Journal of Robotics and Control (JRC)
Volume 6, Issue 3, 2025
ISSN: 2715-5072, DOI: 10.18196/jrc.v6i3.25604

The Intelligence Behind Robotic Arms: A Deep Dive into Control Evolution

Abdelrahman T. Elgohr [1], Mahmoud A. A. Mousa [2*] Ahmed Reda Mohamed [3], Hatem A. Khater [4], Alfian Ma'arif [5], Iswanto Suwarno [6]
[1] Department of Mechatronics Engineering, Faculty of Engineering, Horus University Egypt, New Damietta, Damietta, Egypt
[2] School of Mathematical and Computer Sciences, Heriot Watt University, Dubai, UAE
[3] Interdisciplinary Research Center for Communications Systems and Sensing, King Fahd University of Petroleum and Minerals (KFUPM), Dhahran 31261, Saudi Arabia
[4] Department of Electrical Engineering, Faculty of Engineering, Horus University Egypt, New Damietta, Damietta, Egypt
[5] Department of Electrical Engineering, Universitas Ahmad Dahlan, Yogyakarta, Indonesia
[6] Department of Electrical Engineering, Universitas Muhammadiyah Yogyakarta, Yogyakarta, Indonesia
Email: [1] atarek@horus.edu.eg, [2] m.mousa@hw.ac.uk, [3] ahmed.mohamed@kfupm.edu.sa, [4] hatem.a.khater@gmail.com, [5] alfianmaarif@ee.uad.ac.id, [6] iswanto_te@umy.ac.id
*Corresponding Author

***Abstract*—The intelligence behind robotic arms has evolved significantly, incorporating advanced methodologies from kinematics to brain-computer interfaces. This review critically examines the sequential steps in robotic arm control, covering Kinematic Analysis, Path Planning, Trajectory Optimization, and various Control Techniques, with a particular focus on Brain Signal Acquisition and Classification Approaches. While substantial progress has been made, key challenges persist. Traditional kinematic models often struggle with real-world uncertainties, computational inefficiencies, and singularity issues, limiting adaptability in dynamic environments. Path planning and trajectory optimization face constraints in real-time applications, where trade-offs between accuracy, computational speed, and obstacle avoidance remain critical. Control methodologies, from classical techniques to AI-driven approaches, must enhance robustness and energy efficiency to ensure stability in practical deployments. Furthermore, brain-controlled robotic arms, despite promising breakthroughs, contend with signal variability, low resolution, and the need for extensive training, raising concerns about reliability, ethical implications, and data privacy. This review consolidates recent advancements while addressing the fundamental challenges impeding seamless integration in industrial and biomedical applications. By bridging these gaps, future research can refine robotic arm intelligence, fostering more autonomous, precise, and human-integrated systems.**

Keywords*—*Robotic Arm Control; Kinematic Analysis; Path Planning; Trajectory Optimization; Brain Computer Interface.

I. Introduction

Robotic arms (Fig. 1) have historically been fundamental to automation, revolutionizing sectors including manufacturing, logistics, healthcare, and assistive technologies [1]. Their capacity to perform exact, repetitious, and intricate jobs with minimal human involvement has propelled considerable progress in control approaches. Throughout the years, advancements in kinematics modelling, path planning, trajectory optimization, and intelligent control approaches have empowered robotic arms to execute progressively complex tasks. The current incorporation of artificial intelligence (AI), reinforcement learning, and brain-computer interfaces (BCIs) has enhanced their capabilities, facilitating adaptive, autonomous, and human-integrated control [2]. Nonetheless, despite the considerable potential of these breakthroughs, the realization of fully controlled, intelligent robotic arm systems continue to pose a substantial barrier owing to technical, computational, and ethical constraints [3].

Fig. 1. Robotics arm control

The advancement of high-performance control techniques is impeded by numerous computational and practical limitations. Conventional control techniques, like PID and model predictive control, face challenges in sustaining efficiency inside dynamic and uncertain contexts, where sensor imperfections and external disturbances may undermine stability [4]. AI-driven methodologies, although providing flexibility, necessitate substantial computational resources, vast training datasets, and real-time processing abilities, rendering their application in industrial and assistive contexts extremely challenging [5]. Moreover, brain-controlled robotic arms, despite advancements in neuroprosthetics and rehabilitation, have low signal-to-noise ratios, user variability, and prolonged calibration durations, constraining their practical application. Guaranteeing secure and dependable human-robot interaction is a critical issue, particularly in high-risk fields such as surgical robotics and collaborative automation, where system malfunctions may result in severe repercussions [6]. Moreover, ethical concerns about data privacy, cognitive strain, and accessibility must be resolved as robotic arms become more integrated with human-centered applications [7].

In addition to these technical obstacles, achieving a balance between computing efficiency and adaptability continues to be a significant issue in robotic arm control [8]. Conventional control systems frequently inadequately address environmental uncertainty and sensor noise, requiring the implementation of hybrid control frameworks that integrate classical model-based methods with machine learning-enhanced flexibility [9]. Moreover, BCI-driven robotic systems, despite transforming neuroprosthetics, must address neurological variability, inconsistent signal acquisition, and the requirement for extensive user training prior to reliable implementation in practical applications. As robotic arms gain autonomy, it is essential to address safety, robustness, and interpretability within AI-based and neural control frameworks to ensure reliable, human-compatible robotic assistance [10].

This review aims to bridge that gap by systematically analyzing key methodologies, highlighting their interdependencies, and identifying the most promising research directions, As illustrated in Fig. 2, which explains the study methodology by reviewing the series of operations required to control the robotic arm. A critical assessment of existing approaches is provided, addressing their strengths, limitations, and applicability to real-world scenarios. This study follows a structured methodology to ensure a balanced and rigorous review. It synthesizes research findings from diverse sources, including classical control theories, optimization techniques, artificial intelligence-based strategies, and brain-machine interfaces.

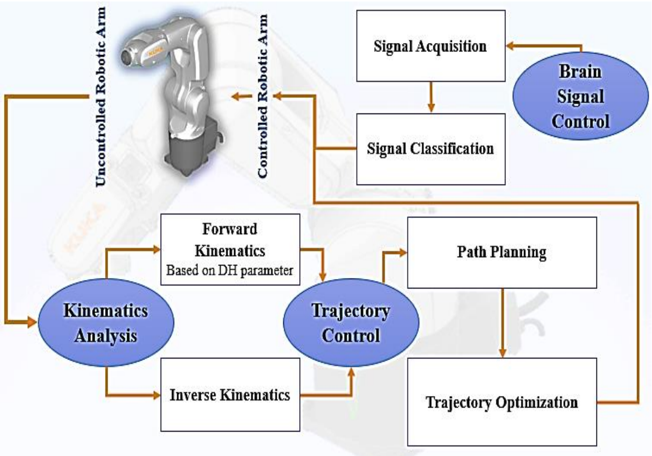

Fig. 2. The methodology of the review study

The paper critically evaluates computational efficiency, adaptability, robustness, and ethical considerations associated with these control methodologies. By integrating insights from kinematic modeling to cognitive control mechanisms, this review serves as a roadmap for researchers and practitioners aiming to enhance robotic arm intelligence and autonomy. The goal is to provide a holistic, forward-looking perspective on robotic arm control, identifying challenges that hinder real-world implementation and guiding future innovations in industrial automation, healthcare robotics, and neuroprosthetics.

