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A Review of Artificial Intelligence Algorithms used for Robotic Manipulator

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Abstract: This paper introduces some of the artificial intelligence (AI) algorithms and applications presently being used for robotic manipulator. These AI algorithms can be classified as adaptive, neuron network, fuzzy logic, evolutionary algorithms, swarm intelligence and deep learning for motion controller design, path planning, dynamic parameters identification, robot vision and grasping applications. Problems in robotic manipulator are reviewed and applications of AI for them.
Keywords: Artificial Intelligence, Robotic Manipulator

I. INTRODUCTION

Robotics and AI amplify human potentials, increase productivity and are moving from simple reasoning towards human-like cognitive abilities. Current AI technologies are used in a set area of applications, ranging from healthcare, manufacturing, transport, energy, to financial services, banking, advertising, management consulting and government agencies [1]. The autonomy of a robot in an environment can be subdivided into perceiving, planning and execution (manipulating, navigating, collaborating). The main idea of converging AI and Robotics is to try to optimize its level of autonomy through learning. This level of intelligence can be measured as the capacity of predicting the future, either in planning a task, or in interacting (either by manipulating or navigating) with the world. An important application of AI in robotics is for the task of perception. Robots can sense the environment by means of integrated sensors or computer vision. Perception is not only important for planning but also for creating an artificial sense of self-awareness in the robot.

In recent years, the industrial applications of robotic manipulators have significantly been increased. They have been extensively used in the applications such as paint spraying, welding, accurate positioning system etc. Due to complexity of the task, AI has been used more and more for robotic manipulator, especially in grasping, and path planning with obstacle avoidance. The applications of AI are detailed in section 2 and 3.

The remains of this paper are organized as follows. Section 2 introduces important problems in robotic manipulator and application of AI. Section 3 presents some of the AI algorithms used for robot manipulator. A detailed description how to apply AI to motion planning is given in section 4. Section 5 concludes this paper and presents future work.

II. PROBLEMS IN ROBOTIC MANIPULATOR

A. Path Planning and trajectory Planning

In order to move the manipulator (end effector) from an initial posture to a final assigned posture, the first problem needs to be solved is that path planning and trajectory planning. A path denotes the locus of points in the joint space, or in the operational space, which the manipulator has to follow in the execution of the assigned motion; a path is then a pure geometric description of motion. On the other hand, a trajectory is a path on which a timing law is specified, for instance in terms of velocities and/or accelerations at each point [2].

There are various ways to create trajectories that interpolate pose (or joint configurations) over time. These are trapezoidal velocity, polynomial, spline. Trapezoidal velocity trajectories are piecewise trajectories of constant acceleration, zero acceleration, and constant deceleration. This leads to a trapezoidal velocity profile, and a "linear segment with parabolic blend" (LSPB) or s-curve position profile. Fig 1. is the trapezoidal velocity profile [3].

Trajectory planning can be performed either in the joint space or operational space. Trajectory planning in the operational space allows path constraints such as obstacles to be accounted. However, it has disadvantages such as computationally expensive due to inverse kinematics, unknown how to set the total time to traverse the path, ... [4].

It can be conceived that the inputs to a trajectory planning algorithm are the path specification, the path constraints, and the constraints imposed by manipulator dynamics, whereas the outputs are the end-effector trajectories in terms of a time sequence of the values attained by position, velocity and acceleration [2]. Inputs and outputs of the trajectory planner can be illustrated in Fig 2.

