

Wheeled Mobile Robot Path Planning and Path Tracking Controller Algorithms: A Review

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Abstract

The two major problems in wheeled mobile robot technology is path planning and path tracking. The former evaluates and identifies an obstacle free path for a mobile robot to traverse within its environment and the later deals with the controller design for a mobile robot to track the reference path with precision. Hence, researchers have proposed and applied several solution approaches to these problems over the years. The sustained integration of wheeled mobile robot to task that further require their operation within the human environment characterized with uncertainty makes a review of these solution approaches very significant. Thus, this paper therefore, presents a review of wheeled mobile robot path planning algorithms and path tracking control algorithms applied within the last decennium.

Keywords: Path planning, Path tracking, Wheeled mobile robots, Algorithms, Robots

1. Introduction

Wheeled mobile robots (WMRs) have become more versatile in their application to various tasks in recent time. The application environments of these robot's ranges from industrial, military, hospitals, schools, offices etc. [1-3]. These environments most often are not precisely engineered for WMRs inclusion. However, with the development of computers and sensory technology, the WMRs industry has seen continual development and received extensive research attention. WMR is a robot that autonomously traverse from a specific start coordinate to a desired goal coordinate within a predefined environment while achieving a specific task [4]. The predefined environment is categorized as static or dynamic and the obstacles within the environment can be static obstacle, dynamic obstacle or a combination of both [5,6]. The development of WMRs requires solution to path planning and path tracking problems [6]. Solution to these problems develops intelligence into the robot capable of achieving relation between perception and action [4].

Path planning algorithms evaluate and identifies an obstacle free path for a mobile robot to traverse within its environment [7] and path tracking deals with the controller design for a mobile robot to track the reference path with precision [8]. In literature, path planning algorithms are sub-categorized as global and local [7, 9]. Global path planning algorithms such as Dijkstra algorithm is applied exclusively to static environment with static obstacles and the robot has comprehensive knowledge of the environment. The path to traverse is generated off-line before the translation of the robot within the environment [9, 10]. Local path planning

algorithms such as Neural Network [11], Simulated annealing algorithm [12], Near shortest path for Mobile Robot [7] enable the robot to generate a new path in real-time in response to onboard sensory information [13]. This allows the robot traverse safely in clustered environment [4].

Path planning controllers such as hybrid back stepping and adaptive integral sliding mode controller [6,14,15], Proportional Integral Derivative (PID) controller with advance tuning algorithms [2, 16] have been applied in the design of appropriate path tracking controller in literature. However, the effective design of these controllers involves the WMR kinematic model and dynamic model [8]. WMR kinematic model presents the constraints between the positions, velocities, and accelerations of the WMR body, wheels and steering links to determine the WMR's linear velocity and angular velocity [1,4]. Kinematic model is of forward and inverse relation. Given the WMR individual wheel angular velocity the forward kinematic determines the position and orientation of the WMR and the inverse kinematic does the direct opposite. Dynamic model of WMR predicts its movement. Forward dynamic model defines the WMR response in relation to a given force or torque utilized by the motors and the inverse dynamic model determine the forces or torque to be utilized by the motors to attain the WMR predefined trajectory [1,4].

Therefore, this paper present's a review on WMR path planning and path tracking control algorithms applied within the last decennium. Hence, the following aspects of WMRs are considered: path planning algorithms, path tracking controller design, kinematic modeling, dynamic modeling, model reference adaptive control, sliding-mode control, fuzzy and neural control, vision-based control etc.

The remainder of this paper is organized thus, literature review of path planning algorithms, formulation of kinematic and dynamic model of WMR, literature review of path

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controller algorithms, and finally conclusion of this review paper.

2. Path Planning Algorithms

Within the last decennium researchers have approach the path planning problem by modelling the WMR environment and applying a distinctive method to determine the solution. Sheth et al [17] presents a vision-based system for path planning of a WMR within a workspace environment. The overhead camera captures the image of the workspace environment including the start and finish coordinate with obstacle positions in a single frame. The homographic function in Open Computer Vision (OpenCV) is use to process the image, then obstacle characteristic and location is evaluated from the homograph image. The Rapid Exploring Random Tree (RRT) Artificial Intelligence algorithm map out an optimal path accordingly. Although the proposed approach is applicable but the environment must be captured within a single frame of the camera. Culler and Long [18] has design the path planning of a multiply collaborative WMR using vision-based approach. Kinect camera is use for image capturing and OpenCV is use for image processing and onboard sensors for obstacle detection. Ito et al [19] present similar work using small imaging sensor named Single-Photon Avalanche Diode (SPAD) LIDAR. Kala et al [20] address the time complexity problem with Evolutionary Algorithm (EA) for path planning for WMR in dynamic environment using hierarchical EA. Coarser hierarchy EA is responsible for optimization of global path and finer hierarchy EA determines the real-time traverse of the mobile robot on the global path. Simulation of the proposed algorithm was done using a simulator built on JAVA platform. Results exhibits the capability of the WMR to solve complicated maps, avoid static, dynamic and sudden obstacles and successfully attain the goal coordinate.

Tazir et al [21] present a static and dynamic hierarchy path planning algorithm to take advantage of the global static map and local information from onboard sensors. In the static hierarchy, the global optimal path is plan using Genetic Algorithms (GA) with Dijkstra Algorithm (DA) through static obstacles. The local path planning algorithm using DA to generate new path engages when a dynamic obstacle suddenly intercepts the reference path from the static hierarchy path planning algorithm. Computer simulation in Matlab R2010a software shows that the robot attains the target point, in less execution time with optimal path without collision with obstacle in a dynamic complex environment. Toolika et al [22] applied the GA for robot path planning in a dynamic environment. Silva-Ortigoza et al [23] describe the application of artificial potential field for optimal path generation and obstacle avoidance within a workspace environment for a differential drive WMR. Computer simulation in Matlab-Simulink presents the effectiveness of the approach in the generation of obstacle free path for the two wheeled differential drive WMR. Qing [5] presents an improve DA for path planning for WMR in a dynamic environment base on based on the shortest path and travel time optimization criterion. The improve DA stores all equidistant shortest path from start point and goal point during path search. Then considering the number of turns the algorithm identify the optimal path. This is the improvement over the conventional DA. Simulation model was developed with Visual C++ 2010 and result shows that this algorithm presents the shortest path from equidistant shortest path having considered the number of turns. Zhang and Li [9]

design a rapid path planning algorithm with the combination of the Dijkstra's algorithm, A* algorithm, and rolling window principle for mobile robot in dynamic environment. The initial global path is search using the Dijkstra's algorithm. If the possibility of collision with an inbound dynamic obstacle on this reference path is evident, this will activate the rolling window principle. This principle determines a local optimal target state within the detection range of the sensors for the robot to wait. The A* algorithm then activates to find a new optimal path to the goal point form this target state (current location of the robot). Simulation is use to investigate the efficacy of the algorithm and performance comparison with Ant Colony Optimization (ACO) algorithm, A* algorithm, and D* algorithm. The result show that the algorithm is not only applicable to dynamic obstacle but also having the least re-routing time of about 99.7 % compared with the other algorithm considered.