Section 2 demonstrates the review of kinematics analysis of robotic arms. Section 3 shows the review path planning literatures while Section 4 is for trajectory optimization literatures. Section 5 starts with control techniques revision while Section 6 reviews the brain computer interface fields. Section 7 concludes the paper and presents the future work.

II. Robotic Arm Kinematics Analysis

Understanding the motion and behavior of robotic arms is essential for their effective usage and control, with kinematics analysis serving as a cornerstone in this endeavor. This analysis makes a specialty of two essential standards: forward kinematics (FK) and inverse kinematics (IK) [11]. Forward kinematics involves determining the end-effector's role and orientation based on joint angles or lengths, facilitating unique control and manipulation through mapping the robotic arm's joint space to its mission space. Conversely, inverse kinematics includes figuring out joint configurations to reap favored end-effector positions and orientations, permitting autonomous computation of required joint angles for duties that include manipulation, grasping, and trajectory execution [12].

As in Fig. 3, traditional techniques for kinematics evaluation often rely upon mathematical formulations and geometric adjustments, which may be computationally extensive and at risk of complexities in robotic arm configurations. However, current advancements in soft computing strategies, such as neural networks, genetic algorithms, and fuzzy common sense, provide alternative strategies. These strategies offer sturdy solutions capable of handling the non-linearities and uncertainties inherent in robotic arm structures, thereby enhancing performance and reliability in realistic programs [13].

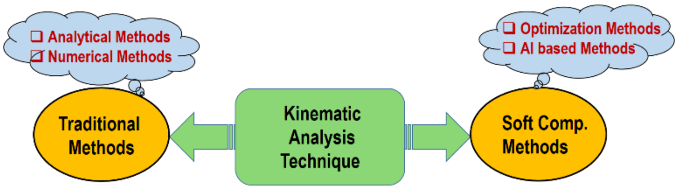

Fig. 3. Kinematics analysis problem solving techniques [14]

A. Traditional Methods

Traditional methods for robotic arm kinematics rely on well-established mathematical and engineering principles to determine joint configurations, end-effector positions, and movement trajectories. These methods generally fall into two categories: analytical and numerical approaches. Analytical methods seek exact, closed-form solutions based on geometric and algebraic principles, making them highly precise but often impractical for complex robotic structures [15]. Numerical methods, on the other hand, use iterative algorithms to approximate solutions, offering greater flexibility at the cost of increased computational load. While these methods provide a solid foundation for robotic arm control, their effectiveness is often constrained by factors such as kinematic redundancy, singularities, non-linearity, and real-time computational feasibility. Understanding these methods in depth is essential for evaluating their applicability, efficiency, and limitations in modern robotic systems [16].

A cornerstone of traditional kinematic analysis is the Denavit-Hartenberg (DH) convention, which provides a standardized mathematical representation for describing robotic arm structures. The DH method simplifies forward kinematics by systematically defining homogeneous transformation matrices, which relate each link of a robotic arm to the next through a series of rotational and translational transformations [17]. This transformation is governed by four key parameters, each uniquely defining the spatial relationship between consecutive links, as shown in Fig. 4 and following [13]:

- Link Length (a_i) – The distance between two successive joint axes along the common normal.
- Link Twist (α_i) – The angle of rotation between two consecutive joint axes around the common normal.
- Link Offset (d_i) – The displacement along the z-axis between two linked joints.
- Joint Angle (θ_i) – The rotational movement around the z-axis of a joint.

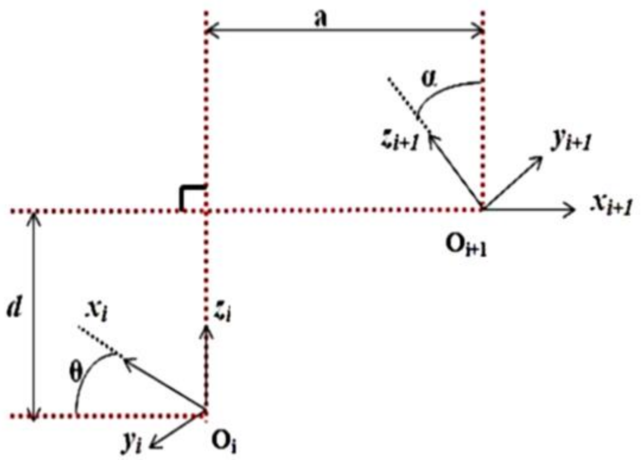

Fig. 4. DH parameter assistance frames [18]

Once the DH parameters are defined, the homogeneous transformation matrix for each link is derived using:

$$T_i^{i-1} = \begin{pmatrix} \cos\theta_i & -\sin\theta_i \cos\ \alpha_i & \sin\theta_i \sin\ \alpha_i & \alpha_i \cos\theta_i \\ \sin\theta_i & \cos\theta_i \cos\ \alpha_i & -\cos\theta_i \sin\ \alpha_i & \alpha_i \sin\theta_i \\ 0 & \sin\ \alpha_i & \cos\ \alpha_i & d_i \\ 0 & 0 & 0 & 1 \end{pmatrix}$$

By sequentially multiplying these transformation matrices from the base to the end-effector, the overall position and orientation of the robotic arm in 3D space can be determined. While the DH convention is a powerful modeling tool, it is not without limitations. It struggles with kinematic redundancy, singularities, and complex joint configurations, particularly in robotic arms with non-serial structures or closed-loop mechanisms. Consequently, for more advanced robotic systems, alternative formulations such as product of exponentials (PoE) representation or optimization-based approaches may be required to enhance computational efficiency and robustness [19], [20].

1) *Analytical Methods*

Analytical methods for resolving robotic arm kinematics entail formulating explicit mathematical equations that connect joint angles to end-effector positions. These strategies generally employ geometric, algebraic, or trigonometric formulations to derive precise solutions, guaranteeing great precision and low computing expense when utilised for uncomplicated robotic systems. The main benefit of analytical approaches is their deterministic quality, which removes the necessity for iterative convergence and improves computational efficiency. Nonetheless, their efficacy declines for robots possessing six or more degrees of freedom (DOF), non-spherical wrists, or complex joint limitations, rendering the acquisition of closed-form solutions progressively difficult or unattainable. Although analytical methods are precise, they encounter difficulties in managing singularities and highly redundant systems, requiring hybrid approaches that incorporate optimisation or heuristic modifications.