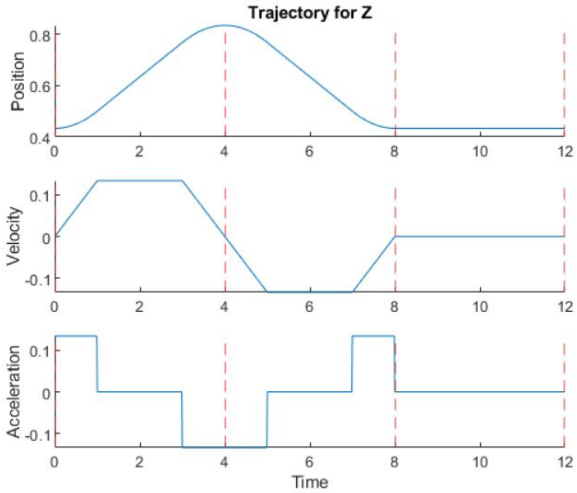


Fig. 1 Trapezoidal velocity profile

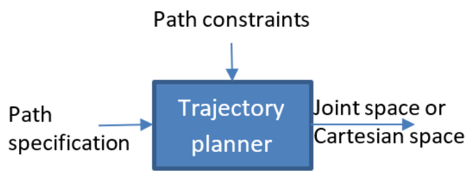


Fig. 2 Trajectory planner

B. *Motion Control*

Once the entire trajectory is planned, there needs to be a control system that can execute the trajectory in a sufficiently accurate manner. Due to highly nonlinear and time varying dynamic, the trajectory tracking control is one of the challenging problems. In addition, uncertainty in the parameters of both mechanical part of manipulators and the actuating systems would cause more complexity. In controlling robotic manipulator, there are two methods: classical method that using conventional theory and modern method that using artificial intelligence theory.

In this motion control review section, authors will focus on the classical control including linear controller (PID) and nonlinear controller (CTC, VSC, SMC) and modern control including adaptive control, fuzzy logic control, neural network control, learning control.

1) *Classical control: PID:* These are the simplest controllers for controlling robotic manipulators. In the article [5], authors presented an overview of PD control with desired gravity compensation of robot manipulators. The subjects the authors have addressed include the boundedness of solutions for the closed-loop system and conditions for equilibrium uniqueness. Besides, the authors have also reviewed PD control with adaptive desired gravity compensation that is able to overcome the parameter uncertainty problem. In the paper [6], authors showed that the PID control law stability depends only on the inertial parameters of the robot and proved the semiglobal stability of robot manipulators under the action of classical PID control. In the paper [7], authors proved that under classical PID control, semiglobal stability can be assured with arbitrary small output tracking error. In the paper [8], a simple decentralized continuous sliding PID controller for tracking tasks that yields semiglobal stability of all closed-loop signals with exponential convergence of tracking errors is proposed. In the paper [9] authors proposed a new saturated nonlinear PID regulator for solving the problem of global regulation of robot manipulators with bounded torques. An approach based on Lyapunov theory is used for analyzing the global asymptotic stability. In this sense, this proposal gives a step ahead in the search of a global asymptotic stability analysis for the practical PID. In [10], a Fractional adaptive PID (FPID) controller for a robot manipulator was proposed. The PID parameters have been optimized by Genetic algorithm. The proposed controller is found robust by means of simulation in a tracking job. The scheme of this proposed controller as in Fig 3. To solve the strong nonlinearity and coupling problems in robot manipulator control, two novel robust adaptive PID control schemes are proposed in paper [11] with known or unknown upper bound of the external disturbances. Invoking the two proposed controllers, the unknown bounded external disturbances can be compensated and the global asymptotical stability with respect to the manipulator positions and velocities is able to be guaranteed.