Nguyen and Xuan [7] develop and employ the Near-shortest path for Mobile Robot (NSPMR) local path planning algorithm for WMR. The merit of the NSPMR is in twofold; one is that this algorithm considers the shortest path from the start point to the target point and ensures the robot traverse the best moving direction. two, the issue of infinite loop traps of several obstacles in unknown environments is address by the intelligent obstacle avoidance employed. The robot localizes itself, evaluate is traverse direction and distance covered through its onboard Global Positioning System (GPS) and Compass modules. Simulation in Matlab with performance comparison with Bug 1 and Bug 2 algorithms shows with the NSPMR the robot traverses the shortest path. Wu and Feng [24] describe a path planning method for mobile robot within an environment with static and dynamic obstacles based on the combination of static global and the dynamic local path planning methods. The A* algorithm is use to obtain the static optimal path within the desire coordinates base on initial static obstacle assumption. Then real-time collision avoidance with dynamic obstacles is achieved using trajectory prediction. The artificial potential-field approach is use for local navigation and the local adjustments to the global optimum path using the local rolling window enables the robot to evade inbound dynamic obstacle. Computer simulation shows the effectiveness of the approach which combines the advantage of global path planning in a static environment with the efficiency of local navigation under a dynamic environment. The algorithm adjusts of the path derived from global path planning using the result obtained from the rolling window during local navigation to avoid dynamic obstacles. Raja and Pugazhenti [25] illustrates a method of global path planning for a mobile robot within a cluttered environment with static and dynamic obstacles having arbitrary shape, size and location. The choice of shortest path between the desire coordinates is on the bases of shortest Euclidean distance. Simulation result of the algorithm in dynamic obstacles having concave, convex and curved shapes shows it efficiency and effectiveness in terms of shortest path, and minimal execution time compared to vertex heuristics algorithm.

El Khaili [26] address the extensive processing time problem with path planning in dynamic environment using a pictorial approach. Authors presents two algorithms for path search using a visibility graph constructed by sliding on the edges of obstacles. Mandal et al [27] presents an algorithm for mobile robot path planning using attractive and repulsive potentials for goal point and obstacles within the unknown environment respectively. Yun et al [28] presents a WMR navigation method in unknown environment with static and

dynamic obstacles using Genetic Algorithm (GA) base Dynamic Path Planning Algorithm (DPPA). Authors emphasis is on searching the algorithm that avoids acute shaped obstacles in the environment. The research object is the Team AmigoBot™ Robot and the real-time implementation confirm the practicality and robustness of the proposed algorithm. Li et al [29] combines the kinematics and dynamics equation of an omnidirectional wheel mobile robot and potential field method for it control and navigation in a specific workplace environment. Authors address the local minima problem and the goal non-reachable with obstacles nearby problem peculiar to potential field method by incorporating distance between robot and obstacle in the repulsive potential functions for motion planning. For robust controller performance the model predictive control (MPC) has been incorporated. Qualitative result from simulation data shows effectiveness of the proposed approach for omnidirectional wheel mobile robot's navigation. Sprunk et al (2016) describe a navigation system for omnidirectional robots in industrial environment consisting of distinct modules for mapping, localization, trajectory generation and robot control. Computer simulation and implementation of the navigation system on the KUKA omniRob platform was also presented. Xu et al [30] presents a mobile robot path planning method combining Dubbin's path and Bug algorithm for WMR navigation in unknown static environment considering the kinematical characteristics. Simulation result shows the effectiveness of this method for a WMR to avoid static and dynamic obstacles within the environment. Ayomoh et al [31] describe a path planning mathematical model for a mobile robot in a multi-goal environment comprising of unknown static and dynamic obstacles. However, in recent literature, there has been a paradigm shift from the classical geometric method of environment modelling as a result of excessive computational time and the local minimum problem [32]. Hence, recent literature has been largely on human behavioral and bio-inspired approach and Machine Learning for local path planning [33].

3. Human Behavioral and Bio-inspired Approaches

Ren et al [34] Developed human like intelligence into WMR operating within a dynamic and unknown environment using fuzzy logic. Hence, the robot understands it environment through perception. Farooq et al [35] described the effectiveness of zero order Takagi-Sugeno and Mamdani-type fuzzy logic controller for mobile robot navigation and obstacle avoidance. Onboard ultrasonic sensor provides sensory data for these controllers to control the linear and angular velocity of the robot wheel actuators. Performance comparison of these controller reveal the superiority of Mamdani-type fuzzy logic controller to zero order Takagi-Sugeno controller in terms of path smoothness. However, zero order Takagi-Sugeno controller utilizes less memory space for real-time microcontroller implementation. The autonomous navigation of a WMR has been achieved using ATMEGA microcontroller based fuzzy logic controller. Sensory information from onboard sensor provides necessary data for the controller to control the wheel actuators [36].