Kucuk and Bingul (2004) highlight those analytical approaches are designed to obtain solutions in a mathematical form, which improves the efficiency and accuracy of calculations. These answers are especially beneficial in unconventional robot configurations, where researchers have investigated several approaches such as geometric and algebraic methodologies. Conversely, numerical approaches depend on iterative procedures to discover answers, which can offer greater flexibility but often require more computer complexity [1].

Expanding upon these fundamental ideas, several inventive techniques have arisen to address the inverse kinematics problem in more intricate situations. Z. Fu, W. Yang, and Z. Yang (2013) proposed a new method that utilises geometric algebra to address the inverse kinematics problem for 6R robot manipulators with an offset wrist. This method not only streamlines the computation process but also improves numerical stability. The authors substantiated the superiority of their approach using simulations, illustrating that it surpasses current methodologies in terms of precision and computing efficacy [21]. In a similar vein, Li et al. (2023) introduced a technique that incorporates variations in geometric attributes to enhance the accuracy of inverse kinematics computations. The authors successfully implemented this technique on a robotic arm with six degrees of freedom, resulting in a significant improvement in movement accuracy. This finding emphasises the potential influence of the technique on industries including manufacturing and medicine [2].

Alternative mathematical frameworks have been investigated by other scholars to address the inverse kinematics problem. In their study, M. Wenz and H. Worn (2007) conducted a comparison between knowledge-based approaches and linear algebra-based techniques. They discovered that while knowledge-based methods perform well in simpler tasks, linear algebra-based strategies are more efficient in dealing with complex manipulator geometries and singularities [22]. In addition, Zaplana et al. (2022) proposed the adoption of geometric algebra as a comprehensive framework for solving inverse kinematics problems in serial robots. This method combines rotations and translations into a unified mathematical entity, streamlining computations and enhancing both precision and effectiveness. The efficacy of the method was confirmed using a six-degree-of-freedom robot, showcasing its superiority compared to conventional techniques [23]. These achievements demonstrate the continuous development of techniques for solving the inverse kinematics problem, with each new method enhancing the reliability and efficiency of robotic systems.

2) Numerical Methods

Numerical approaches offer an alternative to analytical answers by utilising iterative algorithms to approximate inverse kinematics (IK) solutions. These approaches are especially beneficial when closed-form solutions are unattainable, as they can handle intricate kinematic configurations, redundancy, and limitations. The prevalent numerical techniques are Newton-Raphson iterations, gradient descent methods, and Jacobian-based algorithms, including the Jacobian Inverse and Jacobian Transpose methods. Although these strategies are versatile, they entail considerable processing demands, necessitating numerous iterations to achieve an optimal solution. Moreover, numerical approaches exhibit sensitivity to initial circumstances, are susceptible to divergence in ill-conditioned systems, and require substantial computer resources, hence complicating real-time applications. To resolve these challenges, researchers frequently employ regularization techniques or optimisation heuristics to enhance numerical stability and convergence rates.

Arikawa (2020) introduced a symbolic computation technique that extends the methodology proposed by Raghavan and Roth. This approach employs a computer algebra system to translate the outcomes into a symbolic representation. This method greatly enhances the precision and effectiveness of inverse kinematics computations for 6R manipulators. Arikawa's methodology was evaluated using different 6R manipulators, and the findings verified its efficacy in accurately computing the inverse kinematics for all tested setups. This represents a significant advancement in robotics by providing a more efficient solution for universal 6R manipulators [24].

Recent progress in the field includes the research conducted by Shen et al. (2021), who developed a new parallel manipulator with symbolic kinematics. This manipulator incorporates partial decoupling, allowing for three degrees of freedom in translation. This design is especially well-suited for applications that need a high level of precision, such as micro/nano manipulation and assembly. The authors utilised symbolic kinematics to obtain both the forward and inverse kinematic equations, hence improving computational efficiency. Their methodology, which integrates analytical and numerical techniques, was employed to compute the operational range of the manipulator. When compared to conventional manipulators, the suggested design offers a greater range of movement and enhanced motion homogeneity. This highlights its promise in precision-driven fields [25]. Significant advancements have been made in the research of iterative and numerical methods for inverse kinematics. Aristidou and Lasenby (2009) conducted a thorough examination of several methods, including analytical, numerical, and hybrid approaches, and also developed a new iterative solver. Their work emphasised the constraints of analytical approaches when applied to intricate systems and the adaptability of iterative procedures, although the latter may encounter difficulties with convergence and computational complexity. The authors' introduced iterative solution exhibited higher performance, accuracy, and resilience in comparison to current algorithms [20].

In a similar manner, Saad (2018) devised a comprehensive numerical method to solve a 6-degree-of-freedom fully-articulated manipulator, which was executed using MATLAB. The algorithm provided shown superior performance in terms of both accuracy and efficiency compared to other approaches. It has potential uses in controlling robotic arms and planning paths [26]. In their study, Iakovlev et al. (2020) highlighted the efficacy of iterative methods in determining accurate locations and orientations for robotic manipulators. These techniques involve calculating joint angles repeatedly to achieve precise results. Their approach demonstrated exceptional precision and effectiveness in solving the inverse kinematics problem of a 6-degree-of-freedom robotic manipulator [27]. In their 2023 publication, Quiñonez Y. et al. introduced a numerical technique called the Iterative Optimal Solution Trajectory via ζv-Homotopy Former (IOSTV ζv - HF). This technique is specifically designed to minimise oscillations and ensure smooth and stable trajectories for robotic systems. This versatile technique consistently shown high velocity and reduced deviations in jobs involving following a specific path, making it a flexible tool for a wide range of robotic applications [28].

Despite their prevalent usage, traditional methods to robotic arm kinematics encounter numerous intrinsic obstacles that affect their efficiency and usability in practical situations. Analytical approaches, despite their mathematical rigour, prove impracticable for high-DOF robotic arms, as obtaining accurate solutions is often infeasible or computationally prohibitive due to the nonlinear characteristics of joint interactions. These approaches also encounter difficulties with singularities, where little alterations in joint angles can result in significant, unanticipated motions of the end-effector, culminating in a loss of control [29]. Numerical approaches, while more adaptable, provide distinct issues such as elevated computing expenses, sensitivity to starting estimates, and sluggish convergence. The dependence on iterative methods renders them less appropriate for real-time control, as they demand considerable computer resources and may not yield a viable solution in time-critical scenarios. Moreover, in highly dynamic situations characterized by external influences and sensor noise that create unpredictability, both analytical and numerical methods exhibit a lack of flexibility, necessitating the use of hybrid or AI-enhanced techniques to attain robustness. Addressing these constraints is a vital focus of inquiry in robotic kinematics and control [30].