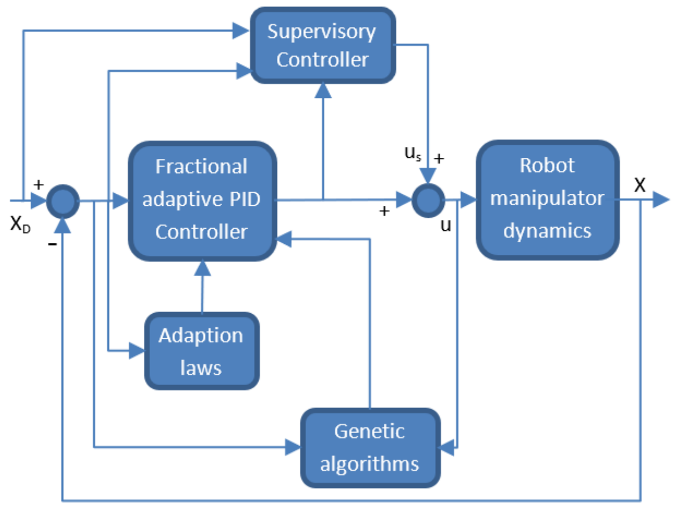


Fig. 3 Robust fractional adaptive PID control for robot manipulator system

2) *Computed torque control (CTC):* Due to performance limitations of classical controllers, the computed torque control is usually desirable in advanced applications. This control strategy ensures global asymptotic stability for fixed symmetric positive definite (proportional and derivative) gain matrices. In the paper [12], authors showed that global asymptotic stability also holds for a class of gain matrices depending on the manipulator state. The authors used fuzzy self-tuning algorithm to select the proportional and derivative gains according to the actual tracking position error. Experiments on a two degrees of freedom robot arm shown the usefulness of the proposed approach. Although computed torque control is an effective motion control strategy, it requires precise dynamical models of robotic manipulators. To handle this impossibility, in the paper [13], a new approach combing computed torque control and fuzzy control is developed for trajectory tracking problems of robotic manipulators with structured uncertainty and/or unstructured uncertainty. Computer simulation results on a two-link elbow planar robotic manipulator are presented to show tracking capability and effectiveness of the proposed scheme. The authors in the paper [14] proposed two types of adaptive fuzzy computed torque control, where feed-forward and feed-back fuzzy compensators are used to compensate modelling uncertainties and external disturbances. Comparisons of their performances with conventional computed-torque controllers under the condition of these uncertainties are carried out. Comparative results demonstrate that the two types of adaptive control schemes are effective in improving control performances in terms of modelling uncertainties and external disturbances. Simulation results show that the trajectory tracking errors of the robotic manipulator can be significantly reduced.
3) *Variable structure control (VSC):* Variable structure theory provided a technique for the design of the controller such that robust to uncertainties in the model of the system, as well as being inexpensive from a computational point of view. Authors in the paper [15] concluded that variable structure control is readily applicable to industrial robots for the robust control of positions. Variable structure control has a major drawback is that undesired phenomenon of chattering due to high frequency switching, which will often excite undesired dynamics. In the paper [16], authors embedded the variable structure control strategy with a new adaptive control law, it provides an ability to compensate the effect of uncertainties, disturbances, and unmodeled system dynamics.
4) *Sliding mode control (SMC):* Sliding mode controller is a powerful nonlinear controller which has been applied to robotic manipulator. In recent years, artificial intelligence theory has been used in sliding mode control systems. Neural network, fuzzy logic and neuro-fuzzy are synergically combined with sliding mode controller and used in nonlinear, time variant and uncertainty plant (e.g., robot manipulator) [17]. In [18], a novel fuzzy sliding mode controller based on RBFNN is proposed. RBFNN is used to compute the equivalent control. An adaptive rule is employed to on-line adjust the weights of RBFNN. Using fuzzy controller to adjust the corrective control gain in sliding mode control, system performance is improved. Chattering problem in the classical sliding mode controller is minimized. The authors in the paper [19] proposed an adaptive backstepping sliding mode control to solve the precise trajectory tracking under external disturbances with complex environment, and the dynamic response characteristics of a two-link robotic manipulator are described in this paper. Simulation results show that the proposed control system has good tracking performance and strong robustness for the external disturbance.