Abdessemed et al [37] presents a hierarchical fuzzy control design base on the combination of fuzzy rules and stereo vision system for navigating collision free path for indoor mobile robot. Algabri et al [38] attempt the improvement of a WMR navigation performance through

membership function parameters optimization of the fuzzy controller. This was achieved by merging fuzzy logic and another optimization algorithm such as Particle Swarm Optimization (PSO). Hmeyda and Bouani [32] has presented a vision-based approach to perceive static obstacle and generate optimal path using PSO for a WMR. External USB Camera is used for image capturing then image processing algorithm extracts the robot position, static obstacle positions and target position. PSO is used to generate optimal path from the robot current position to the target position avoiding static obstacles. Similarly, Mahmud et al [39] similarly presented a vision based Kohonen-type artificial neural network. Ahmadzadeh and Ghanavati, [40] described a navigation method for multiple robot in an environment using a PSO algorithm. The effectiveness of the proposed algorithm is evident in the capability of the robots to navigate in relation to the global best position of a particle in every iteration. Castillo et al [41] in the design of an intelligent controller for a WMR the hybridization of PSO algorithm and ACO algorithm was presented. The hybridized algorithm was used to optimize the membership function of a fuzzy controller. Zhang et al [42] the path planning problem in a dynamic environment has been addressed using a Multi-Objective PSO Algorithm. Shiltagh and Jalal [43] in order to improve the convergence rate of PSO a modified PSO was presented. The effectiveness of the modified PSO was investigated in the searching of shortest path in environment for mobile robot between two defined coordinates avoiding obstacles. Chung et al [44] The autonomous navigation of WMR was achieved using two levels of control. Authors applied PSO algorithm for navigation through obstacles in the environment and fuzzy control for turning angle control.

Juang and Chang [45] presents the possibility of automatic learning of fuzzy logic system through evolutionary-group-based PSO has been presented and applied to WMR navigation in an unknown environment. Allawi and Abdalla [46] have applied PSO algorithm in the determination of optimal parameter of fuzzy type-2 controller input/output membership function and used for multiple mobile robot navigation. Dongshu et al [47] develop a behavior-based fuzzy logic controller to address the navigation problem of WMR in a dynamic and unknown environment. Their focus with this approach is to develop intelligence in the robot to evade a cul de sac. Similarly, A multi-agent fuzzy logic intelligent control system has been developed by Ayari et al [48] for autonomous navigation of WMR in a dynamic environment. Nichols et al [49] design a wall following WMR using biologically inspired neural network. Al-Jarrah et al [50] proposed a probabilistic neuro-fuzzy architecture a combination of first order Sugeno fuzzy inference model and adaptive neuro-fuzzy inference system. The possibility of the proposed architecture for achieving multiple WMRs path planning and coordination within a predefined environment was presented. The control of position and orientation of the WMRs follows the model of leader-follower. Kim and Chwa [51] address the problem using a type-2 fuzzy neural network for WMR. The inputs of the proposed methodology are distance from robot to the goal and nearby obstacle, the goal angle and obstacle angle. The output is the controlled linear and angular velocity of the robot to navigate through the environment avoiding the obstacles and reaching the goal. Brahmi et al [52] presents the feasibility of recurrent neural network in the development of intelligent path planning algorithm for autonomous WMR navigating within an undetermined environment. Zhao and Wang [53] addressed the navigation problem of WMR by

merging sensory information from sonar sensors with neural network. Kumar and Dhama [54] motion and orientation control of WMR within a clustered environment with the combination of fuzzy rule-based and neural network was presented. Pothal and Parhi [55] presents the navigation of multiple WMRs using a sensor based adaptive neuro-fuzzy inference system. The controller enables the robots to navigate through a highly clutter environment avoiding obstacles and reaching the goal successfully.

Mohanta et al [56] the navigation path length optimization for multiple mobile robots has been design using a Petri-genetic algorithm in an unstructured environment. Tuncer and Yildirim [57] compared the performance of the conventional genetic algorithm to a proposed a new mutation operator for a genetic algorithm for mobile robot navigation in a dynamic environment. Computer simulation for the validation shows the superiority of the proposed algorithm. Arora et al [58] describe a genetic algorithm approach to path planning of mobile robot in a dynamic environment. Authors improved on the conventional genetic algorithm by introducing a fitness function based on the Euclidean distance formula between the robot and obstacle. Hussein et al [59] improves the slow convergence rate of the conventional simulated annealing algorithm by combining it with other two metaheuristic optimization algorithms: Tabu Search and genetic algorithm. The design three metaheuristic optimization algorithm is then applied for path planning of mobile robot. Zhang et al [60] proposed the more efficient navigation speed of a mobile robot using a combination of simulated annealing and Ant Colony Optimization (ACO). Synodinos and Aspragathos [61] addressed the local minima problem of mobile robot during traverse with the combination of simulated annealing algorithm and artificial potential field method. Algabri et al [62] presents a differential drive WMR navigation and obstacle avoidance within an unknown environment using an adaptive neuro-fuzzy technique inference system. The validity of the design was done using computer simulation in the Khepera Simulator environment. Singha et al [63] illustrates the efficacy of a biologically inspired neural network (BNN), considering dual weight calculation with an obstacle detection sensor for WMR path planning and mapping in an unknown environment. Computer simulation for validity testing that the target weight algorithm generates less turns and a smaller number of grid cell traversed compared with the local weight algorithm. Hossain and Ferdousand [64] present an optimization technique for autonomous robot path planning in dynamic environment with dynamic obstacles based on Bacterial Foraging Optimization (BFO) method. Liang et al [65] describe the development of a bio-inspired path planning algorithm based on an Adaptive Bacterial Foraging Algorithm (ABFA) for mobile robot. Patle et al [13] presents a real-time navigation algorithm for WMR using a modified Firefly Algorithm (FA) which is studied over Normal Probability Distribution (NPD) in a static clustered environment. Computer simulation and real-world study of the algorithm is done with the Khepera robot programmed using C++ for path planning in real time environment amidst static obstacles. Result shows the effectiveness of their algorithm to find an optimal path for WMR amidst regular shaped static obstacles. Liang and Lee [66] design a local path planning algorithm for multiple WMR application heading for same goal point within a workspace environment using Efficient Artificial Bee Colony (EABC) algorithm. The EABC considered the hybrid objective functions for distances between target, other mobile robots, and obstacles for real-time path planning of each mobile

robot. Computer simulation and comparison of the EABC with ABC shows that with the EABC presents accurate performance than the conventional ABC. However, the computational time of the EABC was expanded due to the adoption of multiple strategies.