B. Optimization Based Methods

Optimization-based methods provide a sophisticated technique for addressing inverse kinematics by framing the issue as an optimisation problem, aiming to identify a joint configuration that meets specified constraints while optimising for factors such as minimal energy consumption, collision avoidance, or smooth trajectory generation. These methods are especially advantageous for high-DOF robotic arms, when conventional techniques encounter challenges related to complexity and computing viability. Common methodologies encompass Particle Swarm Optimisation (PSO), Genetic Algorithms (GA), and Sequential Quadratic Programming (SQP), each presenting unique benefits regarding convergence velocity, adaptability, and management of nonlinear constraints. In contrast to analytical and numerical methods, optimization-based approaches offer versatility in managing redundancy, workspace limitations, and dynamic impediments, rendering them ideal for real-time adaptive control. These methods necessitate meticulous parameter calibration, substantial computer resources, and clearly stated cost functions, as wrong formulation may result in poor or unstable solutions [31], [32].

1) Particle Swarm Optimization

Particle Swarm Optimisation (PSO) has become more popular in recent years as a highly efficient approach for solving the inverse kinematics problem in robotic systems. PSO algorithm is a computational technique that draws inspiration from the collective behaviour of birds flocking or fish schooling, as shown in Fig. 5. In this algorithm, a group of potential solutions, referred to as particles, navigate around the solution space in order to locate the most optimal solution. Each particle adapts its position based on its own past experiences and the experiences of nearby particles, giving it a resilient and effective method for solving intricate optimisation problems [33].

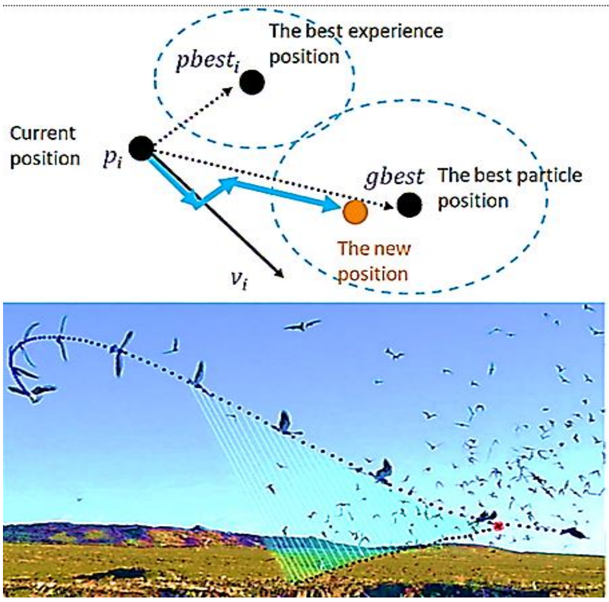

Fig. 5. Comparison between birds' swarm hunting technique and PSO algorithm [23]

Alkayyali and Tutunji (2019) introduced a solution based on PSO to tackle the inverse kinematics problem in the field of robotic arm manipulators. Their methodology utilises swarm optimisation to efficiently discover optimal solutions for the configurations of a robotic arm, specifically for a robotic arm with six DOF. The findings indicated that this strategy, based on PSO, exhibited higher convergence in terms of both speed and accuracy when compared to other competing strategies. This highlights the versatility and efficiency of the PSO-based method across different types of robotic arm manipulators [34].

Deng and Xie (2021) made improvements to the PSO technique, specifically designed for serial robotic manipulators with multiple DOF. Their approach included a novel fitness function that took into account the constraints on joint mobility and the distance between the end effector and the target. Additionally, they employed a dynamic parameter setting technique and an adaptive inertia weight. The enhancements resulted in quicker convergence and increased precision, surpassing both PSO-based and non-PSO-based methods in their investigation, demonstrating the method's potential in robotics applications [36]. The work of Danaci H. et al. (2023) demonstrates additional progress in PSO for inverse kinematics. They successfully utilised a PSO approach to obtain convergence for a comprehensive end-effector position. The authors showcased the parallelization of inverse kinematic calculations utilising POSIX threads by utilising the Baxter Research Robot, which is equipped with two seven-joint arms, as a demonstration platform. This method enabled the simultaneous processing of the collective movement of the swarm particles, resulting in a substantial improvement in computational efficiency. The technology may be easily adjusted to work with any traditional serial robotic manipulator, highlighting its wide range of applications and the ongoing development of PSO in the field of robotics [37].

2) Genetic Algorithm

Genetic Algorithms (GA) are a type of optimisation algorithms that draw inspiration from the process of natural selection as in Fig. 6. In this process, the most fit individuals are chosen for reproduction, resulting in the production of offspring for the following generation. GA are highly efficient at addressing intricate optimisation issues through the iterative evolution of a population of potential solutions. This concept has been extensively utilised in the realm of robotics, particularly for addressing the inverse kinematics problem. This challenge involves determining the joint angles required to position a robot's end-effector at a certain location [38].

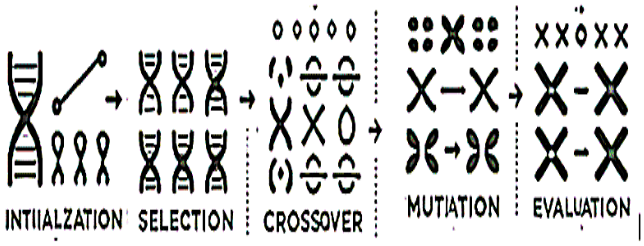

Fig. 6. Genetic algorithm vs biological background

In the early 2000s, Her and M Karkoub (2002) proposed a new method that integrates fuzzy logic and GA to calculate the inverse kinematics solution of a robot. GA was utilised to optimise the parameters of the fuzzy logic system. This involved iteratively adjusting the system's parameters and membership functions in order to improve the accuracy and convergence of the inverse kinematics solution. Although the experimental findings showed that fuzzy logic approximations were beneficial, the study also pointed out that employing these approximations in highly accurate settings could result in inaccuracies in the inverse kinematics solutions [39]. Köker (2013) proposed a method that utilises neural networks to minimise mistakes in robotic manipulators by incorporating evolutionary algorithms into inverse kinematics. This approach utilises a genetic algorithm to instruct the neural network in minimizing the positioning error of the end-effector. The fitness function employed in this approach evaluates the neural network's performance and chooses the most ideal members for future generations. The findings demonstrated that this approach successfully solved the inverse kinematics issue, with an average discrepancy of only 0.3 mm in a 6-DOF robotic manipulator [40].