5) *Adaptive control:* Adaptive control has been recognized as an effective approach for mechanical robot manipulator controller design due to the presence of nonlinearities and uncertainties in robot dynamic models. In [20], authors presented an in-depth review of these existing developments whereby the robot adaptive control problems and solutions are systematically studied. The various design techniques are categorized into three groups; (i) model-reference adaptive control, (ii) Self tuning adaptive control, and (iii) Linear perturbation adaptive control. In [21], the author proposed two adaptive control schemes to realize the objective of task-space trajectory tracking irrespective of the uncertain kinematics and dynamics. The proposed controllers have the desirable separation property. A robust adaptive control method is systematically proposed in the paper [22] to significantly reduce the relatively tracking errors of 6 degree of freedom (DOF) industrial robots under both external disturbances and parametric uncertainties. The robust adaptive control law is formulated based on the robot dynamics in the task space of the robot end-effector. The control law is designed by combining robust term and adaptive term to track the desired trajectory of the end-effector with sufficient robustness and accuracy in the presence of unknown external disturbances and parametric uncertainties. The trajectory tracking performances of the proposed control are finally guaranteed based on Lyapunov function and Barbalat's lemma. Test results are obtained to show that the combined robust adaptive control reduces the final trajectory tracking error significantly as compared with conventional control
6) *Fuzzy logic and neural network control:* In the above sections, we have seen that fuzzy logic and/or neural network were combined with classic controller to compensate tracking error due to nonlinearities and uncertainties in robot dynamic models. Besides, fuzzy logic and neural network are also used to compensate physical constraints such as saturation nonlinearities of actuators and friction phenomena at the robotic joints. The authors in [23] proposed a novel global asymptotic stable set-point fuzzy controller with bounded torques for robot manipulators. This fuzzy controller for robot manipulators assures that the steady state position errors are inside a region which can be arbitrarily reduced closed to zero when friction is present. In case of absence of friction such a controller produces a global asymptotic stable closed-loop system. For both cases, it is always guaranteed that the torques delivered by the actuators are inside prescribed limits given in agreement with actuators torque capabilities. Experimental tests conducted on a robotic arm confirm the theoretical outcomes. The authors in [24] developed the adaptive fuzzy neural network control (AFNNC), including indirect (IAFNNC) and direct (DAFNNC) frameworks for an n-link robot manipulator, to achieve high-precision position tracking. Numerical simulations and experimental results of a two-link robot manipulator actuated by dc servomotors are given to verify the effectiveness and robustness of the proposed methodologies. Using neural networks for the control of robot manipulators have attracted much attention and various related schemes and methods have been proposed and investigated. In the paper [25], the authors reviewed research progress about controlling manipulators by means of neural networks. The problem foundation of manipulator control and the theoretical ideas on using neural network to solve this problem are analyzed and then the latest progresses on this topic in recent years are described and reviewed in detail. Obstacle avoidance is an important subject in the control of robot manipulators, but is remains challenging for robots with redundant degrees of freedom, especially when there exist complex physical constraints. In the paper [26], the authors proposed a novel controller based on deep recurrent neural networks. By abstracting robots and obstacles into critical point sets respectively, the distance between the robot and obstacles can be described in a simpler way, then the obstacle avoidance strategy is established in form of inequality constraints by general class-K functions. Using minimal-velocity-norm (MVN) scheme, the control problem is formulated as a quadratic-programming case under multiple constraints. Then a deep recurrent neural network considering system models is established to solve the QP problem online. Theoretical conduction and numerical simulations show that the controller is capable of avoiding static or dynamic obstacles, while tracking the predefined trajectories under physical constraints
7) *Learning Control:* Learning control for robotic manipulators has been developed over the past decade and it is still in its infant development stage and will become one of the most promising directions in the control area in robotic manipulators [27]. Learning control in robotic manipulators is mainly used to address the issue that the friction at the joints of robotic mechanisms and other uncertainties may exist in the dynamic models, which are very complex and may even be impossible to model mathematically. Learning control design through simulating human internal control and nervous systems for robot manipulators is worth exploring so as to make the control system more intelligent. The combination of the mechatronic design approach and learning control design approach for robotic manipulators also has great potential for future enhancements. One of the applications of the learning control approach could be addressing safety issues such as those found in robotic-based manufacturing industries.

C. Dynamic Parameters Identification

The knowledge of the dynamic parameters of the manipulator play an important role in designing model-based algorithms for controlling robot exactly. A number of methods have been proposed to identify dynamic parameters of robot. In [28], authors used the least squares (LS) method and the particle swarm optimization (PSO) technique to estimate the distinct inertia parameters of Staubli RX-60 robot. These experimental results show that the estimated inertial parameters predict robot dynamics well. In [29], authors demonstrated the possibility of identification methods including least squares, extended Kalman filter, Adaptive Linear Neuron (Adaline) neural networks, Hopfield recurrent neural networks and genetic algorithms in order to obtain parameters characterizing the industrial robot dynamics, specifically in SCARA robots. In the paper [30], the author introduces an application of the Shuffled Frog Leaping Algorithm in identifying the dynamic parameters of UP6 manipulator without parameterization. The simulated results show that SFLA gives response results close to the real model.

D. Robot Vision

Vision technology has become a critical component for many industrial robot applications such as robots guided by vision can locate parts to be picked up, determine where to apply a weld, inspect parts that have been assembled or determine where to place a part [31, 32].

Combination of visual sensing and robot manipulator in a feedback control loop is a principle concern in any application. There are two different control schemes are generally used for the visual servoing of a dynamic system. The first control scheme is called direct visual servoing and the second control scheme is called indirect visual servoing. Most of the visual servoing follows an indirect control scheme as Fig 4 [33].

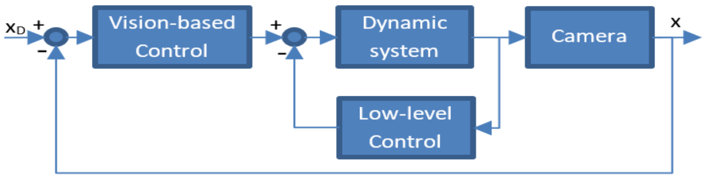


Fig. 4 Indirect visual servoing system

Reliable grasping is critical to successfully perform any grasp and properly recover for any error for any robotic application from industrial pick-and-place to service assistance. In the paper [34], the authors proposed a novel vision approach for monitoring the grasping tasks and verifying any lost of the held object. The underlying idea is the recognition of the contact points between the robot manipulator and the grasped object.