Brand and Yu [67] presents the comparison of the FA with ACO algorithm in the determination of optimal path for a mobile robot in a 2D static and dynamic environment. Their result shows the superiority of FA to ACO algorithm in the considered performance metric: path length and computational cost. Mohajer et al [68] presents an optimization algorithm inspired by BFA for local path planning of mobile robot. The proposed optimization algorithm: Random Particle Optimization Algorithm randomly search optimal path in a dynamic and unknown environment with dynamic obstacles using onboard sensory information's. Purian and Sadeghian [69] presents WMR path planning using ACO and fuzzy logic algorithm in an unknown dynamic environment. The optimal value from the fuzzy rule table is searched using the ACO thus, minimizing the path length from start coordinate to goal coordinate. Ganapathy et al [70] an improved ACO was presented and evaluated based on three behaviors: goal seeking, wall-following and obstacle avoidance for WMR navigation optimization. Hsu et al [71] presents an improve ACO for WMRs path planning by incorporating a phenomenal updating parameter. Ganganath et al [73] presents a local path planning algorithm for a non-holonomic WMR using ACO algorithm. Juang et al [73] presents the optimal navigation of two mobile robots cooperatively carrying object in an unknown environment using fuzzy controllers, continuous ACO and PSO. Fuzzy controllers are applied for navigation and continuous ACO and PSO for obstacle boundary following objective. Other representative references with differs complexities and applications are in [74 – 79]

4. Machine Learning Approach

The Machine Learning approach applied in robotics path planning is Reinforcement Learning (RL). Similar to how humans discover their environment through continual interaction, RL is the competence of an autonomous agent to learn and improve its behavior based on its experience in its environment [80]. The agent (WMR) through RL autonomously uncover an optimal behavior through trial-and-error interactions with its environment. RL is premise on reward and sanction. For every good behavior the agent gets a scalar reward or a scalar sanction if otherwise. Therefore, an agent primary objective is to maximize the accrued reward over its lifetime. Thus, it's an associative study between environment states and actions [81, 82]. Fig. 1 illustrates the principle of RL.

The value functions in RL; shortest path, the path with the shortest time, the safest path, or any combination of different sub-objectives are to be maximized through the action policy to attain a predefined goal state. Exploration and Exploitation are referred to as the control strategy in RL. Exploration is when an agent takes an action with nonzero probability in every found state to learn the environment. However, in exploitation the agent adopts exclusively its present knowledge in anticipation of good performance by selecting greedy actions [84]. Thus, the goal is for the agent to achieve a balance between Exploration/Exploitation through some strategy such as ϵ -greedy exploration, Boltzmann exploration, Optimistic Initial Value (OIV), Extreme learning machine

(ELM) etc. [82, 83, 85, 86]. The Q-Learning algorithm developed by Watkins is one of the most frequently used techniques in solving RL problems [87]. Its mathematical model is premised on the Markov chain and dynamic programming in combination with the knowledge of animal behavioral psychology, to attain an agent online learning [83, 85].

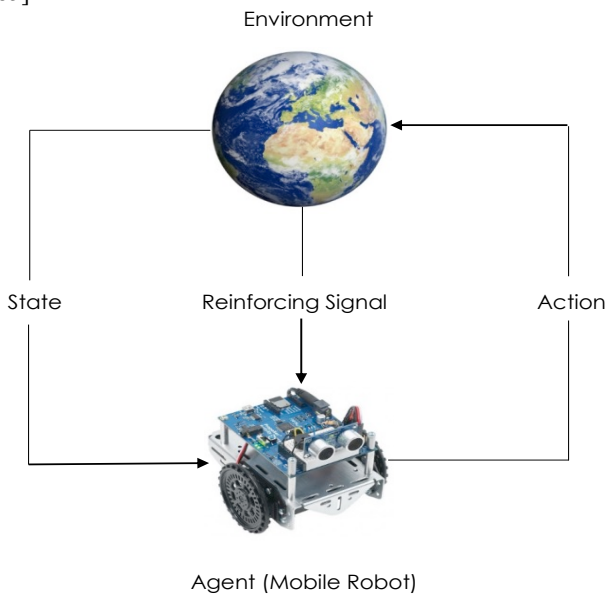


Fig. 1. Principle of RL

Xiaoyun et al [33] presents the combination of ϵ -greedy (epsilon-greedy) and Boltzmann exploration strategy in a modified Q-learning algorithm for selecting an action at the current state for learning agent navigation policies in a model-free manner. The aim of merging this exploration strategy is to avoid local minimum and stimulate the convergence rate. Computer simulation in Matlab environment, under constant reward matrix and a varying reward matrix with probabilistic outcomes was considered. The value function is the shortest path with reward maximization. Qualitative results show that a discount factor (γ) ≤ 0.9 achieved the shortest path with maximum accumulated reward. Similarly, at $\gamma \leq 0.9$ the modified Q-learning converged faster compared with the conventional Q-learning (that only uses ϵ -greedy exploration) which is yet to converge at the end of the training episodes. Ribeiro et al [86] describe the application of two distinct Q-learning algorithms for path planning of an agent premised on the ϵ -greedy exploration strategy. The distinctive feature of these algorithms is that; one allows the agent to take an action at predefined interval even when the state space signal is constant and the other permits an action of the agent only when the state space signal changes. Simulation results show that the latter approach outperforms the former in terms of learning quickness and robustness.

Watchanupaporn and Pudtuan [88] attempt to increase the learning rate of a group of WMR heading for the same goal point by combining Q-learning algorithm with PSO within a simulated grid environment. Authors modified the conventional Q-learning algorithm for multi-robot problem and combined this algorithm with the PSO algorithm. The training of the algorithm adopts four methods: Q-learning (QL), modified Q-learning (mQL), QL+PSO, and mQL+PSO. This algorithm was trained using 5, 10, 15, 20 and 25 robots per group respectively and performance compared accordingly. Simulation of this approach in three different environments with diverse levels of difficulty shows that the learning rate increases with the number of robots. Learning performance of the