Zhou et al. (2018) made significant progress in using machine learning and genetic algorithms for inverse kinematics. They utilised the Extreme Learning Machine (ELM) in conjunction with a Sequential Mutation Genetic Algorithm (SMGA) to tackle the problem. The ELM approach is used to forecast the joint angles needed to place the end-effector, and the SMGA is then employed to refine these forecasts and determine the most optimal solution. The ELM-SMGA method was found to be superior to other commonly used methodologies in terms of both accuracy and efficiency, making it a reliable solution for inverse kinematics in robotics [41]. In their study, Hernandez-Barragan et al. (2022) put out an approach that utilises metaheuristic optimisation, notably Genetic Algorithms, to address the inverse kinematics problem in mobile dual-arm robots. Their methodology, which circumvents the utilisation of the Jacobian matrix, adeptly tackles concerns pertaining to singularities and is especially suitable for coordinated manipulation tasks. The precision and effectiveness of this strategy were proved through validation using simulation and real-world experiments with the KUKA Youbot robot. This validates its applicability for both coordinated and non-coordinated operations [42].

3) *Novel Methods*

Research in robotics has resulted in the development of novel strategies that utilise diverse algorithms and optimisation methods to solve IK challenge. In 2008, Courty and Arnaud proposed a technique named "Inverse Kinematics by Particle Filtering." This approach combines Sequential Monte Carlo (SMC) methods with particle filtering to efficiently solve the inverse kinematics problem for a human arm model. This method employs a set of particles to represent possible combinations of joint positions. These particles are adjusted based on data from sensors, and have been proven effective in monitoring arm motion in real time. This approach also shows potential for use in fields like motion capture and robotics [43]. Martin et al. (2018) introduced the natural-Cyclic Coordinate Descent (CCD) algorithm, a new approach developed to address the IK problem for hyper-redundant and soft robots with a large number of degrees of freedom. This method utilises the principle of natural curvature in the robot's configuration space to direct the optimisation process. It enables gradual modifications of joint angles until the desired end-effector position is reached [44]. In their study, Amiri M. et al. (2021) presented a novel approach called Genetic-Swarm Optimisation (GSO) to tackle the IK problem in robotic arms. This approach combines the advantages of GA and PSO to optimise the parameters of a Proportional-Integral-Derivative (PID) controller. This leads to a highly efficient control of each joint. The usefulness of the methodology was demonstrated by validating it using statistical analysis and comparing it with typical optimisation approaches. This validation process showcased the approach's ability to effectively represent and regulate dynamic systems inside a virtual environment [45].

Optimization-based methods have arisen as effective solutions for overcoming the constraints of conventional inverse kinematics techniques, especially in intricate robotic systems where closed-form solutions are unfeasible. The main benefit of these systems is their capacity to manage redundant degrees of freedom, workspace limitations, and multi-objective functions while optimising for criteria including energy efficiency, smooth motion, and collision avoidance. Methods provide flexibility, rendering them very efficient for real-time path planning and adaptive control in dynamic settings. Moreover, optimisation techniques do not necessitate detailed system modelling, enabling their application to robots with diverse kinematic configurations.

Nonetheless, these methods possess inherent limitations. Their principal constraint is computational expense, as optimisation methods frequently necessitate multiple iterations to achieve convergence to an ideal solution, rendering real-time applications difficult, particularly in high-velocity robotic activities. Furthermore, numerous optimisation methods depend on precisely defined cost functions and hyperparameter adjustment, which may lead to inferior performance if configured incorrectly. Moreover, global optimisation methods like Genetic Algorithms and Particle Swarm Optimisation may experience premature convergence or protracted execution periods, hence constraining their applicability in situations necessitating immediate decision-making. Notwithstanding these hurdles, optimization-based methods are crucial for addressing inverse kinematics and motion planning issues, and current research in parallel computing, metaheuristics, and hybrid AI-enhanced frameworks seeks to alleviate these computational inefficiencies.

C. *Artificial Intelligence Based Methods*

1) *Artificial Neural Network*

Artificial Neural Networks (ANNs) are computational models that mimic the structure and function of the human brain. They are composed of linked layers of neurones that are responsible for processing and transmitting information. ANNs have emerged as a highly effective tool in the field of robotics, particularly for tackling intricate problems like inverse kinematics. Inverse kinematics involves the task of identifying the correct joint angles needed to attain a desired position for the end-effector. ANNs are highly suitable for solving the inverse kinematics problem due to their adaptability and ability to learn, which allows them to effectively handle the complex and multi-dimensional aspects of the problem [46]. In 2014, AV Duka conducted research on the application of neural networks to forecast the movement path of robotic arms. The focus was on solving the inverse kinematics problem for a robotic arm with six degrees of freedom. Duka suggested using a neural network that was trained on a dataset generated through forward kinematics to create a relationship between joint angles and end-effector positions. The outcomes of this methodology, evaluated on a simulated robotic arm, exhibited exceptional precision in following a desired path with negligible mistakes. The neural network-based method demonstrated superior performance compared to classic inverse kinematics techniques in terms of both accuracy and convergence speed, hence emphasising the efficacy of neural networks in this particular field [47].

ARJ Almusawi, LC Dülger, and D Özdemir (2016) devised a new ANN approach to solve the inverse kinematics problem of a Denso VP6242 robotic arm, building upon previous applications of ANNs. Their approach employed a feedforward neural network (FNN) that was trained via backpropagation. The FNN consisted of two hidden layers, each containing 20 neurones. The FNN effectively produced the necessary joint angles for precise robot positioning, attaining an average error rate of only 0.0076. The use of ANNs in this methodology showed faster and more accurate results compared to iterative methods. This highlights the potential of ANNs in improving the precision and efficiency of robotic arms [48]. In a recent study, Lu et al. (2022) presented a sophisticated neural network structure that effectively incorporates the position and orientation of a robot's end-effectors as input to produce the required joint angles. Their model underwent training and testing using both simulated and real-world robot data. The results demonstrated greater performance in comparison to existing methods, such as analytical techniques and numerical optimization-based approaches. The model demonstrated a level of accuracy above 98% when tested with simulated data and exceeding 94% when tested with real robot data, highlighting its resilience and suitability for real-world situations. This study reinforces the significance of neural networks in addressing the inverse kinematics problem, especially in situations that demand great accuracy [49].

2) Adaptive Neuro-Fuzzy Inference System

The Adaptive Neuro-Fuzzy Inference System (ANFIS) is a hybrid intelligent system that synergistically integrates the capabilities of neural networks and fuzzy logic. ANFIS utilises the capacity of neural networks to enhance the performance of fuzzy inference systems, making it an effective tool for addressing intricate challenges in robotics, such as inverse kinematics. This system has the capability to simulate the complex connections between inputs and outputs, offering a reliable solution for activities that demand accurate control and prediction [50].

