimension of the configuration area. The configuration area is defined as the space that a physical system might attain relative to the environmental constraints. Choset et al. [8] define it as the space of all arrangements that a robotic can reach.

Path planning algorithms have actually been explained in detail by several authors in the fields of Artificial Intelligence [9], autonomous system [10], [11], as well as computer science [12]. it is required that the path planning algorithm can navigate and re-plan in the presence of unseen constraints in a repetitive way till it reaches its goal [13]. Autonomous robots do not require any kind of human manager to remotely control their activities. Path planning of mobile robots depends substantially on information about the environment [10].

Path-planning algorithms are evaluated based upon the following concerns [9]: Completeness, Optimality and Time intricacy. For successful path planning in a dynamic environment, path re-plan is inevitable, as such, the computational time needed must be less since more time is needed to readjust its motion. For that reason, time intricacy of the algorithm is considered to gauge its computational performance.

1.1 Bibliometric analysis

Bibliometric analyses, defined by Pritchard [14], is the application of mathematical and statistical methods to books and other means of communication. Bibliometric analysis has actually been used to systematically evaluate the progress of a details scientific field [15]. It has been used to review the distribution patterns of authors, journals, institutions, key phrases, topics, development patterns, as well as predict future research directions based on the search engine result. Bibliometric analysis has ended up being an important tool to measure the scientific progress in numerous fields [16].

There has been little effort made on the systematically review in path planning studies and in order to show the growth of the path planning, this article aims to analyze and visualize the existing path planning articles published with details such as the publication chronological distributions, the most appropriate scientific journals, and the popular key word phrases. Using " robot path planning " as the major key phrase, we determined over 14000 articles prior to being categorized into 5385 main related articles. All these are taken mainly from the Web of Science Core Collection. With the selected 5285 articles, we did an analysis by creating the connection between the abstract, title, publication, citation, research study area, geographical allocation and also the keyword phrases used. Through bibliometric co-citation, analysis of literature, this article fills the research gap on robot path planning review

1.2 Contribution and organization of the paper

The major contribution of this survey are as follows:

- The robot path planning approaches were discussed which are categorized into two main classes: Classical and Heuristics.
- We present the advantages and drawbacks of these approaches
- We present a bibliometric analysis on the path planning articles published between the year 2000 and 2020.

The main aim of this survey paper is to represent the path planning approaches used in the field of robotics. These approaches are designed with the ability to avoid any hitch or obstacles to aim a certain position. We perform a bibliometric analysis aiming to answers the following questions

- How are path planning articles clustered?
- What are future path planning research questions that provide opportunities to further the role of robot path planning?
- Which channels (journals, articles, and countries) arse the most influential in Path planning?

Finally, this paper discusses the patterns by summarizing the substantial research study and highlighting possible future tracks robot path planning.

The rest of the article is organized as follows: section II provides a detailed description of the different path-planning strategies. In section III discuss the research gab by describes the challenges and strength of the proposed path planning approaches. section IV and V describes the Bibliometric methods and results respectively. Finally, section VI concludes the survey.

PATH PLANNING TECHNIQUES

Depending on the data received from the environment, path planning approaches are categorized into: Global and Local path planning Qin et al. [17]: Planning in a well-known environment is termed as global path planning, whereas path planning in a partially known or unknown environment is identified as Local path planning. It is also classified as off-line or static path planning and as online or dynamic path planning based on the characteristics of the obstacles in the environments. If the path is a predefined choice in the case of stationary obstacles, then the planning is termed offline (static) path planning. Online (dynamic) path planning is situation whereby the path choice is made when the obstacles are moving [18]. In different situations, both of these approaches have their pros and cons. Global and local path planning uses these methods to determine an optimal path for the robot in a given environment. Global path planner produces lesser degree plan of the environment while Local path planner generates a higher degree plan of the environment [19], [20]. Several algorithms have been established over the last few years to produce real time path planning system for autonomous robots both static as and dynamic environment. These can be either belonging to the classical or heuristic (intelligent) methods [21-24]. The difference being intelligent algorithms make use of meta-heuristics, changing conditional guidelines, to enhance a preliminary solution.

The methods used in in solving path planning problems have been categorized by Masehian and Sedighizadeh [25] into classical and heuristic-based.

Classic algorithms in comparison only utilize heuristics, conditional guidelines, to limit the application of the base algorithm. Each technique has both advantages and disadvantages. they are differentiated based on how the algorithm interprets the environment. The classic approaches suffer from numerous negative aspects, such as computational intricacy and local minima, which proves them to be ineffective in practice [25] As a result, the application of the heuristic strategies was extended due to their achievement in attending to such problems [26]. The authors in [24] stated that classical algorithms discover optimum solution if one exists while heuristic based methods search for solution with good quality in lesser time. However, classical algorithms need higher amount of calculations to be done while heuristic-based methods might not be reputable in complex problems as a result of their failure to discover good results in many cases [24]. Figure 2 shows the major path planning algorithm classification. In the following sub sections, a review of some of these methods have been presented.

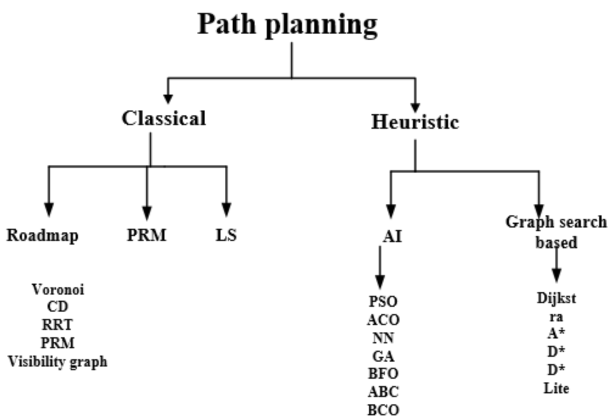

Figure 2. Path planning taxonomy

1.1 Heuristic methods

As pointed out previously, a navigation problem is influenced by the precision of the map and localization strategy. The dynamic as well as unpredictable nature of the real-world applications frequently makes the navigation task challenging. This is due to the fact that in such scenarios the map is not reliable [27]. The Heuristic path planning techniques, emerges recently when compared to the Classical methods which have actually obtained a lot of relevance because of their human like behavior-based characteristics. Several of the prominent methods of this class includes: Artificial Neural Network (ANN), Genetic Algorithms (GA), Particle Swarm Optimization (PSO), Ant Colony Optimization (ACO), Wavelet, Fuzzy Logic (FL) and Tabu Search (TS) [28]. These approaches are known as population-based or behavior-based in some literatures [29], [30]

Cheng and Zelinsky [31] recommended making use of behavioral-based strategies to resolve real world environment constraint. In behavioral-based approaches a set of straightforward, predefined behaviors would certainly be created in a manner to address complicated situations. Despite the fact that these techniques are reliable in dynamic environments, they still have difficulties with unpredictability.

2.1.1 Artificial Intelligent Methods

- *Neural Network (NN)*

NN has been widely made use of in search optimization, discovering, as well as pattern recognition problems as a result of its capability to provide an ideal solution. The use of easy processing elements which resembles the brains neurons is the basic aspect of ANN [27]. The total operational characteristics of the network would certainly be defined based upon the possible and also the nature of neurons' interconnections. The NN-based methods can be classified based upon different aspects:

- The arrangement of their layers: Single Layer, Multi-Layer, Competitive Layer.

- Their training technique: Supervised training unsupervised training, Fixed weights (no training), and also Self supervised training [27]. The idea of using Neural Networks path planning was first utilized in [32]. Path planning problem is addressed in [33] using Hopfield neural networks in a fuzzified environment. D. janglova [34] proposed a collision-free path built based on the two neural networks theorems shown in figure 2 and 3 respectively; Principal component analysis (PCA) and a multilayer perceptron (MLP).