group was improved when QL and mQL was combined with PSO. Also, as difficulty level increases QL tends to slow down as the number of robots increases; however, mQL still learns faster even with an increased number of robots. Ren et al [83] describe the feasibility of Q-learning based on an extreme learning machine (Q-ELM algorithm) in addressing mobile robot path planning problems. These problems include; high dimensionality, training difficulty and slow learning speed associated with the application of behavioral psychology neural network in mobile robot path planning. Authors substantiate the feasibility of the Q-ELM through experiments carried out by Matlab 7.0. Results show that the stability and convergence of the algorithm are proved by the number of episodes. The advantage of ELM in terms of fast computing power, inherently accelerates the implementation of Q-learning in the agent and improves the learning rate. Valiollahi et al [89] describe the combination of fuzzy logic and Q-learning algorithm for autonomous navigation of a Khepera mobile robot. Sensory data by limited range infrared sensors is the fuzzy input. The fuzzy outputs are the robot speed and steering angle. Every sensed data is fuzzified for efficient handling of uncertain, imprecise, or noisy information. Q-learning algorithm is used for the online tuning of the fuzzy inference. This provides a flexible decision-making system, with inherent adaptability to unknown environments. Experiment carried out on 30 simulated environments reveals goal reaching probability is 95% and the tendency of the robot to go beyond the safe margin from obstacles or walls is 15%. Xu et al [90] attempt the reduction of computation time and memory space of Q-learning algorithm. They simplified the algorithm discrete value table into a new version that stores only one optimum action and its Q-value rather than storing every action's Q-value in each state for conventional Q-learning. Authors implemented their simplified online Q-learning (SOQ) algorithm in Java language using the LeJOS implementation for the Lego Mindstorms EV3 robot. Experimental result shows the SOQ algorithm promising capability of reduced memory complexity when dealing with thousands of state-action values. Zheng et al [91] describe a solution to the autonomous obstacle avoidance problem of a mobile robot in static and dynamic environments. They applied feature level fusion to fuse the sensory information of laser sensor and sonar sensor to complement their single application drawbacks. Q-learning algorithm is then applied to avoid dynamic obstacles as the robot heads for the goal coordinate. Their experimental setup is divided into; simulation in Matlab and actual mobile robot experiment. Experimental result shows that the robot can navigate through obstacles and safely attain the goal coordinate.

Muhammad and Bucak [87] attempt to solve the rate of convergence of the Q-table in large state-action space associated with mobile robot application. The Q-table stores the state-action pair. Their approach in solving this problem is to store all the state-action values visited by the mobile robot from start coordinate to the goal coordinate and then replaying or backtracking these state-action sequences to use the updated Q values after the goal state has been reached. The exploration/exploitation strategy of action-selection mechanism is the Boltzmann or soft-max distribution. Simulation of this approach and its comparison with the conventional Q-learning algorithm in terms of cumulative change in Q-value and rate of change of the Q values was presented. The result shows significant improvement in the rate of change of the Q-table by the proposed algorithm as compared to the conventional Q-learning. Yang and Li [85]

describe the navigation control algorithm of a mobile robot base on Q-learning method. The authors considered only obstacles within 180o range ahead of the robot for algorithm simplicity and obstacles position is divided into the left, right and ahead directions. The Boltzmann selection mechanism is adopted for the training process to action selection. The feasibility of this algorithm is verified by two different simulation environments setups. Results after 237 training episodes presents a feasible path compared and robot attains the goal coordinate safely. Lakhmi and Atulya [82] propose a modification of the conventional Q-learning (CQL) algorithm and evaluate it increase performance in the path-planning problem. Their approach consists of four conditional rules for balancing the exploration/ exploitation factor. The feasibility of the proposed algorithm is evaluated using computer simulation and a created real-world environment. In the computer simulation a grid map of 20×20 under four experimental settings were used to compare the performance of the MQL, EQL and CQL. result shows MQL outperforms the CQL and EQL in all cases. Sichkar [92] evaluates the performance of Q-Learning algorithm and its modification SARSA reinforcement algorithm for global path planning for mobile robots. Cumulatively, 50 experiment were conducted for Q-Learning and SARSA algorithm with different parameters. The results show that Boltzmann distribution temperature parameter T from 0.01 to 0.04 for 1000 episodes achieved optimal solution between quality and learning speed.

Jiang and Xin [93] describe a novel learning algorithm for path planning of mobile robots in a large state space environment. Fuzzy rule is applied to fraction the state and action. Their approach is critical in large space application with Q-learning algorithm where the number of states and the lengths and directions of the actions are infinite. To achieve a trade-off between exploration and exploitation authors combine the ϵ -greedy with a described area allocation strategy to improve the learning convergence speed. Experimental set up was applied to evaluate the feasibility of the describe approach. The superiority of the proposed algorithm over the ϵ -greedy method and the SoftMax is evident. Li et al [94] describe an innovative path planning method based on improved Q-Learning algorithm (IQL) and some heuristic searching strategies for mobile robot path planning problem in dynamic environment. The IQL combines the ϵ -greedy exploration with Boltzmann exploration to attain the balance between the exploration and exploitation appropriately. The heuristic searching strategies shows it significance in reducing the number of iterations in learning process and controlling the variation range of robot orientation angle. Authors validate their IQL approach via experimental set up and compare it performance with the performance of the IQL was compared with CQL, A* and EQL algorithm. Qualitative result shows IQL superiority to CQL in both distance and orientation angle of the path. Although the A* presents shorter distance but it doesn't take the safe range with the obstacle nearby. Motlagh et al [95] design obstacle avoidance and goal seeking competence in a mobile robot with the combination of reinforcement learning and neural networks. Roy et al [96] presents the combination of image processing and Q-learning to solve the path planning problem of WMR in an indoor environment. The environment image is captured using a ceiling mounted camera. This image processed and the obstacles in the environment is processed using Adaptive Gaussian Threshold. Trajectory tracking for the robot is done using OpenCV template matching.

5. Path Tracking Algorithms

The efficient controller design for a differential drive WMR requires the incorporation of it kinematic and dynamic model. The general schematic of a differential drive WMR is given in Fig. 2.