In a study conducted by J. Narayan and A. Singla (2017), they showcased the efficacy of ANFIS in analysing the kinematics of a SCARA robot and accurately forecasting its trajectory. The ANFIS model accurately predicted the robot's joint angles and end-effector location by analysing input and output data from testing and simulations. The model achieved mean absolute errors between 0.017 and 0.039. This work emphasised the capacity of kinematic analysis utilising ANFIS to improve the accuracy and effectiveness of robotic systems [51]. Desmukh and colleagues (2021) utilised the ANFIS model to address the inverse kinematics and forward dynamics of a 3-DOF serial manipulator. Their methodology combined the benefits of neural networks and fuzzy logic, meticulously choosing input and output variables, and training the ANFIS model to produce precise forecasts. The simulation findings validated the efficacy of the ANFIS-based approach in addressing the inverse kinematics and forward dynamics of the manipulator, showcasing its suitability in intricate robotic systems [52].

In a recent study, MRA Refaai (2022) utilised numerous ANFIS models to enhance the resolution of the inverse kinematics problem in a robot arm's trajectory. The work aimed to overcome the drawbacks of traditional inverse kinematics systems in terms of their accuracy and efficiency. It proposed a segmented approach, where the Adaptive Neuro-Fuzzy Inference System (ANFIS) is employed to compute the inverse kinematics for each segment of the robot arm. The results suggested that this technique offered a superior and more effective solution in comparison to earlier methods, demonstrating the capabilities of ANFIS in advanced robotics [50]. In addition, Demby et al. (2019) investigated the application of Artificial Neural Networks (ANNs) and Fuzzy Neural Networks (FNNs) to solve the inverse kinematics problem in serial robots. Their research compared the performance of artificial neural networks (ANNs) with fuzzy neural networks (FNNs), and discovered that FNNs surpassed ANNs in terms of both convergence speed and accuracy. This highlights the advantages of combining fuzzy logic with neural networks for tasks involving robotic control and prediction [53].

AI-based techniques signify a transformative change in robotic arm control, providing unparalleled adaptability, learning capacities, and job generalization. In contrast to conventional techniques that depend on explicit mathematical models, AI-driven methodologies empower robotic arms to learn from data, rectify errors autonomously, and adjust to changing environments. These methods are proficient in managing nonlinearities, high-dimensional spaces, and intricate joint coordination, rendering them especially beneficial for jobs necessitating precise motor control, human-robot interaction, and real-time adaptability. Furthermore, deep learning models can enhance their performance progressively, diminishing the necessity for human adjustments and pre-established models.

Notwithstanding their potential, AI-based methodologies possess considerable constraints. A significant challenge is data reliance, as deep learning models necessitate extensive, high-quality datasets for optimal training. Insufficient training samples may lead these models to demonstrate inadequate generalization, erratic behaviour, or catastrophic forgetting in unfamiliar situations. Moreover, computational intensity presents a significant problem, as AI-driven techniques, especially deep learning architectures, require substantial processing power and memory, complicating real-time implementation for low-resource or embedded robotic systems. A further disadvantage is the absence of interpretability, as numerous AI models function as black boxes, complicating error diagnosis and the assurance of system reliability in safety-critical applications. As AI advances the limits of robotic control, hybrid AI-classical control models and explainable AI (XAI) methodologies are being investigated to mitigate these issues, hence ensuring autonomy and reliability in robotic systems.

The selection of a suitable kinematic analysis approach for robotic arm control is contingent upon several aspects, including computational efficiency, precision, real-time viability, and adaptation to dynamic settings. Although conventional analytical and numerical methods yield accurate and deterministic solutions, they frequently encounter difficulties with complicated, redundant, or highly nonlinear robotic systems. Optimization-based methodologies provide enhanced flexibility and robustness; nevertheless, they also include computational overhead and convergence challenges. AI-driven models utilize data-driven learning and adaptive control, allowing robotic arms to function in unstructured and uncertain situations. Nonetheless, these methodologies necessitate substantial training datasets, significant computer resources, and meticulous calibration to guarantee stability and dependability.

Table I presents a detailed and organized comparison of the essential qualities, benefits, drawbacks, computing demands, and practical uses of several kinematic analysis methods. This comparison study allows researchers and engineers to evaluate the trade-offs among several methodologies and choose the best appropriate strategy according to specific application requirements, system limitations, and performance criteria. This study seeks to enhance informed decision-making in robotic arm control by assessing these elements, thereby reconciling classical kinematic formulations with contemporary AI-enhanced approaches.

TABLE I. COMPARATIVE ANALYSIS OF KINEMATIC ANALYSIS METHODS FOR ROBOTIC ARM

Method	Approach	Strengths	Weaknesses	Computational Complexity	Real-Time Feasibility	Handling of Redundancy	Robustness to Noise & Disturbances	Applications
Analytical Methods	Closed-form mathematical solutions using algebraic and geometric methods.	High precision; deterministic; low computational cost for simple systems.	Difficult to apply to high-DOF systems; struggles with singularities.	Low for simple systems, but grows rapidly for complex structures.	High for simple robotic arms; infeasible for complex, redundant systems.	Poor; requires extra constraints for redundant manipulators.	Poor; highly sensitive to sensor inaccuracies and singularities.	Simple robotic arms, industrial manipulators with limited DOFs.
Numerical Methods	Iterative computational techniques to approximate solutions.	Flexible for complex systems; can handle redundancy and constraints.	Computationally expensive; sensitive to initial conditions.	High due to iterative nature and convergence dependencies.	Limited; may be too slow for real-time adaptive control.	Good; numerical solvers can handle redundant DOFs.	Moderate; requires filtering and stabilization techniques.	Complex robotic arms, systems requiring high precision.
Particle Swarm Optimization (PSO)	Swarm intelligence-based heuristic optimization method.	Good convergence properties; handles multi-objective optimization.	Requires tuning; may suffer from slow convergence.	Moderate to high; depends on swarm size and iterations.	Moderate; feasible with efficient implementation.	Excellent; can optimize redundant DOFs dynamically.	Good; heuristic nature allows adaptation to disturbances.	Trajectory optimization, industrial automation, bio-inspired robotics.
Genetic Algorithm (GA)	Evolutionary computation-based global optimization technique.	Can explore a wide search space; effective in avoiding local minima.	Performance depends on parameter tuning; computationally expensive.	High; evolutionary operators require many fitness evaluations.	Limited; convergence speed can hinder real-time applications.	Very good; allows optimization with redundancy handling.	Good; mutation and crossover operators add robustness.	Autonomous robotic systems, adaptive control applications.
Deep Reinforcement Learning (DRL) [54], [55]	AI-based self-learning framework for robotic motion control.	Learns optimal control strategies; adapts dynamically to changing environments.	Requires large training datasets; prone to instability and catastrophic forgetting.	Very high; requires extensive computation during training.	High for trained models; real-time inference is feasible.	Good; policy-based methods can optimize redundancy.	Moderate; performance depends on reward function design.	Autonomous robotics, adaptive real-time control.
Hybrid AI-Based Optimization [56], [57]	Combines AI-based learning models with optimization techniques.	Can leverage AI's adaptability with optimization's efficiency.	High complexity; requires hybrid model tuning.	Very high; requires both AI and optimization resources.	Limited; depends on computational power and model efficiency.	Very good; adapts dynamically to constraints.	Good; AI improves optimization robustness.	High-precision robotics, real-time adaptation in uncertain environments.
Quantum-Inspired Optimization [58], [59]	Utilizes quantum computing principles for optimization tasks.	High-speed convergence; capable of handling large search spaces efficiently.	Theoretical and experimental; limited real-world implementations.	High; requires quantum-inspired solvers and specialized algorithms.	Limited; current applications are still in the research phase.	Potentially excellent; but practical implementations are lacking.	High-dimensional robotics, futuristic optimization models.	
Natural-Cyclic Coordinate Descent (CCD) Algorithm	Iterative optimization method that modifies joint angles sequentially to minimize	Fast convergence; computationally efficient for real-time applications.	Can be trapped in local minima; struggles with high-DOF redundant robots.	Low to moderate; depends on number of iterations.	High; suitable for real-time robotic control.	Moderate; may need additional constraints for redundancy.	Moderate; susceptible to local errors but stable under controlled conditions.	Real-time robotic motion control, inverse kinematics in manipulators.