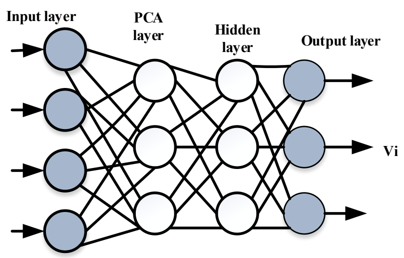

Figure 2: PCA Topology

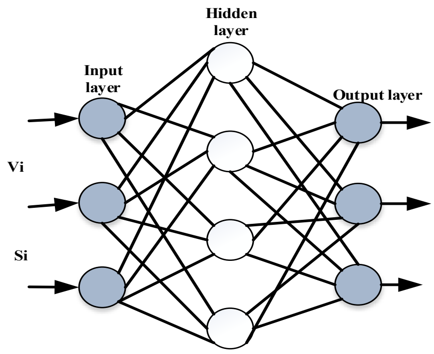

Figure 3: MLP Topology

Zou et al. [35] categorized using NN in robot navigating to 3 groups (Translating the sensory data, Obstacle avoidance, and Path planning) and also recommended that the hybrid approaches that uses variations of NN with other Artificial Intelligent based methods such as fuzzy logic, knowledge-based systems, and also evolutionary approaches are more appropriate for dealing with the robot navigating issue in real-world applications [35]. An NN technique is presented in [36] for dynamic task assignment of multi robots. Ultimately, RL-ART2 NN-based mobile robot path planning is developed in 2007 in [37]. Yangmin and also Xin [38] made use a hybrid of Particle Swarm Optimization (PSO) and adaptive NN in a mobile robotic navigating application. In their study, PSO is made use of as the path planner with the purpose of supplying a smooth trajectory for the adaptive NN controller that drives the mobile robotic towards the destination without collision. Pugh and Martinoli [39] utilized a single-layer discrete-time ANN as controller of a heterogeneous robotic swarm in parallel multi robot learning with obstacle avoidance [29]. M. K. Singh et al. [40], [41] proposed Neural network algorithm which allows movement of the robot in either a known or unknown environment. The input to the NN consist of the left obstacle distance (LOD), front obstacle distance (FOD) and right obstacle distance (ROD). The input, target (TA) and the output made up the robot steering angle as shown in Figure 4

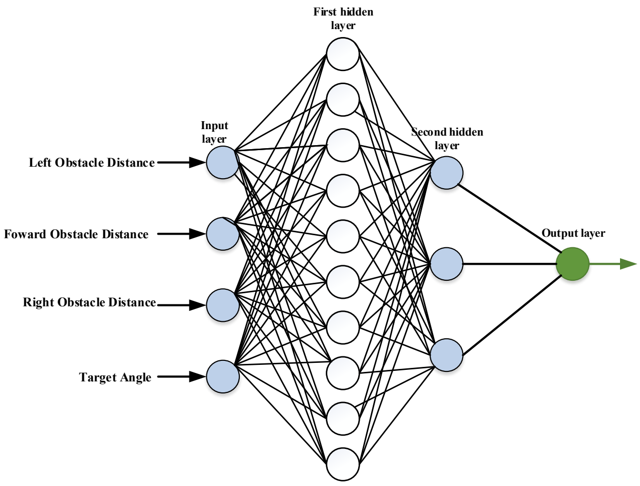

Figure 4: NN robot path planning [40]

- *Fuzzy Logic (FL)*

The principle of fuzzy sets was first proposed by Zadeh [42] in 1965. This technique has vast application in the robot path planning as it offers a formal strategy for representing as well as executing the human experts' heuristic knowledge and perception-based actions. The method of a Fuzzy Logic controller(FLC) is extremely helpful in handling real life unpredictability without the need of an absolute model of the environment [43]. A path planner based on Fuzzy logic and also filter smoothing in a dynamic environment is implemented on a mobile robot in [44]. A FLC for an Unmanned Aerial Vehicle(UAV) in a 2-D space is presented in [45].

Fuzzy MP with the Takagi-Sugeno method was presented in [46]. An algorithm on the basis of NN and FL for RMP is created in [47]. The path planning problems is solved in [33] using Hopfield NN in a fuzzified environment. A hybrid algorithm utilizing Fuzzy logic as well as genetic algorithm was for path planning of a mobile robot in [48]. The GA was utilized to modify the input as well as outcome membership function for the FLC. A path planning approach for humanoid robotics based on Fuzzy Markov Decision Process (FMDP) is proposed in [49]. The suggested method is concentrated on the issue of unavailability of extensive sensory details of the environment.

A technique on the basis of FL is introduced in [50] for an unknown environment. A Prune-able unclear ART neural design for robot map discovering and also navigating in dynamic atmospheres is established in [51] Lately, a Fuzzy-Logic-Based method for mobile robotic course monitoring is demonstrated in [52].

- *Particle Swarm Optimization (PSO)*

Particle Swarm Optimization (PSO) is a population-based algorithm motivated from animals' social behaviors that favors global optimum. It was invented by Kennedy and Eberhart in 1995 while attempting to imitate the choreographed, elegant motion of swarms of birds as part of a socio cognitive research study investigating the idea of "collective intelligence" in biological populaces. In PSO, a collection of randomly generated solutions propagates in the layout space in the direction of the ideal solution over certain iterations based on huge amount of details about the design space that is assimilated and also shared by all members of the flock. PSO is inspired by the capacity of flocks of birds, school of fish, and herds of animals to adapt to their environment, locate food, as well as stay clear of predators by implementing a " data sharing" approach, hence, establishing an evolutionary advantage [53].

PSO is more favorable in handling as it considers the particles to be real numbers without the need for encoding to binary as with GA. The experiences gathered from the individual particle's social experience is used with their internal velocity in updating themselves. First, the generations are updated based on their optimal layout after some random solutions. The target location is determined by changing the search particles to a promising area [54]. The performance status is evaluated through the fitness function. The PSO position update of particle j in i iterations is illustrated in figure 5.

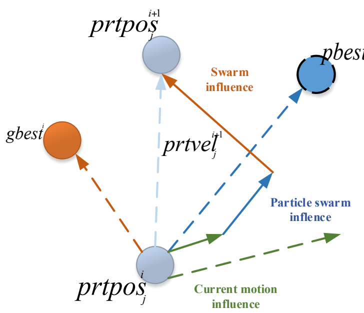

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Figure 5. Depiction of a particles position update in PSO [54]

[55] presents a negative Particle swarm optimization (NPSO), later on, the use of the NPSO was employed and use in robot motion planning application as proposed in [54]. In NPSO, the particles determine an optimal value by updating its position in the opposite direction to its own previous and group previous worst positions. The worst position using these process is avoided. This is shown in figure 6

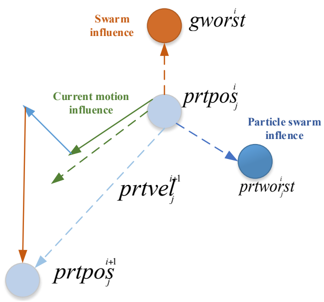

Figure 6: Depiction of a particles position update in NPSO [55]

In basic PSO particles are specified based on their placement and also their velocity in the search space.

Particles get attracted toward positions in the search room that represent their best individual findings and also the swarm's best finding [56]. The particles in the swarm update their positions in the search space by adding their updated velocity to their last place in the search space. PSO has weak points in regards to: controlling parameter, premature convergence, and lack of dynamic speed modification which causes the inability to hill-climb solutions [57], [58]. To resolve the problem of controlling parameters various modifications are suggested. As a result of PSO possibility in solving intricate problems it has actually been extensively made use of in numerous situations as well as domains. Qin et al. [59] pointed out easier implementation and fewer parameters as the main benefits of PSO contrasted to GA.