III. ALGORITHMS USED FOR ROBOTIC MANIPULATOR

A. Evolutionary Algorithms and Swam Intelligence

The popularity of metaheuristics, especially Swarm Intelligence and Evolutionary Algorithms, has increased rapidly over the last two decades. Numerous algorithms are proposed each year, and progressively more novel applications are being found [35]. Fig 5. lists some of the algorithms in these groups.

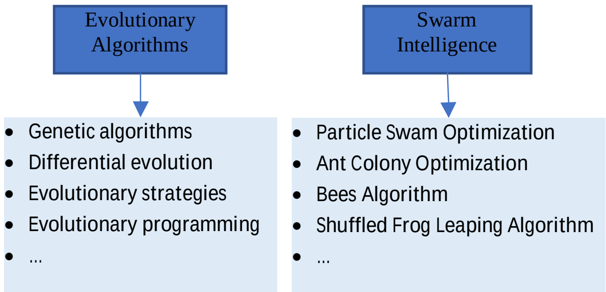


Fig. 5 Metaheuristics based optimization algorithms

Evolutionary Algorithms and Evolutionary Algorithms have been widely used in robotics design optimization [36, 37], path planning optimization [38, 39], optimizing the parameters of the controller [40] or parameter identification of robot manipulators [41].

B. ANN and Fuzzy logic

ANN and fuzzy logic have many applications but in robot manipulator area, they are mainly used for control system. Due to the influence of non-linearities, disturbances, gravity and load effects, Fuzzy Logic Controllers (FLC) or Artificial Neural Network (ANN) is adopted [42, 43].

C. Deep Learning

More recently, deep learning approaches have shown impressive performance across a wide range of domains, including computer vision, audio processing, natural language processing, and others. These algorithms are based on neural networks, highly-parameterized models which use multiple layers of representation to transform data into a task-specific representation and excellent choice for robotic applications [44]

A few works have applied deep learning directly to robotic manipulation. In the paper [45], authors presented an asynchronous deep reinforcement learning approach that can be used to learn complex robotic manipulation skills from scratch on real physical robotic manipulators. In the paper [46], authors have developed and implemented two RL-based compensation schemes to improve the suboptimal tracking performance of a feedback controller in a multi dof robot arm. The capacity to self-optimize the controllers of robot arms is essential in the Industry 4.0 setting. Deep learning algorithm is also employed to learn the inverse dynamics models [47]. In the paper [48], authors proposed a reinforcement learning (RL) based, cognition-enhanced six-axis industrial robot for complex motion planning along continuous trajectories as e.g. needed for welding, gluing or cutting processes in production.

IV. AI APPLICATIONS FOR MOTION PLANNING

This section describes how to apply AI for path planning problem. Fig. 5 illustrates control system for motion planning. In this system, motion planner block receives 3D coordinators from user and obstacle information from vision system to build global path and send control signal to joint controller to control robot tracking to desired path. AI such as PSO, Fuzzy, … will be used for building 3D global path with avoiding obstacle as well as designing controller for tracking trajectory are our research in near future.