	end-effector error.							
Genetic-Swarm Optimization (GSO)	Hybrid method combining GA and PSO for improved convergence and accuracy.	Enhanced search efficiency; reduces premature convergence issues of GA and PSO individually.	Computationally expensive; hybridization increases processing requirements.	High; requires extensive fitness evaluations and parameter tuning.	Limited; real-time feasibility depends on computational resources.	Excellent; hybrid approach improves redundancy handling.	Very good; robustness improved over standard GA or PSO.	Adaptive robotic motion control, multi-objective optimization problems.
Artificial Neural Networks (ANN)	Data-driven learning model trained on input-output relationships.	Learns from data; adaptable to nonlinear problems; fast inference.	Requires large training datasets; can be a black-box model.	High; depends on model architecture and training data.	High for trained models; real-time inference is fast.	Good; neural networks can model redundancy implicitly.	Excellent; neural models can generalize well with sufficient training.	Medical robotics, human-robot interaction, real-time control.
Neuro-Fuzzy Inference System (NFIS)	Hybrid system combining fuzzy logic with neural networks.	Interpretable learning; handles uncertainty better than pure AI models.	Needs significant training; model complexity increases computation time.	Moderate to high; dependent on fuzzy rule complexity.	Moderate; hybrid nature makes real-time application challenging.	Good; fuzzy logic adapts to redundant inputs efficiently.	Very good; fuzzy logic handles noisy inputs effectively.	Neuroprosthetics, adaptive robotics, uncertain environments.

III. ROBOTIC ARM PATH PLANNING

The path planning process as shown in Fig. 7, is essential for robotic arms to navigate from their starting positions to desired goals while avoiding obstacles and adhering to kinematic constraints. Real-world tasks often demand coordinated and obstacle-free movement, especially for robotic arms with six degrees of freedom (6 DOF), which offer increased flexibility. However, achieving effective path planning is challenging due to the irregularity of obstacles, limited visibility, and intricate geometries present in real-world environments [60].

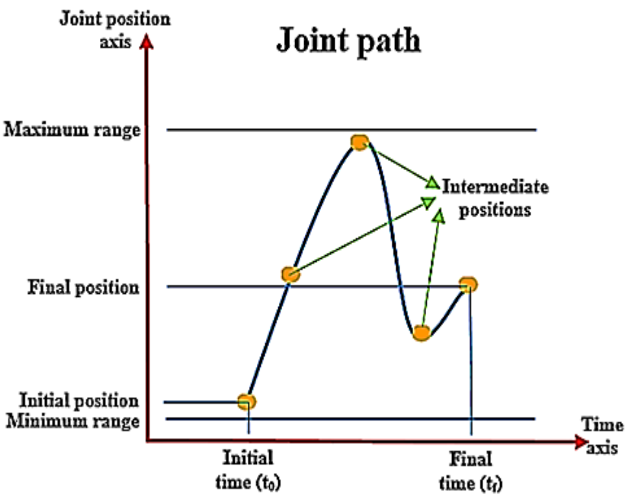

Fig. 7. Path planning process

To simplify path planning, Cartesian motion planning methods as mentioned in Table II, focus on specifying the desired trajectory of the robotic arm's end-effector directly in Cartesian space, defined by its position and orientation. These methods manipulate the end-effector's Cartesian coordinates, often disregarding joint angles, making them particularly effective for tasks requiring precise positioning and orientation control, such as pick-and-place operations in manufacturing. Cartesian motion planning methods offer straightforward solutions to complex path planning problems and are adaptable to various robotic arm configurations and environments [61].

Learning by demonstration methods for robotic arm path planning, which mentioned in Table II. offer an alternative approach by teaching the robot how to perform tasks through observed demonstrations provided by a human operator or another robot. These methods leverage machine learning techniques such as imitation learning and reinforcement learning to extract patterns and strategies from demonstrated motions. By learning from demonstrations, robotic arms acquire task-specific knowledge and adapt their path planning strategies to different scenarios autonomously. This capability allows them to improve their performance over time through experience and feedback, making learning by demonstration methods valuable tools for applications where manual programming or predefined trajectories are impractical or insufficient [62].

Path planning is a critical difficulty in robotic arm control, since it influences the efficiency, precision, and adaptability of motion execution in dynamic situations. The diverse path planning methodologies examined in this research present unique benefits and limitations, affecting their appropriateness for particular applications. Conventional geometric and graph-based techniques, including visibility graphs and A algorithms*, deliver deterministic and computationally efficient solutions, rendering them appropriate for structured situations. Nonetheless, they encounter difficulties in high-dimensional environments, real-time adaptability, and dynamic obstacle evasion. Sampling-based techniques, such as Rapidly-exploring Random Trees (RRT) and Probabilistic Roadmaps (PRM), provide superior scalability in high-dimensional and crowded settings, but with the trade-off of non-deterministic outcomes and the possibility of inferior trajectories [79], [80], [81], [82].