In many research studies, PSO has actually been revealed to do in addition to or better than GA [60-64]. Modified versions of PSO are made use of in path planning, path search, and navigation. In [65] a modified variation of PSO that having advantage of mutation factor is used for path planning. In [66] a mutation-based PSO is introduced to handle the conveying jobs. Pugh et al. [63], [64] used regional community variation of PSO in multi-robot search optimization problem in which the PSO technique surpassed GA. In [67] a customized variation of PSO called DEADALUS is utilized for resolving cul de sac problem of robotics in obstacle evasion situations. An algorithm for path preparation for mobile robot using PSO with mutation operator is presented in [68]. In 2005, a technique for obstacle avoidance with multi-objective optimization by PSO in dynamic atmosphere was developed in [69]. Likewise, an algorithm is established in [70] for robot path planning making use of PSO of Ferguson Splines. Obstacle avoidance path preparation for football robots using PSO has been extended in [71]. Ultimately, a smooth path planning of a mobile robot using Stochastic PSO is implemented in [72].

In [73] PSO is utilized in an obstacle evasion situation in which robotics are implied to navigate between static and dynamic obstacles. The study suggested a stream function called Potential flow as obstacle evasion technique. In [74-77]. Area Extension PSO (AEPSO) as well as Cooperative AEPSO (CAEPSO) are employed to navigate swarm of robotics in dynamic and static environments. AEPSO as well as CAEPSO take advantage from macro scoping modeling of PSO in addition to added heuristics that use principles such as reinforcement and cooperative learning. Despite the fact that PSO is extensively used by various path planning as well as navigation circumstances, conceptually, these attempts do not present substantial difference from the basic PSO. It is due to the fact that these researches main investigation is concentrated on upgrading the velocity parameters aiming to attain far better as well as quicker convergence. Although several attempts have been made to solve basic PSO problems, a lot of the proposed solutions are not reliable in real-world and also dynamic environments. Moreover, majority of these methods do not have the domain generality [27].

PSO is used in UAVs to in finding an optimized and obstacle free path. This algorithm has been used by authors in [78- 81] for planning a trajectory path between a start and goal point within the shortest possible time.

A self-adapting learning PSO, was proposed by Li et al. [82] the path navigation was achieved using two methods. The navigation in a clustered environment while avoidance obstacles in am effectively smooth way was achieved by using a minimization multi-objective optimization. Lastly, the self-adaptive learning mechanism was adapted by the PSO in a more complex environment to improve the searchability. A hybrid of PSO and gravitational search algorithm (IGSA) algorithm was proposed by Das et al. [83]. This algorithm is used with multiple robots to find an optimal path in a complex environment

- *Ant Colony Optimization (ACO)*

The very first ACO algorithm called the ANT System is introduced by Marco et al. [84]. ACO method is influenced from ants' social habits and imitates the cumulative habits of ants foraging from a nest towards a food resource in order to locate an optimum in the search area [61] Ants use a chemical compound called pheromone to mark the taken routes. This helps them to track the path. The quality of a path would be analyzed based on the quantity of pheromones left by ants that passed from that path using percentage and concentration. Proportion and concentration of the pheromones indicate the length of path and the number of ants passing through that route respectively. Ants select paths with highest possible chance of proportion to the concentration of the pheromone [85].

In [86] an optimum path planning for mobile robotics based upon intensified ACO algorithm is created. Likewise, in 2004, ACO was made use of to plan the optimal path [87]. ACRMP is presented in [88]. A RMP utilizing ACO is introduced in [89].

Lucas and Guettier [90] utilized ACO in hybrid with Constraints Programming in dynamically adopting vehicle with the contribution of having dramatically faster search exploration while maintaining the optimality of the solution. Zhang et al. [91] utilized the mix of ACO, Substitute Annealing (SA), and also framed-quad tree in order to boost the path planning efficiency. In the study, ACO is made use of to give better initial solution for SA while framed quad tree is made use of to improve the disintegrated effectiveness of the atmosphere. The attained performance from SA indicates the potential of the suggested crossbreed technique in regards to offering collision free path courses with boosted navigation time. Lee et al. [92] took on the global path planning problem by proposing a heterogeneous ACO strategy that modifies the conventional ACO utilizing Transition Probability Function (TPF) with Path Crossover (PC) as well as pheromone Update. The recommended strategy out-performed GA in simulated sinarious by giving smoother path. Hao et al. [85] utilized ACO in crossbreed with Artificial PF (APF). The suggestion is to make use of ACO as a global path preparation as well as APF as local path planning methods. The teamwork between ACO and APF is based upon using pheromone trajectory of ACO in APF to stay clear of local minima in the multi robotic path planning scenario. McLurkin and also Yamins [93] recommended 4 algorithms and compare them in role changing in between robotic members of a swarm in a dynamic environment. Shi et al., [94] recommended the hybrid of ACO and also PSO formulas in a robotic path planning problem. In their study, ACO is used for paths planning gin robots transitable region and PSO role is to enhance the parameter of ACO. Typical ACO has some constraints such as needing a long period of time to reach to local minimum if the size of the problem is big. In traditional ACO, the pheromone concentrations of all aspects are equally initialized. So the solutions are created blindly at the evolutionary stage and it takes a very long time to find a much better path from a great number of smoother path. [27].

- *Genetic Algorithm (GA)*

GA is an optimization tool that is most commonly used to create premium quality solutions for combination optimization issues and search problems. The GA is inspired from the procedure of natural selection as well as relies on evolutionary operators like mutation, crossover as well as selection. The GA starts without understanding of correct solution as well as totally relies on the reactions of the environment as well as the above stated evolutionary operators and reach the best solution [95]. GA use natural characteristics such as: selection, crossover and mutation characteristics to solve combination optimization problems. GA is efficiently applied to issues such as the classical travelling salesman problem, flow-shop optimization, and also job shop scheduling in which the purpose is to either enhance or locate the very best option out of a number of possibilities [96]. The inherently parallel search attribute of the GA makes it attractive for establishing near-optimal solutions [24].

Selection is the operation of ranking chromosomes based upon their fitness (below, physical fitness describes chromosomes ranges from objective) and also sub-selecting high ranked chromosomes (those that stand for shorter or smoother paths) for generating new populace. Crossover is the procedure made use of for generating brand-new population from the sub-selected chromosomes by selection operator. Normally, the crossover operator divides the sub-selected chromosomes into two components and exchanges their parts with each other in order to produce the brand-new populace. Mutation is the operation in which one or a group of chromosomes are picked to be totally or partly randomized. It is typical to utilize mutation operator whenever the population is converged toward local optimum, entrapped in between barriers, or the efficiency is not enhanced for a number of generations due to the absence of genetic variety. Elitism is the act of preserving (duplicating) the very best chromosome from each generation.

Various research studies have been done based on utilizing GA in path planning domain. The concept of using genetic algorithms for RMP was first used in [97], [98]. The application of GA to the mobile robotic path preparation problem calls for the advancement of an appropriate 'chromosome' representation of the path, a path assistance mechanism, a method to provide for obstacle avoidance, as well as a suitable constraint definition providing mechanism to minimize path distance, along with offering smooth paths. It is assumed that the setting is fixed and known. For the objective of representing the workspace is discretized in bit-map form with the barriers offering coloring to help the obstacle evasion [53]. In [99], a GA based path planning algorithm is suggested in which chromosome has a variable length. A global path planner based upon GA is proposed in [100]. In the proposed method, the length of the binary strings is reduced by projecting 2D coordinates of points in the workspace into one 1D. In [101], GA is utilized in a dynamic multi-cast transmitting scenario, [102], [64] utilized GA in multi path planning scenarios. Sadati and Taheri [103] use a hybrid of Hopfield neural network and GA in a path planning problem. Ergezer and Leblebicioglu [104] utilized a customized GA for path planning for UAVs intending to generate paths that optimize collected info from regions of interests while avoiding prohibited areas. In a similar study, Xiao-ting et al. [105] investigated the capacity of an improved version of GA in flight path planning for UAVs highlighting the GAs capacity to attain global optima via improving both local and global search. The proposed modification is concentrated on diversifying the GA's population making use of dual-population concept [105]
Zein-Sabatto constructed a numerous path planning for a team of mobile robots in a 3D atmosphere utilizing GA [106]. A unique GA searching approach for dynamic constrained multicast movement is developed in [99]. Likewise, in [107], an Identical GA is made use of for search and also constricted multi objective optimization. An optimal path planning for mobile robotics based on a Crossbreed GA has been expanded in [108].