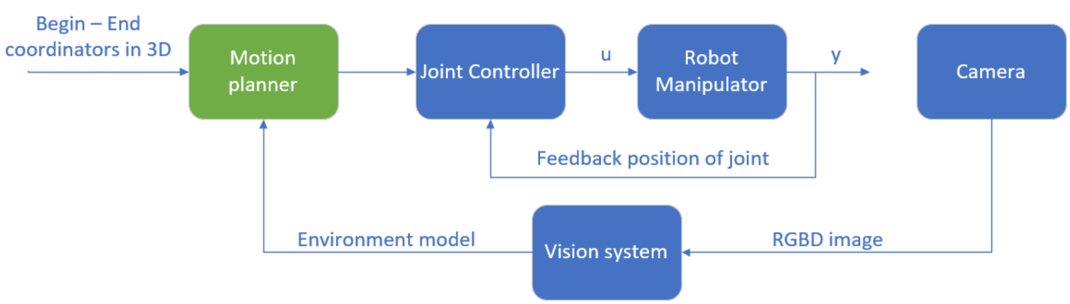


Fig. 6 Control system for motion planning

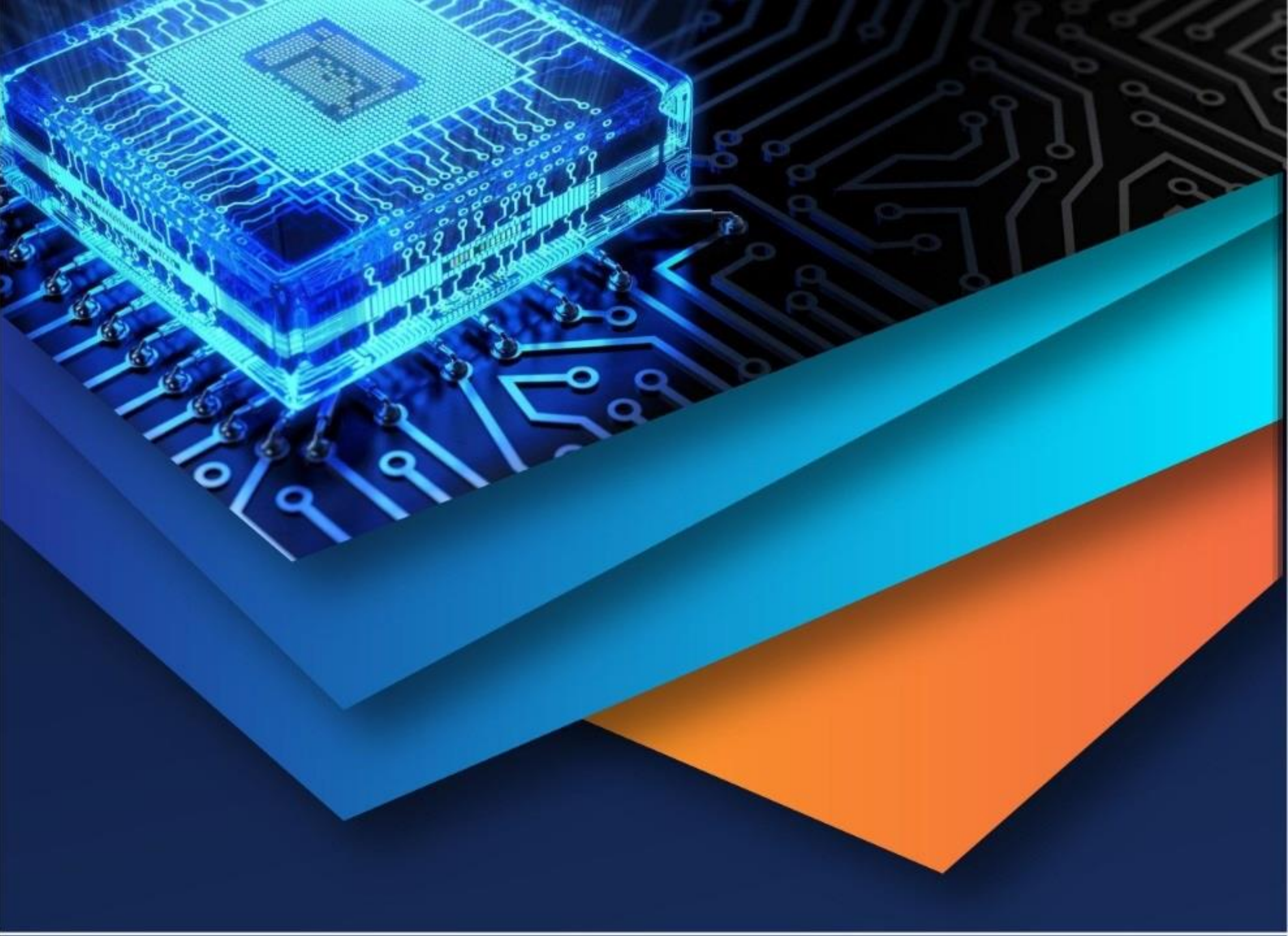
V. CONCLUSIONS

The literature review of this research has revealed that there was a significant trend toward the development of AI algorithms for applying in robotic manipulator. Many articles had been directed to accomplish this goal, especially in motion planning and grasping. In this paper, we have also discussed AI algorithms for 3D path planning with application vision system in order to avoid obstacle.