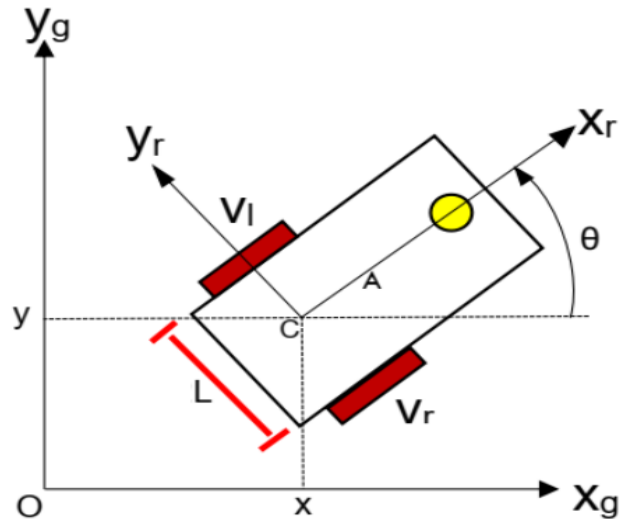


Fig. 2 General Schematic of a Differential Drive WMR

where $\{x_g \ O \ y_g\}$ represents the global reference frame and $\{x_r \ C \ y_r\}$ represents the mobile robots local reference frame. The left and right wheel velocity is v_l and v_r respectively. The position of the center of the robot wheel at C relative to the global reference frame is located by coordinate x and y . ϕ is the difference in orientation between the global and local reference frames. The kinematic model of the mobile robot as described by [1, 8, 97] is given below:

$$\begin{cases} x = \frac{r}{2}(v_r + v_l)\cos\phi \\ y = \frac{r}{2}(v_r + v_l)\sin\phi \\ \dot{\phi} = \frac{r}{L}(v_r - v_l) \end{cases} \quad (1)$$

Eq.1 presents the differential drive wheeled mobile robot kinematic model. Showing how v_l and v_r transforms to \dot{x} , \dot{y} and $\dot{\phi}$. Where r is the wheel radius, L is the distance between the wheels; and $L/2$ is distance of individual wheel to the center C of the mobile robot. However, is it more convenient to describe the linear velocity and rotation velocity of a WMR using single variable v_{robot} and ω_{robot} rather than v_l and v_r as in Eq.1. Hence, the kinematic model of a differential drive WMR is mapped with that of its unicycle WMR counterpart [8, 97]. The kinematic model of a unicycle is

$$\begin{cases} x = v \cos \phi \\ y = v \sin \phi \\ \dot{\phi} = \omega \end{cases} \quad (2)$$

Comparing Eq.1 and Eq.2

$$V_{robot} = \frac{r}{2}(v_r + v_l) \quad (3)$$

$$\omega_{robot} = \frac{r}{L}(v_r - v_l) \quad (4)$$

So, Eq.3 and Eq.4 establish the connection between the translational velocity v of the robot to wheel velocities v_l and v_r and angular velocity ω of the robot to wheel velocities v_l and v_r respectively. Solving Eq.3 and 4 simultaneously we obtain Eq. 5 and 6 for v_r and v_l respectively:

$$v_r = \frac{2V_{robot} + \omega_{robot}L}{2r} \quad (5)$$

$$v_l = \frac{2V_{robot} - \omega_{robot}L}{2r} \quad (6)$$

Hence, from Eq. 5 and 6 we have v_l and v_r in terms of the design parameter v and ω and the measured parameter L and r .

Similarly, the relation between the wheel velocities v_l , v_r and the robot velocity v and angular velocity ω as given by [1, 8]:

$$\begin{cases} \omega_{robot} = \frac{(v_r - v_l)}{L} \\ V_{robot} = \frac{(v_r + v_l)}{2} \end{cases} \quad (7)$$

It is important to state that the wheel velocities v_l , v_r is derived from the DC motor velocities ω_l and ω_r with the relations [1, 8]:

$$\begin{cases} v_r = r\omega_r \\ v_l = r\omega_l \end{cases} \quad (8)$$

Inserting Eq.8 into Eq.7, Eq.9 is obtained:

$$\begin{cases} \omega_{robot} = \frac{(r\omega_r - r\omega_l)}{L} \\ V_{robot} = \frac{(r\omega_r + r\omega_l)}{2} \end{cases} \quad (9)$$

$$\begin{cases} \omega_{robot} = \frac{r}{L}(\omega_r - \omega_l) \\ V_{robot} = \frac{r}{2}(\omega_r + \omega_l) \end{cases} \quad (10)$$

So, Eq.10 presents the relation of robot translational velocity and rotational velocity to DC motor velocity.

The Dynamic model of a differential drive WMR can be derived from the Euler - Lagrange formulation with the general form [1, 8, 114]:

$$\frac{d}{dt} \left(\frac{\partial L}{\partial \dot{q}_i} \right) - \frac{\partial L}{\partial q_i} = Q_i \quad (11)$$

Where, L is the Lagrange function, expressed as the difference between the WMR Kinetic Energy (K.E) and WMR Potential Energy (P.E)? However, the P.E is set as zero since robot is required to traverse on a plane. Hence, $L = K.E (K)$.

$$\frac{d}{dt} \left(\frac{\partial K}{\partial \dot{q}_i} \right) - \frac{\partial K}{\partial q_i} = Q_i \quad (12)$$

The summation of K.E on the WMR is:

$$K = K_t + K_r + K_{wr} \quad (13)$$

q_i is the WMR global coordinate

Q_i is the global force acting on the WMR?

K_t is the K.E associated with WMR translation

K_r is the K.E due to WMR rotation

K_{wr} is the K.E due to WMR wheel and rotor rotations.

The nonlinear nature of the WMR system makes the need for a controller inevitable. Thus, controller design have been adopted in literature to compensate for the system uncertainty and input disturbance. Hmeyda and Bouani [32] has presented a dual PID controller to output the linear velocity and angular velocity of a WMR wheel motor. The reference path is generated using PSO-Trajectory algorithm. However, the kinematic and dynamic model of the WMR was not incorporated and advance tuning algorithms for PID gains was not considered. Hence limiting the robustness of these approach to static environment with static obstacles. Rai and Rai [98] describe the speed control for an Arduino Uno microcontroller-based DC motor. They merge a multilayer neural network controller and PID controller to improve the performance of the controller. Rossomando and Soria [99] address the trajectory tracking control problem of a WMR using their designed adaptive neural network PID controller. Al Mutib and Mattar [100] have design ta differential drive WMR wheel actuator speed control using neuro-fuzzy controller. The input to the controller is the sensory information from onboard ultrasonic sensor for obstacle detection. Baturone et al [101] describe a car-like mobile robot control using an embedded neuro-fuzzy controller.