Cheng et al. [109] counted advantages such as ability to supply sub-optimum solution without calling for full understanding of the problem domain in addition to be computationally much less intensive for GA as path planner for unmanned underwater lorries over linear and Dynamic programing strategies. Elshamli et al., [24] utilized an enhanced version of GA called Genetic Algorithm Planner (GAP) in mobile robot path planning problem. In GAP, the concept is to the length chromosomes for path encoding. Even though the preliminary test done with GAP showed its usefulness in dynamic and fixed environments, it still lacks the generalization and is not ideal for all settings. Similarly, Trojanowski et al. A knowledge-based genetic formula for path preparation is proposed in [110]. In this, the drivers are used based on heuristic knowledge to the parents from the initial generation. [111] addresses path planning in dynamic setting utilizing a GA formula that utilizes local memory for chromosomes. Although the technique is viable in a dynamic atmosphere, it experiences a high amount of calculation and its performance relies on the setup of the environment. The major drawback of the GA technique in path planning domain name is that it is not viable in dynamic environments. This is because it operates in a grid map or uses a fixed resolution in the search area and also does not regulate the population diversity which causes premature convergence. [27].

2.1.2 Node base methods

- *Dijkstra's*

Named after Dijkstra [112], Dijkstra's algorithm targets for finding the shortest path in a graph where edges weights are recognized. Dijkstra's algorithm is a unique form of dynamic programming and a breath first search method. It finds shortest path which depends simply on local path cost. When applying 3D space, a 3D weighted graph must be built initially; then it searches the whole graph to find the minimum path cost. Authors in [113] recommended an improved Dijkstra's algorithm by adding a center constraint; it works well with tabular objects, which was first proposed by [114]. In the work [115] showed that 3D GIS environment combined approach may be a sensible way to carry out in genuine outdoors, and experimental results are done to verify that Dijkstra's algorithm acts well enough. Yet Dijkstra's algorithm relies on the top priority data structure type, which affects the overall exploring time. [116]

- *A-Star (A∗)*

A* is an expansion of Dijkstra's algorithm, which decreases the total number of states by presenting a heuristic estimation of the cost from the current state to the goal state [117]. The heuristic function can be designed to get the constraints, while the estimation must never ever overestimate the actual price to get the nearest goal node. By applying this directing like heuristic, A∗ can converge really quickly with optimality. A∗ is proposed by presenting an evaluating function [118], which contains post calculation toward the initial state, $g(x)$ and also heuristic estimation toward the goal, $h(x)$. The estimation $h(x)$ of each state tends to be close to the actual cost; thus A∗ has a faster speed to converge based on comparison of the cost of neighbors. Compared with Dijkstra's algorithm, A∗ obtains a faster speed to converge.
For 3D environment, A∗ has been widely applied. Authors in [119] implemented A ∗ with UAV system with an octree based PRM. Niu and also Zhuo [120] introduced "cell" and also "region" concept to boost the environment understanding of A ∗, therefore enabling adaptable depiction of 3D atmospheres. Koenig and Likhachev suggested an environment-representation differing adaptive A ∗, that is, Lifelong Planning A ∗ (LPA) [121]. LPA ∗ can adapt to setting changes by utilizing previous information along with repetitive re-planning. Williams and also Ragno [122] recommended a conflict-direct A∗; it speeds up the exploration process by eliminating subspaces around each state that are inconsistent. It is proposed in [123] that A∗ can choose any kind of state to be parent state, hence leading to a flatter turning angle, named Theta ∗. The algorithm has the capability to be able to get system restrictions; therefore, it can find much shorter as well as much more realistic path.

Chen et al [124] proposed and presents an approaches that provides an optimal path in UAVs with lesser fuel consumption. This approach was compared with the GA and ACO algorithm to describe their pros and cons. In a comprehensive study of the real time path planning methods was presented by He et al. [125]. After comparison of the algorithms (ACO, Dijkstra, Floyd), it was evaluated that Dijstra algorithm which is an equivalent to the A* algorithms finds an optimal path much better. De Filippis et al. [126] applied both Theta ∗ and also A ∗ in 3D environment, and a speculative contrast is given to show that Theta ∗ lowers the searching compared to A ∗. Although Theta ∗ acts well compared to A ∗, but when put on 3D environment, it consumes much time to check unforeseen neighbors. Line-of-sight check technique, called lazy Theta ∗ [127], is recommended to stay clear of unexpected neighbors. Authors in [128] presented a method to recycle information from previous expeditions and update info with the affected and relevant parts of the exploring area. This might cause added computational time, however it can deal with dynamical threat and converge quickly. [116]. Another algorithm using A* for finding a collision free path in a windy and clustered environment was proposed by [129]. Using local rolling optimization approach, the authors in [130], describe the optimal path findings between UGVs and UAVs
An improve A* algorithm was proposed by Chengjun et al. [131] for UAVs path planning while taking the cost path (fuel consumption), obstacle avoidance and other factors into consideration.

- *D-Star (D∗)*

D∗, short for Dynamic A∗, is renowned for its wide use in the DARPA unmanned ground car programs [132] [133]. D∗ is a sensor based algorithm that handle dynamic obstacles by real time transforming its edge's weights to form a temporal map and afterwards moves the robot from its current place to the goal location in the shortest unblocked path. D∗, As well as A∗, assesses the cost by taking into consideration the post calculation and forward estimation. D∗ preserves a list of states which is made use of to propagate information about modifications of the arcs cost function [116]

- *D* Lite*

Incremental search approaches recycle information from previous searches to find solutions to a collection of comparable search tasks a lot faster than is feasible by solving each search job from the start. Dynamic SWSF-FP [134] is a popular incremental search algothrim that is appropriates for only a small number of path changes. The LPA* [135], an incremental version of A*, identifies the shortest path from a start to goal point. It generalized both the Dynamic SWSF-FP as well as A * algorithms i.e., incorporates these incremental and also heuristic algorithms to decrease its re-planning time [136]. Building on the LPA*, D* Lite is a lot more efficient than D* as it simplifies the analysis of the program flow with no complex nested if-conditions. As the D* algorithm is complicated and also generally used as a black box system, it motivated the development of D* Lite, another algorithm for robotic navigation in unknown terrain which is less complex and also much shorter yet much more reliable than the original D* approaches [137]. It is amongst the extremely few strategies in the classification of incremental heuristic searches which take into consideration the fact that the start location changes gradually as the robot searches through the environment. incremental search methods were designed to resolve re-planning problems after it was revealed that earlier techniques, such as repeatedly running searches, were quite ineffective. In robot navigating, the D* Lite concentrates on the problem related to the robot's different positions over time and also analyzes nearly all the states at the very least once by expanding all the nodes with cost of less than or equal to the cost of the present robotic location. Therefore, it makes use of cost heuristics to limit the search area which causes a much smaller sized search space and, as a result, a great renovation in the algorithm's performance. It is far better than the Delayed D * algorithm when a robot is moving in the direction of the goal in a completely unidentified atmosphere [137]. For autonomous vehicles, sensing units play a crucial duty in obtaining various attributes of the working environment as well as, by extracting significant details from these data, the autonomous system can get knowledge regarding its atmosphere [138].

Heuristic-based algorithms do not assure the achievement of a solution, yet it is certain that if they located the ideal option, it would certainly remain in much shorter time compared to classical approaches. It needs to be noted that these techniques might fail in terms of finding the solution or they might discover a bad one [27]. They struggle with lots of downsides, such as time complexity in high measurements, and trapping in local minima, that makes them inefficient in practice. In order to enhance the effectiveness of these techniques, Probabilistic methods have actually been developed, including Probabilistic Roadmaps (PRM) and also Rapidly- exploring Random Trees (RRT), with major benefits is high-speed application. To handle the local minima trouble, lots of Heuristic as well as Mete-heuristic algorithms are used in RMP.