REFERENCES

[1] Javier Andreu Perez, et, Al Artificial Intelligence and Robotics, 2016.
[2] Bruno Siciliano, Lorenzo Sciavicco, Luigi Villani, Giuseppe Oriolo, Robotics - Modelling, Planning and Control, Springer-Verlag, 2009.
[3] Sebastian Castro, Trajectory Planning for Robot Manipulators, MathWorks Editor, 2019.
[4] Václav Hlaváč, Robot trajectory generation, Czech Institute of Informatics, Robotics and Cybernetics.
[5] Rafael Kelly, PD Control with Desired Gravity Compensation of Robotic Manipulators: A Review, The International Journal of Robotics Research, 1997,Vol. 16, No. 5, pp. 660-672.
[6] Jose Alvarez-Ramirez, Ilse Cervantes and Rafael Kelly, PID regulation of robot manipulators: stability and performance, Systems & Control Letters 41. Elsevier Science B.V, 2000.
[7] Ilse Cervantesa and Jose Alvarez-Ramirez, On the PID tracking control of robot manipulators, Systems & Control Letters 42. Elsevier Science B.V,2001.
[8] Vicente Parra-Vega, et al, Dynamic Sliding PID Control for Tracking of Robot Manipulators: Theory and Experiments, IEEE TRANSACTIONS ON ROBOTICS AND AUTOMATION, 2003, VOL. 19, NO. 6