Deshpande and Bhosale [102] introduce the adaptive neuro-fuzzy inference system controller for navigation control of a differential drive WMR with nonholonomic constraints. Al-Mayyahi et al [103] describe the control of a differential drive WMR wheel actuator angular velocity and heading angle control using an adaptive neuro-fuzzy technique inference system controller. Silva-Ortigoza et al [23] address the path tracking problem considering the

kinematic model of a two wheel differential drive WMR using Hierarchical control. The desired velocity profiles of the two wheels are generated using the upper level, input-output linearization control for the movement of the WMR along the reference path avoiding obstacles. A dual PI controller is used to control the DC motor of the right and left actuated wheel velocity respectively at the lower level. The lower level control is responsible for synchronizing the desired velocity obtained at the upper level with the actual velocity of the robot wheel hence, tracking the path. Simulation results show some deviation between the actual velocities and the desired velocities using the PI controller. This indicates the necessity for an advanced optimization algorithm for tuning the PI gains for better performance. Jayaprakash et al [104] presents a sensor fusion method for WMR absolute heading angle detection in an indoor environment. Onboard sensors: Gyroscope (L3G400), encoders and ultrasonic sensors were deployed to measure angular velocity, speed/direction of wheel rotation and obstacle detection respectively. Kalman filter is applied to fuse the data from the gyroscope and encoders to accurately estimate the real-time heading angle of the WMR. PID controller is used to compensate for the deviation of the real-time heading angle and desired heading angle. Simulation results show that using Kalman filter and PID controller effectively correct the heading angle deviation to a marginal tolerable value of about ± 2 degrees. Lee and Chia [105] design a straight path control of a four omnidirectional WMR wheel actuator DC motors using wheel encoder and Proportional controller. The actual wheel velocity is sensed through the wheel encoder and sends the data to the onboard personal computer via serial communication using a USB cable. To track straight path deviation from the encoder reading for the right and left motor must tend to zero, thus the proportional controller compensates for this difference in encoder readings. Comparison of the proposed design with logic control system results show the proportional control system performed better with minimal oscillation. Koubaa et al [106] address the trajectory tracking problem of WMR with unknown skidding and slipping (dynamic model disturbance) using an adaptive sliding mode control. To eliminate the effect of dynamic model disturbance on the actual velocity resulting in its deviation from the desired velocity, the adaptive sliding-mode dynamic controller is proposed. The confirmation of system stability and the convergence of the tracking errors to zero is done using the Lyapunov theory. Illustration of the effectiveness of the proposed controller through computer simulation presents its robustness and efficiency superior to kinematic/torque controller.

Arantes and Sena Esteves [107] describe the wheel actuator velocity control for a four Mecanum wheels omnidirectional mobile robot using PID controller. Susan et al [108] presents a fuzzy hybrid PID controller for steering control for an omnidirectional mobile robot with three-wheels. The proposed controller is implemented on an autonomous wheel chair with active caster wheels to improve its maneuverability and environment accessibility. Ren et al [109] achieve the friction compensation of a three-wheeled omnidirectional mobile robot using a reduced-order extended state observer (ESO) based sliding mode control scheme. The comparative advantage of the proposed approach is that; precise friction model is unnecessary resulting in minimal computational cost. Mousavi [110] presents a path tracking controller for a mobile robot in a deterministic environment using fuzzy logic. The input variables are distance and angular difference and the two control inputs are linear and angular velocities. Simulation illustration of the proposed

method and comparison with model predictive controller (MPC) shows its superiority in terms of speed, robustness and simplicity. Mahgoub and Sanhoury [111] develop a path tracking controller model for a WMR using backstepping approach. The controller development considers the kinematic model of a WMR and the system stability is confirmed using Lyapunov function. Alouache and Wu [112] applied the GA as an advanced optimization algorithm to improve the performance of a PID controller in terms of control precision and speed of convergence for a mobile robot. Investigation of the effectiveness of the proposed GA-PID controller in comparison to PID in tracking a reference trajectory presents its superiority and robustness. Esmacili et al [113] address the balancing and trajectory tracking problem of Two Wheeled Balancing Mobile Robots using backstepping Sliding Mode Controller (SMC). Lagrangian method with dynamics of DC motors is used to derive the mathematical model of the robot. Mallem et al [114] presents a path tracking method based on PID fast terminal sliding mode dynamic inverse control for WMR. The method considers the kinematics and dynamics models of WMR to ensure the asymptotic stabilization of the robot's position and orientation around the desired trajectory. Simulation results show the practicability of the proposed method in real-world mobile robot application. Allagui et al [115] presents the trajectory tracking of Khepera II WMR using three fuzzy logic PI controllers. The fuzzy logic output is the gains of the PI controller, thus, the quality of trajectory tracking and navigation is improved. Simulation results of the fuzzy PI controller and comparison with PI controller show the proposed fuzzy PI controller eliminates the sensitivity problem associated with PI controllers. Nikranjbar et al [81] design a path tracking controller for a three-wheel mobile robot in the presence of varying-size triangular regularly shaped dynamic obstacles using an hybrid backstepping kinematic control along with the repressor based adaptive integral sliding mode. This presents the kinematic and dynamic control speed of the robot respectively. Simulation shows significant input disturbance suppression characteristic.

Alakshendra et al [15] evaluate the performance of the Integral sliding mode controller (ISMC) and adaptive integral sliding mode controller (AISMC) for tracking a U-path on a three-wheeled omnidirectional mobile robot considering friction disturbance and bounded uncertainties. Results present the superiority of the AISMC to the ISMC in tracking the desired path. Alakshendra and Chiddarwar [14] discuss the nonlinear trajectory tracking competence of a 4-Mecanum Wheeled Mobile Robot (4-MWMR) using second order sliding mode controller (SSMC). Authors incorporate the equation of motion derived using Newton Euler formulation with regard to motor dynamics, external forces and uncertainties which may vary the mobile robot from its trajectory. Simulation results showed a significant achievement of their proposed controller in ensuring that the 4-MWMR tracks a non-linear reference trajectory successfully. Urrea and Muñoz [116] appraise and report the performance of adaptive PID (ADP PID), model reference adaptive controller (MRAC), and fuzzy controller (FC) employed on a model two Wheeled Mobile Robot for autonomous path tracking on a model farm. The performance metric is the path trajectory generated by the controller and the torque requirement by the actuating motors. Qualitative results of the applied indices show MRAC presents better results on both metrics. Vinod Raj and Abraham [8] address the response delay problem of controller to disturbances using a