1.2 Classical methods

The classical techniques have remained in use prior to the 2000s though heuristic strategies sprung into domination later [139]. The classical path planners either discover a solution or confirm that such solution does not exist. In classic approaches either a solution would certainly be found or it would certainly be proven that such a remedy does not exist. The primary drawback of such methods is their computationally intensiveness and their inability to cope with unpredictability. Such disadvantages make their usage weak in real-world applications. This is because of the natural attributes of such applications which is being unforeseeable and also uncertain. Approaches such as Cell Decomposition (CD), Potential Field (PF), Road Map, and Subgoal Network are used in path planning and, in here, are categorized as classical approaches. [28], [27]

2.2.1 Potential Field Method (PFM)

The field of collision-free navigating has two significant directions called: i) Artificial Intelligence (AI) and ii) Potential Field(PF). The AI instructions describes global path planning using optimization algorithms. As Vadakkepat [140] mentioned AI-based approaches offer intricate computing and are much more reliable when the environmental is unknown

Cetin et al. [141] discussed about using Artificial PF for offering chain of interaction relay in dynamically changing environment in the presence of obstacles between Unmanned Aerial Vehicles (UAVs). Jaradat et al. [142] used a fuzzy-based PF for path planning of simulated robots in dynamically transforming simulated environments with static and dynamic targets. In the research two separated fuzzy methods are made use of to produce both attractive and repulsive forces. Subramanian et al. [143] utilized multipoint PF in an obstacle avoidance problem. The possibility of the recommended strategy is examined in both dynamic and also static environments in which minimal position monitoring errors are observed and the created paths are smooth.

Although PF algorithm has a basic framework as well as it is very easy to carry out, it has weak points in situations where obstacles are located close to each other. Such a circumstance in PF would certainly be finished by trapping between obstacles somewhere near them creating local minimum convergence issue in PF [144]. Valbuena and also Tanner [145] performed out the use of PF for crash avoidance as well as movement planning in non-holomonic mobile robotics. The suggested approach permits simultaneous convergence of both orientation as well as position while lessening the online switching operation between control laws. Song et al. [146] used decentralized PF-based controllers in teams of robots to approach, trap, and transport objects toward a predefined destination. The study presented a decentralized technique that is utilized as controller and trajectory generator for robots. The robots plan their trajectory using their sensory info by setting their habits in such a way to provide suitable communication with the environment. Even though the literature has actually presented numerous improvements to manage local minimum issue of PF [147], [148], their techniques are not general as well as they are just suitable to restricted classes of objects shapes and configuration [27]. Considering that the existing of surrounding obstacles gives a high quantity of repulsion as well as back-wards motion minimizes the attraction, consequently, robots would be stagnated in the local optimum. The idea of using temporary goals in random direction helped robotics to pass the obstacles as well as move themselves somewhere away from them. Dai et al [149] presents a hierarchical PFM approach to path planning of UAVs in unreachable, clustered environment. The problem of local minima was solving with the incorporation of some rotational forces between the UAVs.

Bai et al. [150] proposed a further introduce a longitudinal factor to improve the PFM in order to tackle the local minima problems associated with UAVs. Their performance is assured by B-spline interpolation method. Several other approaches have been proposed by researcher [151], [152] to overcome obstacle avoidance and associated problems with the PFM.

2.2.2 Probabilistic Roadmap (PRM)

The road-map technique is also called the Retraction, Skeletal system or Highway strategy. The roadmap is built by a set of paths where each path consists of collision-free area connections [6]. In this method, the roadmaps are constructed with a set of paths where each path consist of collision free area connections. Using this approach, path planning can be seen as locating the shortest path between feasible path from start position towards the goal position making use of road-map network [77]. A kinodynamic PRM method that uses a non-linear predictive control model was proposed by Mansard et al [153]. The control model was used to initialize and control the trajectories for optimal path in UAVs

These roadmaps are later made use of for path planning. The path planning is hence lowered to searching for a series of roads from start to goal point from a road network linking the initial as well as objective points [154]. A safe clearance path planning approach using Voronoi diagram is suggested in [155] with an effort to solve the optimality issue.

Visibility and also Voronoi graphs are 2 popular techniques for developing road-maps. A visibility graph is a chart whose edges consist of the start, target and also the vertices of polygonal obstacles. Its edges are the edges of the obstacles as well as edges joining all sets of vertices that can see each other. Consequently, the resulting path for the most part would be minimum-length solution [6]. Among the disadvantages of visibility graph is that the resulting shortest path touch obstacles at the vertices or even edges and also thus are not safe. Voronoi diagrams can resolving this downside. Although such a drawback of the visibility graph technique makes it use challenging, it is still valuable in environments in which objects are following polygonal shapes in either distinct or continuous space. This is because of the visibility graph search ability in terms of readily utilizing obstacle polygon description. [27]

A Voronoi diagram of a set of sites in the plane is a collection of areas that separate the plane. Each area corresponds to one of the sites and all the points in one region are better to the site representing the region than to any other website. In other words, in Voronoi diagram, roads are created in such a way to be far from barriers. It is necessary to state that the use of a Voronoi diagram is very reliant to the length of localization sensory units and their precision. It is due to the fact that this method tends to optimize the distance in between the obstacles and robotics. As a result, such an approach cannot be used by robots that make use of short range sensing units as their localization sensory unit.

The Voronoi diagram is differentiated from other obstacle avoidance strategies as a result of its subtle advantage. Execute ability is thought about as the ability of being carried out by physical robots in real-world robotic applications. Robotics with proper sensory devices can capitalize from Voronoi diagrams using simple control rules [6]. Yan et al. [156] made use of a Probabilistic Road-Map (PRM) that takes advantage from adaptive cross sampling for simulated multi-robot motion planning. The proposed method used 3 steps of C-space sampling, roadmap building, and motion planning. The outcomes indicated considerable planning time decrease with minimal collision in the designed multi-robot circumstances. Rantanen et al. [157] improved the execution time of roadmap in a multi-robot planning research using an intelligent mechanism in the learning stage that enables deactivation of least probable arrangement. Along with the resulting time reduction in constructing the roadmaps, the proposed technique likewise significantly minimized the size of the roadmap which leads to streamlining the roadmap planning task. Nazif et al. [158] used utilize single query roadmap in mapping situations within unidentified environment making use of swarms of robots. In the study the roadmap information of local areas of the environment is given to the robots. The authors asserted benefits such as effectiveness to failure as well as effectiveness in chaotic environment with narrow passages. In a similar research to [157], Rantanen et al [159] used an enhanced probabilistic roadmap method that minimizes the configuration space by intelligently identifying locations of the configuration space that are hard to navigate. The algorithm showed substantial improvement inefficiency compared with other path planners under numerous environmental constraints along with achieving decrease in the size of the roadmap. Yang et al. [160] employed Elastic roadmap structure for motion planning in mobile robotics with capacity of dealing with different constrains including kinematic and dynamic limitations of the robot, difficulties develop from the existent of relocating obstacles, constraints develop from the task and also the connectivity of the workspace. The recommended technique is practical in both simulation and also real-world application [27]

2.2.3 Rapidly exploring Random Tree (RRT)

Rapidly exploring arbitrary tree (RRT) method is first proposed by LaValle [161]. The technique attempted to solve path planning issues under holonomic, non-holonomic, and also kinodynamic constraints. RRT has the advantage of handling multi-DOF problems; thus it is widely used for PR2 and other robots [162]. RRT performs well in practice and also can assure completeness, but it pays virtually no attention to the quality of the results, and it is shown that RRT algorithms are not asymptotically optimal. Karaman et al. [163] addressed non-optimal results problem of RRT by presenting RRG and a heuristic technique RRT*. RRT swiftly search the configuration space to create a path connecting the start node and the goal node. In each step a brand-new node is sampled; if the expansion from the sampled node to the nearby node prospers, a brand-new node will be added. Although RRT can discover a path to the goal, it is still the issue that RRT explores based on Monte Carlo random sampling, which is constantly biasing explored area as it increases with the time. The approach will certainly consume much time to discover a way out when the environments are cluttered, let alone converge to the optimal. In [164] revealed speculative outcomes of RRG, and the contrast to PRM proves the benefit of RRG. Likewise, the conclusion recommended that RRG enables navigating multiple robotics simultaneously. Nonetheless, it creates an intricate network like PRM. and also thus cannot discover the optimal path by itself.