[9] Victor Santibanez, et al, A New Saturated Nonlinear PID Global Regulator for Robot Manipulators, Proceedings of the 17th World Congress. IFAC, 2008.
[10] H. Delavari, et al, Adaptive Fractional PID Controller for Robot Manipulator, The 4th IFAC Workshop Fractional Differentiation and its Applications, 2010.
[11] Jian Xu and Lei Qiao, Robust Adaptive PID Control of Robot Manipulator with Bounded Disturbances, Hindawi Publishing Corporation, 2013.
[12] M.A. Llama, R. Kelly and V. Santibanez, Stable computed-torque control of robot manipulators via fuzzy self-tuning, IEEE Transactions on Systems, Man, and Cybernetics, Part B (Cybernetics), 2000, Vol. 30.
[13] Zuoshi Song, et al, A computed torque controller for uncertain robotic manipulator systems: Fuzzy approach, Fuzzy Sets and Systems 154. Elsevier B.V, 2005.
[14] Yuan Chen, et al, Adaptive Fuzzy Computed-Torque Control for Robot Manipulator with Uncertain Dynamics, International Journal of Advanced Robotic Systems. InTech, 2012.
[15] M.F.Mendes. W.Kraus Jr and E.R.de Pieri, Variable structure position control of an industrial robotic manipulator, Journal of the Brazilian Society of Mechanical Sciences, 2002.
[16] Ya-Chen Hsu, et al, A Fuzzy Adaptive Variable Structure Controller with Applications to Robot Manipulators, IEEE TRANSACTIONS ON SYSTEMS, MAN, AND CYBERNETICS—PART B: CYBERNETICS, 2001, VOL. 31, NO. 3.
[17] Farzin Piltan and Nasri B. Sulaiman, Review of Sliding Mode Control of Robotic Manipulator, World Applied Sciences Journal 18, 2012.
[18] Ayca Gokhan AK and Galip Cansever, Adaptive Neural Network Based Fuzzy Sliding Mode Control of Robot Manipulator, International Journal of Advanced Robotic Systems. InTech, 2008.
[19] Zhu Dachang, et al, Adaptive Backstepping Sliding Mode Control of Trajectory Tracking for Robotic Manipulators, Hindawi, 2020.
[20] T. Hsia, Adaptive control of robot manipulators - A review, proceedings IEEE International Conference on Robotics and Automation, 1986.
[21] Hanlei Wang, Adaptive Control of Robot Manipulators With Uncertain Kinematics and Dynamics, 2016.
[22] Xiuxing Yin and Li Pan, Enhancing trajectory tracking accuracy for industrial robot with robust adaptive control, Robotics and Computer–Integrated Manufacturing 51. Elsevier Ltd, 2018.
[23] Victor Santibañez, Rafael Kelly and Miguel A. Llama, A Novel Global Asymptotic Stable Set-Point Fuzzy Controller With Bounded Torques for Robot Manipulators, IEEE TRANSACTIONS ON FUZZY SYSTEMS, 2005, VOL. 13, NO. 3.
[24] Rong-Jong Wai and Zhi-Wei Yang, Adaptive Fuzzy Neural Network Control Design via a T–S Fuzzy Model for a Robot Manipulator Including Actuator Dynamics, IEEE TRANSACTIONS ON SYSTEMS, MAN, AND CYBERNETICS—PART B: CYBERNETICS, 2008, VOL. 38, NO. 5.
[25] Long Jin, et al, Robot manipulator control using neural networks: A survey, Neurocomputing. Elsevier Science B.V, 2018.
[26] Zhihao Xu, et al, Deep Recurrent Neural Networks Based Obstacle Avoidance Control for Redundant Manipulators, Front. Neurorobot, 2019.
[27] Dan Zhang and Bin Wei, Review On the Development of Learning Control for Robotic Manipulators, Robotics. MDPI, 2017.
[28] Zafer Bingül, Og˘uzhan Karahan, Dynamic identification of Staubli RX-60 robot using PSO and LS methods, Expert Systems with Applications 38, 2011, pp. 4136–4149.
[29] Claudio Urrea, José Pascal, Design, simulation, comparison and evaluation of parameter identification methods for an industrial robot, Computers and Electrical Engineering, 2016, 1–16.
[30] Duc Hoang Nguyen, Dynamic Parameter Identification of UP6 Robot Manipulator Using SFLA, International Journal of Computer Applications, 2018.
[31] E. Malis, Survey of vision-based robot control, Captain Comput. IV Forum, Brest, France, 2002.
[32] KOICHI HASHIMOTO, A review on vision-based control of robot manipulators, Advanced Robotics. Vol. 17, 2003, No. 10, pp. 969–991.
[33] Luis Hernández, Hichem Sahli and René González, Vision-based 2D and 3D Control of Robot Manipulators, InTech, 2010.
[34] Ester Martinez-Martin and Angel P. del Pobil, Vision for Robust Robot Manipulation, Sensors. MDPI, 2019.
[35] Adam P.Piotrowski, et. Al, Swarm Intelligence and Evolutionary Algorithms: Performance versus speed, Information Sciences. Vol. 384. Elsevier Inc, 2016.
[36] B. K. Rout and R. K. Mittal, Optimal design of manipulator parameter using evolutionary optimization techniques, Published online by Cambridge University Press, 2010.
[37] Sébastien Rubrecht, et. Al, Evolutionary Design of a Robotic Manipulator for a Highly Constrained Environment, Doncieux, S. and Bredèche, N. and Mouret, J.-B. New Horizons in Evolutionary Robotics, Springer, pp.109-121. Studies inComputational Intelligence, 2011, Vol. 341.
[38] Sandi Baressi Segota, et. Al, Path planning optimization of six-degree-of-freedom robotic manipulators using evolutionary algorithms. Sensing and Control in Advanced Robotics. International Journal of Advanced Robotic Systems, 2020.
[39] Jeong-Jung Kim and Ju-Jang Lee, Trajectory Optimization With Particle Swarm Optimization for Manipulator Motion Planning, IEEE TRANSACTIONS ON INDUSTRIAL INFORMATICS, VOL. 11, 2015, NO. 3.
[40] Fatiha Loucif and Sihem Kechida, Sliding Mode Control with PID Surface for Robot Manipulator Optimized by Evolutionary Algorithms, 2020.
[41] Danping Yan, Yongzhong Lu, and David Levy, Parameter Identification of Robot Manipulators: A Heuristic Particle Swarm Search Approach, PLoS One, 2015.
[42] ROSELITO A. TEIXEIRA, et. Al, Control of a Robotic Manipulator Using Artificial Neural Networks with On-line Adaptation, Neural Processing Letters 12: 19-31.
[43] Hicham Chaoui, Pierre Sicard and Wail Gueaieb, ANN-Based Adaptive Control of Robotic Manipulators With Friction and Joint Elasticity, IEEE TRANSACTIONS ON INDUSTRIAL ELECTRONICS, 2009, VOL. 56, NO. 8.
[44] Ian Lenz, DEEP LEARNING FOR ROBOTICS, A Dissertation. Cornell University, 2016.
[45] Shixiang Gu, et. Al, Deep Reinforcement Learning for Robotic Manipulation with Asynchronous Off-Policy Updates, arXiv:1610.00633v2, 2016.
[46] Yudha P. Pane, et. Al, Reinforcement Learning Based Compensation Methods for Robot Manipulators, CC-BY-NC-ND 4.0 license http://creativecommons.org/, 2018.
[47] Athanasios S. Polydoros, Lazaros Nalpantidis and Volker Kruger, Real-time Deep Learning of Robotic Manipulator Inverse Dynamics, IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS), 2015.
[48] Richard Meyes, et. Al, Motion Planning for Industrial Robots using Reinforcement Learning, The 50th CIRP Conference on Manufacturing Systems. Elsevier Science, 2017.



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