cascaded PID control for reference path tracking considering the kinematic and dynamic model of the robot. This approach adopts the master and slave controller to control the linear and angular velocity of the robot base on its kinematic and dynamic model respectively. The two controllers are based on PID architecture. Simulation conducted for straight and circular path tracking reveals of the controllers ability in tracking the desired path but with visible deviation. This can be improved by using advanced algorithms in tuning the PID gains. Yousefi Allagui et al [117] describe the application of three fuzzy logic PI controllers for the purpose of goal reaching and trajectory tracking of the Khepera II mobile robot based on its kinematic model. Individual controller consists of designing a classical PI controller and a fuzzy inference system with two inputs and two outputs. The inputs are the error and the error derivative; however the outputs of the fuzzy unit are the parameter corrections of the gains of the PI controller. The approach is based on conversion of linguistic inference systems into automatic control. The simulation of the approach reveals the desired target and trajectory tracking are realized. The comparison of fuzzy PI compared to classical PI gives satisfactory results due to its elimination of sensitivity to initial conditions.

Dwivedi et al [118] presents a hybrid controller comprising of PSO based PID controller and Support Vector Machine (SVM) a supervised machine learning classification algorithm. The PSO based PID controls the wheel velocity and the SVM controls the turning angles by classifying the angles of the next position. The aim of the Authors is to develop a method to find the global optimum value of PID parameters under constraints with simplicity and computational efficiency. Simulation result presents the robustness and accuracy of the controller in tracking random and circular path. Lee et al [119] presents the Taguchi method to determine the optimal design of PID controller parameters in path tracking task. Authors design a step response tracking task, and test the parameters of PID controller. The Taguchi proofs to be fast and efficient in finding the best combination of PID gain parameters. The tuning time is also minimal compared with manual gain parameter tuning. Song et al [120] presents a control strategy combined with fuzzy control based on the Line of Sight (LOS) method. The research object is the Pioneer-3 wheeled mobile robot. The kinematic model of the mobile robot is developed and the path tracking control performance is evaluated on the straight and circular path. Simulation result reveals success of the proposed approach in tracking the straight and circular path with good performance. Shijin and Udayakumar [1] attempts the point tracking control problem of differential drive WMR using a PID controller. Authors describe the speed controller of the DC motors for a differential drive WMR using a PID controller considering its kinematic model and dynamic model. The Ziegler-Nichols method is used to evaluate the PID gains. Qualitative result shows the significance of the controller in ensuring the speed set point of 100 rads/sec is achieved by both wheels. However, on point-to-point tracking the qualitative result shows the mobile robot took a curved path rather than the required straight path. Thus, the need for optimization algorithm such as PSO and GA to optimize the PID gains for quick response of the controller. Heikkinen et al [121] propose a self-tuning-parameter fuzzy PID controller for rotational speed control of a differential drive WMR DC motors. The aim is to complete a straight trajectory using the self-tuning-parameter fuzzy PID controller on the DC motors. Qualitative result shows the effectiveness of their approach in tracking a straight path in

a wide parameter variation range compared with the conventional PID controller. Meng et al [2] investigates the effectiveness of PID controller as speed controller on a two-wheeled differential drive mobile robot for straight and curved path. Their research object is a constructed two-wheel mobile robot platform based on STM32 Micro-controller. Simulation was conducted in Matlab-Simulink for the straight and curved path trajectory to validate the feasibility of the PID controller. Results reveal centimeter deviations from the desired path due to lack of robustness of the PID gain parameters.

Zhi et al [122] presents a shift control based on Neural Network and Fuzzy PID as the DC motor speed controller for a differential drive wheeled mobile robot. These advanced algorithms for tuning of the PID gains are aimed to offset the limitation of conventional PID for the target purpose. Simulation and effect analysis of the proposed method was done in Simulink and the control object is the DC servo motor. The result of the experiment compares the performance of the Fuzzy PID, Neural Network PID and the Neural Network and Fuzzy PID in terms of response time and maximum overshoot (%) of the set point. The Fuzzy PID control shows fast response but with more overshoot compared to the performance of the Neural Network PID control. However, with the Neural Network and Fuzzy PID the demerits both are eliminated and their merits established. Chang and Jin [123] describe the implementation of an adaptive tracking controller based on the PID for mobile robot trajectory tracking. Their approach incorporates the non-linear model of the differential drive WMR kinematics to ensure a precise prediction of the future trajectories. Qualitative result shows that their proposed method has less error and less maximum overshoot than conventional backstepping method and ordinary PID. Ammar and Azar [124] investigate the application of PID controller and Fractional Order PID (FOPID) controller to achieve a robust controller for a differential drive WMR. The research object is the Pioneer-3 Mobile Robot and the control variable is the linear velocity and angular velocity through the linear velocity control loop and angular velocity control loop. Authors apply the Integral square error (ISE), Integral absolute error (IAE), Integral time-square error (ITSE) and Integral time-absolute error (ITAE) tuning algorithms to tune the gains of PID and FOPID. Computer simulation done in Matlab-Simulink and the measured performance metrics are response time, peak time, maximum overshoot (%) and settling time. The result shows that PID-ITAE and FOPID-ISE presents the best parameters for the metric and FOPID-ISE achieved better performance parameter in relation to PID-ITAE. Other representative works are: Tamila et al [125], Salem [126], Barthelme and Zehnter [127], Proaño et al [128].

6. Conclusion

This literature review presents the necessity for path planning and path tracking competence in WMR for its sustained integration to tasks that further require them to operate within the human environment characterized with uncertainty. Although numerous path planning and path tracking algorithms have been applied by researchers, however, static environment with static obstacles consideration are in the majority. Furthermore, performance evaluation of these algorithms is largely based on computer simulation but some researchers equally describe their algorithm feasibility on real-world robot miniature applications. This creates a gap

between available methodologies and their real-world practicability. Hence, this gap motivates the current research on the application of Q-learning algorithm for path planning and PID controller for path tracking with advance optimization algorithm in the development of a unit-load dispatch differential drive WMR in an office environment with static and dynamic obstacles. This present papers' emphasis is on review of WMR path planning and path

tracking control algorithms. Hence, extensive insight on the discussed technology can be found in the sited references.

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