For path findings in UGVs, RRT have been proven to give an improved result as presented in [165], RRT algorithm was used which generates the map. A combination of RRT-connect and APF for an optimal path planning in UAVs was proposed by Zhang et al [166]. The simulation results for the hybrid algorithm was compared to that of RRT algorithm. The later covers a distance of 197.9240m at a duration of 0.7475seconds while the former covers 188.6642 meters in 0.0363 seconds. To solve the feasibility problem and in finding a safe path in UAVs, Wen et al [167]. proposed an RRT algorithm to predict dynamic obstacles faced in online planning. Further optimization was carried out using RRT* algorithm.

RRT have been used in solving path planning problems in UVAs for designing an effective path in the configuration space. Lin et al. [168] explain the three types of this algorithm as:

i. Generating the trajectory
ii. Determining the possible intermediate paths and
iii. Finding the optimal path in a clustered environment

Similarly, an Environmental Potential Field based RRT (EPF-RRT) algorithm was proposed by yang et al [169]. It was further compared with the simulation results of RRT algorithm to determine the average path cost with respect to the path distance. The EPF-RRT covers a distance of

144.3313 meters in 0.351792 seconds while the RRT algorithms moves 180.7879 meters in 0.295861 seconds.

Zu et al [170] stated that the RRT is a better algorithm in finding a path in a clustered environment. When a new obstacle is detected, this method searches for an obstacle free path easily and faster in order to achieve a higher success rate in path planning for UAVs in a non-convex high dimension environments, hybrid approaches were proposed [171]. This enhanced method includes bidirectional RRT, dynamic value and dynamic length which proves to be effective when compared with the RRT algorithm

2.2.4 Cell Decomposition (CD)

Cell Decomposition (CD) is highly used by literature in path planning problems. Cell Decomposition is the representation of search space in the form of individual units called cells. The goal is to give a series of obstacle totally free steps from the starting point to goal. Such a sequence of actions would certainly be provided by utilizing cells without barriers. The cells with barriers are first divided into 2 new cells and after that cells without obstacles are added to the sequence [27]. In CD the concept is to minimize the search space by using a representation based on cells. The goal is to provide a series of collision free cells from starting point to the goal. Such a series would be offered by using pure cells (cells without obstacles). For such an aim damaged cells would be separated in to 2 new cells and the obstacle-free cell would be included in the collision-free path series. As in CD the starting and the ending cells represent the beginning and goal location ns the sequences of cells that connect these 2 cells represent the path in between these two locations [172].

Seda [144] recommended following steps for using CD as movement planner for a robotic.

- Split the search room to connected regions called cells.
- Create a graph via adjacent cells. In such a graph vertices denote cells and also edges connect cells that have a common limit.
- Determine goal and start cells and give a series of collision-free cells from beginning to objective cells.
- Supply a path from the acquired cell series.

Cell Decomposition can be classified into [172]:

- Exact Cell Decomposition
- Approximate Cell Disintegration
- Probabilistic Cell Decomposition.

In the exact CD Cells are figured out based upon the world map and the locations and also shapes of obstacles within it as opposed to their forms and/or sizes being pre-defined. The path contains lines which link centring points of cell boundaries together. Such a configuration results in providing unnecessary turning points in the path that makes the motion abnormal [173]. The cell boundaries correspond exactly to the limits of the planning space and the union of the cells is precisely the same as that of free space in the world. In the approximate CD a grid with higher resolution compared to exact CD is used. In this approach the environment is divided to a grid with high resolution in a way that each cell in the grid represents a part of the environment and each cell consists of a flag that indicates whether it represents a free space or otherwise. Despite the fact that the high resolution of the resulting graph in the approximate CD causes simple execution, it is not effective for path planning given that such decomposition offers no natural representation of the environment. Probabilistic CD (PCD) resembles approximate CD except that cells boundaries do not stand for any type of physical meaning. Additionally, in probabilistic CD, cells have a predefined form. Despite the fact that approximate CD and also probabilistic CD methods have the advantage of rapid application, they are not reliable in an environment in which the free space has a little fraction of the environment.

CD is typically used in robotic motion planning situations [144] Lingelbach [174] made use of a PCD in a robot path planning problem in which the robot task was to bring milk from the fridge and also location it on the kitchen table. The research study provided comparison in between PCD as well as Rapidly-exploring Random Trees method. The standard PCD algorithm used in [174] is disintegrated to some components such as graph search, local planning, cell splitting as well as probabilistic sampling. In [175], a novel approximate cell decomposition technique is created in which the obstacles, targets, sensor's system as well as field of vision (FOV) are represented as closed and also bounded subsets of a Euclidean work area. Foderaro et al. [176] made use of a hybrid of CD and also connectivity tree in order to produce optimum choices for a virtual agent in a game called Ms. Pac-Man. Seada [144] [compared CD with Road Map in 8-dimensional and general path planning. Disadvantages such as combinatorial explosion, limited granularity and producing infeasible solutions are recommended for CD by Seda. Seda declares that road map technique can eliminate CD disadvantages. A path planning strategy using harmonic features as well as probabilistic cell decomposition is presented in [177].

2.2.5 Subgoal(SG)

In the subgoal method the idea is to use a listing of reachable configurations from the starting place to address the motion planning problem [178]. Various research studies employed SN in path and also robot motion planning issues. Chen and Hwang [179] suggested a variation of SN by utilizing hierarchical path search. In their research study, the SN had the role of global planner while a local planner has actually been made use of to check the reachability of subgoals. In Chens and Hwangs method the switching between global as well as local planning is repeated until either a path is found or subgoal series is cleared. The main contribution of this approach is the proportional connection between computational time, the environment complexity, as well as task difficulty.

Chatterjee et al. [180] studied vision-based robotic navigation making use of SN for recognizing the fastest path. The formula operates within a repetitive fashion in which in each of the iterations the quickest path is generated using the SN and the robot is navigated with the objective of reducing the number of movements needed to reach the goal. Keshmiri et al. [181] proposed subgrouping operation for resolving dynamic environment with multi-task multi-robot scenarios. The subgrouping procedure is designed to lower the task area to subgroups that are equal to the number of existing robotics in the group. The performance of the recommended approach is gauged using factors such as elapsed time, distance, and the number of the decision cycle.

2.2.6 Voronoi

Shamos et al. [182] introduced the Voronoi diagram into the field of computational geometry; it is firstly used for finite points in the Euclidean plane and now widely used with a series of improved forms in the field of path planning. Voronoi diagram generates topological connection; the distances from the edges to the nearby obstacles are the same. 3D Voronoi first selects an initial site; this site's coordinates hold the property that the minimal distance to the obstacles nearby is the same. Then it calculates new Voronoi sites based on calculation of the Voronoi channel and defines the Voronoi net bounds. The whole process stops when all the sites are recorded and all the channels are obtained.

Voronoi creates a global or local graph, similar to RRG and PRM; it also cannot create the quickest path at the same time. Therefore, it seeks aid from Dijkstra's formula, A*, D*, etc. Luchnikov et al. [183] initially recommended an intricate 3D Voronoi diagram construction method, which solves 3D complex system path planning issue. Authors in [184 -186] enhanced it to a further stage by recommending a radial edge like data structure which can manage topological characteristics of Euclidean Voronoi diagram of spheres. The topological attributes are area, surface, edge, vertex, and partial edge, which have adjacency relationship. Sharifi et al. [187] appointed Voronoi area to a group of UAV to address the problem of coverage planning for an environment. Voronoi was incorporated with potential field technique in [188], which is efficient to assure quick convergence. An improved VD was proposed in [189], the UAVs in the VD space were being monitored using an automatic dependent surveillance-broadcast (ADSB). Using this method, they were able to conclude that this approach has lessen the chances of collision among both the unmanned and manned aircrafts

2.2.7 Laser simulator

A novel approach using Laser simulator (LS) with vision system was proposed by Mohammed et al. [190,191]. Using this algorithm, the authors were able to navigate a robot through a roundabout in both global and local environments. A LS was further employed on a 2D map in a clear and noisy environment [192]. Simulation result obtained was compared to the A* algorithm where a low computational time and collision rate were achieved with the LS algorithm.

Online path planning and control using LS of a three-wheeled mobile robot was presented in [193,194] using this method, the WRM was able to localize and find a collision free path from a start point to a certain predefine position in a complex environment. Similarly, a WRM for online navigation in a roundabout setting was proposed using LS to find the path in the local maps using sensor fusion. Results obtained shows the effectiveness of the algorithm in building the map and path generation in the given setting [195].

3. RESEARCH GAP

Lacking adaptiveness is the primary drawbacks of the discussed conventional techniques in addition to their unsuitability for dynamic environment. This results from creating a single solution by utilizing a sequential search algorithm. Such a solution may end up being infeasible in dynamic atmospheres. The negative aspect of Metaheuristics is the problem to duplicate the very same solution because they are stochastic. Likewise, in a lot of cases the metaheuristics used for path planning are unable to satisfy the real world constrictions. Multi objective optimization comes to be complex due to optimization of Applying for dynamic environment.

Every algorithm has its very own benefit and also downsides. The hybridization of different algorithms shows the best outcomes yet complexity is enhanced.

3.1 Strengths & Challenges of Heuristic Path Planning Methods

Strength	Challenges
It can be used in hybrid with other optimization algorithms to provide an efficient result both simulation and real time path planning.	In NN complexity of the algorithm increases with increases in the number of layers
They have the ability of imitating the natural perception of living things.	The NN requires a considerably amount of training data to achieve an effective result. However, this tends to be difficult mostly in supervised learning process.
They (NN and FL) have the ability to make decisions in an uncertain situation thereby providing generalization and learning capabilities.	In the neuron system, the number of buried layers are difficult to handle.
A hybrid of NN and FL provides an effective result in path planning of robots in a complex clustered environment.	The NN has a slow convergence. The back propagation in NN faces challenges, it converges easily to local minima in a non-convex mapping situation. The NN has a slow convergence. The back propagation in NN faces challenges, it converges easily to local minima in a non-convex mapping situation.
The GA and ACO algorithm have superior convergence characteristics with optimal performance. PSO is effective, simple and have a lesser computational time.	PSO also have the problem of trapping in a local minimum in clustered environment. GA and PSO are difficult to handle in an unknown environment and can easily get trapped in local minima problem. Also, dynamic data set are difficult to handle as a result of its complex principle. The GA despite being faster in convergence can result in a premature convergence. Determining the factors that have effect in fast convergence is difficult in ACO.
	In creating rules for the FL membership functions, it tends to become difficult as the environment gets more complex. This result in the application of FL algorithm alone for path planning ineffective without combining with algorithms.

3.2 Strengths & Challenges of Conventional Path Planning Methods

Strength	Challenges
They are easy to implement (APF, PRM, A*) APF performs excellently when hybridized with other approaches	As these methods require a mode of collecting data or information of the environment through sensors or cameras]. This reading of data is inaccurate due to interference from noise either form the environment or vehicle dynamics, temperature etc. which results to the in ability to achieve and optimal and effective path planning solution
They are utilized and perform effectively in both known and unknown environments.	These approaches work effectively in simulations as they rely mostly on the information obtained from the environment during navigation. However, they do not perform smoothly in areal word environment as the navigation process is stopped any time the environment needs to be updated
A* is also effective when used in hybrid with other methods to find the shortest path from a start to a predetermined goal point.	Virtual forces from the attraction (goal) and repulsion (obstacles) force in APF which is compared to the environmental data leads to local minima as a result of losses of information regarding the obstacles.
	The performance of APF in an unknown environment with different types of obstacles is very poor. Also APF performs poorly in an environment where the obstacles are closely spaced (narrow path).
	RRT, Voronoi Diagram also performs well in global path planning, however, in local path planning, a local planner is needed. To achieve a good path planning, they need to be combined with other methods.

4. BIBLIOMETRIC METHODS & DATASET

In bibliometric analysis, we aim to show affiliations among articles and also research subjects by examining how frequently an article is cited and co-cited by other articles. The article is the standard unit of evaluation [196], [197]. A fundamental presumption in bibliometric co-citation analysis is that published articles in academic journals develop their research study on articles already published. Bibliometric co-citation meta-analysis can help to disclose underlying commonalities among research study [198].

The ISI Web of Science (WOS) consists of different articles with their bibliographic references, institutions as well as authors [199]. Articles for all years (since1900) are available [200]. It is an item stemmed from "Thomson Reuters Institute of Scientific Information" (ISI) with more than 12,000 journals of different titles and multiple disciplinary [201]. The database gives effective searching choices by enabling various alternatives to filter the search results page [202]. In enhancement to the browsing alternatives, the WOS is additionally able to arrange the journals/articles based on particular specifications such as time added, publication date, citation, significance, and usage count. WOS database allows particular omission by article, author, institutions, countries and many more by fine-tuning the search result.

In order to avoid overlap between the data sources, Scopus and Google Scholar were left out in this study. The uncertainty of Google Scholar in carrying out research analysis and low data quality [199] were some other reasons for its exclusion. Some database (like IEEE Explore, Springer and so on) only index their published articles while WOS combines all the high impact articles and journals from all of the databases. Also, WOS is used in this study due to its popularity in performing a bibliometric analysis of articles in scientific fields [203]. WOS database declares it has more quality than both Scopus and Google Scholar [204].

Topic search was "path planning". The search time span was set from the year 2000 to the year 2020. The retrieval time was 2020.03.28. Topic search suggests search from titles, abstracts, and keywords of the articles. A total of over 14304 articles prior to being categorized into 5385 main related articles were retrieved for bibliometric analysis. In this study, the articles publishing trend were first illustrated. The evaluation was performed based on productivity and research focus. Visual results were further provided using the VOSviewer tool [205] due to its availability and great features used in bibliometric analysis

5.0 RESULTS AND DISCUSSIONS

5.1 Publication trend

Figure 7 shows the year-wise frequency of publications and the trend in the number of publications from 2000 to 2020. It is observed that just a few articles were published between 2000 and 2003. After 2004, the variety of publications began to rise slightly, and also there were more than 500 publications in 2007. Ever since, the number of articles each year has been increasing, which shows that path planning study has received more interest with publication in 2019 having the highest possible number of citations 917 with the year 2020 still counting.

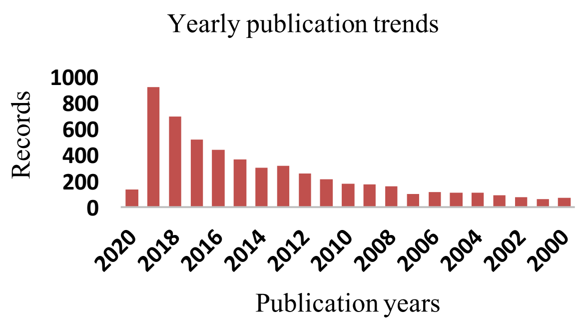

Figure 7: Publication trends

5.2 Publishing journals impact

Relative to the source journals, these 5385 publications were released in 1128 journals. Amongst all the 1128 journals, about 270 journals only released one article in the research study time. Table 1 shows the leading 20 most efficient journals, making up 34.746% of the overall journals. IEEE Robotics and Automation Letters was one of the most efficient journal with 196 write-ups, representing 3.64% of the publication Journal of Intelligent Robotic Systems ranked the 2nd with 171 articles, accounting for 3.179%. The third most productive journal was Robotics and Autonomous Systems, with 157 articles (2.916%).

5.3 Research focus

The keywords frequently used by the published articles in the journals were analyzed. Using the keyword, previously published as well as current articles in the journal can be traced and analyze to identify research gaps. Articles theme with authors keyword have been provided by WOS since 1990 [206], [207]. To measure the co-occurrence link within the path planning keyword phrases, 200 key phrases were drawn out. Nevertheless, the number is also large to classify them into understandable research clusters. Hence, the key phrases were manually further refined to eliminate those words that appeared twice as a result spelling changes, and repetition.181 key phrases were then picked. Fig 8 demonstrate how the key phrases are interlinked with each other in the path planning research study domain. 4 clusters were developed, with the biggest cluster having 65 items while the smallest having 16.

Table 1. Publishing Journals

Source Titles	records	% of 5385
IEEE Robotics and Automation Letters	196	3.64
Journal of Intelligent Robotic Systems	171	3.175
Robotics and Autonomous Systems	157	2.916
International Journal of Advanced Robotic Systems	144	2.674
International Journal of Advanced Manufacturing Technology	133	2.47
IEEE Access	121	2.247
Robotica	121	2.247
International Journal of Robotics Research	113	2.098
IEEE Transactions on Robotics	108	2.006
Sensors	93	1.727
Advanced Robotics	63	1.17
Autonomous Robots	61	1.133
Robotics and Computer Integrated Manufacturing	61	1.133
Applied Sciences Base	53	0.984
Lecture Notes in Computer Science	49	0.91
International Journal of Robotics Automation	48	0.891
Mathematical Problems in Engineering	46	0.854
Computer Aided Design	45	0.836
IEEE Transactions On Automation Science and Engineering	45	0.836
Applied Soft Computing	43	0.799

Cluster # 1 is the one in red color. As seen, it contains one big circles at the center, about three mediums once and then some small scattered ones. The size of a circle indicates the overall occurrence as well as link strength of the key words in the path planning research area. The leading research subject indicated by the big circle is the Path planning. Path planning is the process of finding a Collison-free path from a start to a predefine goal point through a certain given cluttered real world environment. Path planning plays a major rule in the navigation of autonomous vehicles. It is used in several applications such as automation, games, artificial intelligent etc. Other cluster members are algorithm, Optimization, differential evolution, robotics, genetic algorithm etc. Most of which are path planning algorithms and have proven to be effective in finding an optimal path for a robotic system.

Cluster #2 is the one with the green color, and it has 42 items. The most prominent research topic is motion and collision avoidance with 192 and 180 occurrences respectively. Collision avoidance is one of the key features required by autonomous. The next in the cluster is algorithm with 134 links and 169 occurrences. They are all effective path planning features that are often used in path planning research.

Cluster #3 is the one with a Deep-Blue color and contain 37 items in total. The most prominent path planning research keyword is navigation. It appears to be the most significant research area in the entire clusters, as it has the biggest circle size and is densely connected to the other major clusters as shown in figure 9. The remaining phrases are mobile robot, robot navigation etc.

Cluster #4 has 35 keywords, and its denoted by the Yellow color figure 10. The three dominant research phrases in the cluster are system, tracking, optimal control, constraints, trajectory coordination are some of the major trending research optimizers in the cluster.

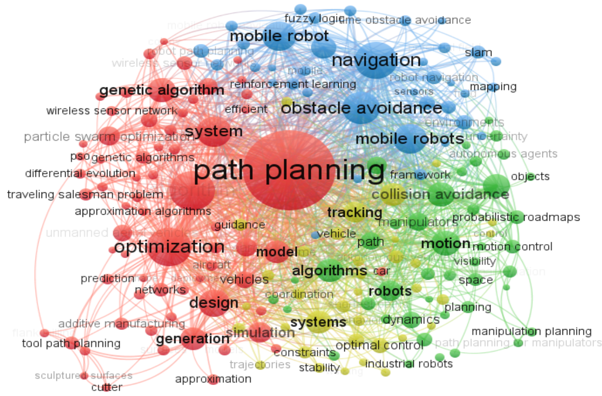

Figure 8. Authors keyword network

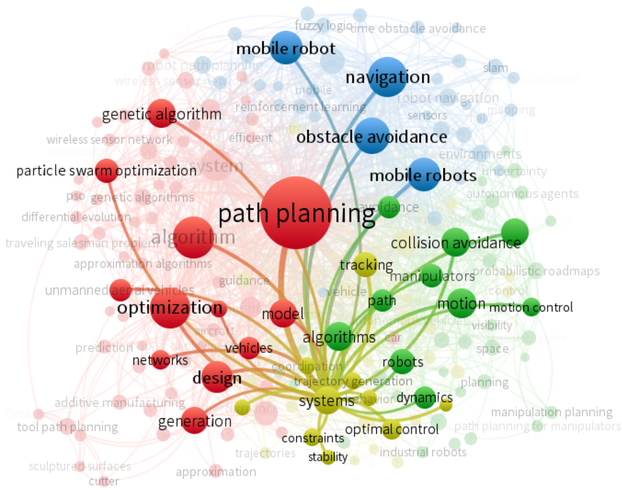

Figure 9. cluster #3 keyword network

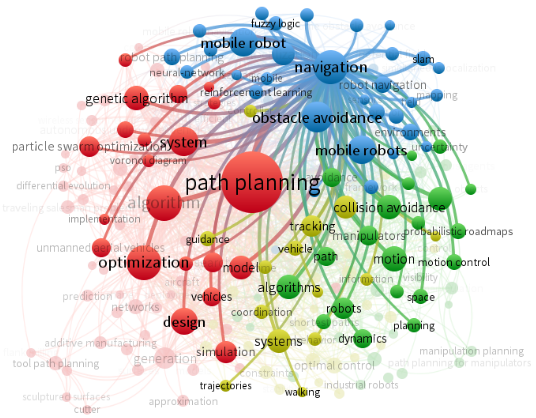

Figure 10. cluster #4 keyword

6.0 CONCLUSION

Path planning has actually been practiced worldwide as such a lot more academic efforts have actually been made in this field. This article provides a comprehensive analysis of path planning literature, by reviewing papers published in major journals and conference proceedings in the last decade. We evaluate relevant articles relative to different path planning algorithms. This research gave a review on the used methods in path planning problems. The review explained various approaches and discussed their benefits and also downsides. As the literature works recommended, classic approaches might not be reliable in the real-world applications as a result of their failure to confront with the dynamic, uncertain and also unpredictable nature of real-world. Moreover, these approaches require great amount of memory and computation while heuristic-based methods can overcome the real-world problems with some modifications. Although simplicity and computational efficiency are the significant benefits of path planning techniques, the general efficiencies in these techniques are based on the information of the map.

In order to summarize the research progression and also suggest future directions of path planning research, this study carries out a bibliometric analysis on the relevant publications published during 2000 to 2020. Result show that 5385 articles were published. The yearly publication rises rapidly after the year 2007, reflecting global interest in the topic. These publications were published in 1128 journals, indicating the publication diversity. IEEE Robotics and Automation Letters, Journal of Intelligent Robotic Systems, Robotics and Autonomous Systems ranked the leading three journals in regards to total publications. keywords search phrases was carried out to track the top topics and research trend. The hot topics includes: path planning, robot navigation, optimization and obstacle avoidance. With the rise of obstacle avoidance and optimization more research will focus concentrate on such an area in the near future. Generally, this research provides useful insights as well as future research study directions on path planning research study so that researchers in this area can better recognize their research study topics and also look for appropriate research partners.

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