TABLE II. PATH PLANNING METHODS SUMMERY

Method	Planning Method	Trajectory generation method	Authors and Year	Robot DOF	Application
Cartesian motion planning	Fourier approximation	Joint trajectories obtained through motion builder (AutoCAD).	(Kim, 2014) [63]	Four DOFs	Joint and muscle rehabilitation: frozen shoulder
	Optimization method based on Riemannian geometry	Geodesic curves.	(Soltani-Zarring, 2017) [64]	Four DOFs	Rehabilitation and activities of daily life tasks.
	Task-based planning method (Circular-arc planning).	Task analysis in order to find a planning task (Circular motion).	(Meng, 2018) [65]	Four DOFs	Rehabilitation tasks.
	Planning based on minimum-jerk model	Inverse kinematics with swivel-angle + minimum-jerk method.	(Wang, 2019) [66]	Five DOFs	Reaching and reach-to-grasp movements.
	Multi cubic Polynomial interpolation Method.	Finds angular positions through inverse kinematics (IK; using reverse coordinate method).	(Li, 2019) [67]	Six DOFs	Reach-to-grasp movements.
	Planning based on Potential energy minimization.	Inverse kinematics (IK) resolution based on zeroing dynamics method (ZD)	(Li-Zhan, 2020) [68]	Six DOFs	Industrial application: manipulation tasks.
	Planning based quadric polynomial coefficients optimization.	Cubic and quadric polynomial functions	Mousa M. (2023) [69]	Six DOFs	Laboratory robotic arm
	Planning based fewer nodes and edges in the graph	Graph construction method	(Malhan R. 2023) [70]	Multiple tool center points (TCPs)	Industrial application
learning by demonstration	Artificial Neural Network model.	Trained ANN model used to resolve inverse kinematics problem	(Chung, 2012) [71]	Five DOFs	Writing, hand waving, beating, and throwing a ball.
	Gaussian mixture model (GMM).	Gaussian mixture regression (GMR)	(Sabbaghi, 2014) [72]	Five DOFs	Healthcare and education
	Modified hidden Markov model (HMM) (Discrete HMM).	Trained modified HMM.	(Garrido, 2016) [73]	Six DOFs	Writing task.
	Neural-network (NN) training + Dynamic motion primitives (DMP) computation	DMP with well-defined landscape attractor,	(Lauretti, 2018) [74]	Six DOFs	Reaching movements, grasping.
	Three distinct artificial neural networks (ANNs).	Predictive model consisted of three ANNs	(Naghibi, 2020) [75]	Six DOFs	ADL movements such as eating and drinking
	Multilevel convolutional NN.	Trajectory extraction (by OpenPose) + threshold-filtering method	(Tao, 2020) [76]	Six DOFs	Upper-limb rehabilitation.
	Deconvolutional neural network (DNN)	trained function approximation DNN.	(Duburcq, 2020) [77]	Six DOFs	----------------
	Deep reinforcement learning	Minimize accuracy, energy consumption, and smoothness	Zhang S. 2023) [78]	Six DOFs	Simulations and physical experiments

The amalgamation of optimization-based and machine learning methodologies has markedly enhanced path smoothness, flexibility, and real-time decision-making. Nevertheless, these approaches incur substantial computational expenses, restricting their practicality for resource-limited or safety-sensitive applications. Furthermore, learning-based methodologies, such Reinforcement Learning (RL) and Neural Motion Planning, necessitate substantial training datasets and considerable computer resources, which raises issues with generalization, stability, and training duration. Moreover, guaranteeing effective collision avoidance and dynamic re-planning in unstructured and unexpected situations continues to pose a significant problem.

Future investigations in robotic arm route planning should concentrate on creating hybrid models that integrate the efficacy of traditional methods with the flexibility of AI-driven techniques. Real-time adaptive algorithms capable of dynamically modifying mobility plans based on sensor feedback will be essential for enhancing autonomy and safety. Moreover, alleviating the computational demands of machine learning-driven planners via streamlined architectures, meta-learning, and neuromorphic computing may promote their wider implementation in industrial and assistive robotics. Ultimately, ethical considerations like secure human-robot interaction, transparency in decision-making, and the dependability of AI-driven motion planning must be addressed to guarantee reliable implementation in practical applications.

IV. Robotic Arm Trajectory Optimization

Trajectory optimization is a fundamental aspect of robotic arm motion planning, where the primary goal is to determine a trajectory that ensures smooth, efficient, and collision-free movement. At the core of this process lies the objective function, a mathematical expression that defines the criteria used to evaluate and optimize the trajectory. The objective function serves as a guiding metric for optimization algorithms, allowing them to iteratively refine the trajectory to achieve better performance [83]. In many cases, trajectory optimization is a multi-objective problem, meaning that multiple factors must be optimized simultaneously. A general form of a multi-objective optimization function can be expressed as [32]:

$$J = w_1.J_1 + w_2.J_2 + \ldots + w_n.J_n$$

where each Ji represents an individual objective (such as execution time, energy consumption, or smoothness), and wi are the corresponding weights that determine the relative importance of each factor. These weights can be adjusted based on application requirements, ensuring that the optimization process aligns with the specific goals of the robotic system.

Several key factors influence trajectory optimization in robotic arms. Execution time is often minimized to ensure fast and efficient movement, particularly in industrial settings where productivity is critical. Energy consumption is another important consideration, as reducing power usage enhances system efficiency and longevity. In addition, ensuring smooth joint motion minimizes mechanical wear and improves precision, which is crucial for applications such as surgical robotics or fine assembly tasks. Path length and joint movement minimization are also common optimization goals, reducing unnecessary movements that could lead to instability or increased computational load [35], [84].

Furthermore, safety and environmental interaction play a vital role in trajectory planning. Obstacle avoidance is a crucial constraint, ensuring that the robotic arm does not collide with objects or humans in its workspace. Similarly, task-specific constraints, such as maintaining a desired force on an object or achieving precise positioning, must be incorporated into the optimization process to meet operational requirements. The objective function acts as the foundation for optimization algorithms, influencing how they search for and refine optimal trajectories. By carefully defining this function and balancing multiple objectives, trajectory optimization can significantly improve robotic arm performance, leading to greater efficiency, accuracy, and adaptability across various applications [85].

Over the years, there has been substantial progress in the construction and optimisation of robotic trajectories. Various approaches have emerged to improve the efficiency and efficacy of robotic systems. Direct transcription approaches for optimising limited paths using comprehensive dynamic models of robots were first developed by Alexander Heim and Oskar Von Stryk in 2000. Their methodology not only enhanced the set points of online robot controllers, but also showcased its compatibility with existing CAR tools and controllers. This was confirmed by simulations and experiments conducted on an ABB IRB 6400 industrial robot [86]. Expanding upon this basis, Christoph Rösmann et al. (2013) introduced the concept of the "timed elastic band" issue as a modified version of multi-objective optimisation. They utilised the sparse system solvers in the g2o framework to effectively tackle the difficulties encountered in VSLAM. Their study demonstrated the durability and computational effectiveness of these strategies in practical robotic experiments [87].

Recent progress in trajectory optimisation has been concentrated on specialised applications, such as robotic grasping in areas with obstructed views. Kahn et al. (2015) investigated trajectory optimisation methods that allow robots to actively explore their environment and determine the best grasping positions even in the presence of obstacles. This methodology, which takes into account the robot's kinematics, dynamics, and uncertainties in its sensory perception, improves the independence and effectiveness of robotic manipulation systems in intricate surroundings [88]. Rabab Benotsmane et al. (2020) developed a technique called "whip-lashing" that improves the movement of a robotic arm by maximising its speed and minimising the time it takes to complete a motion cycle. This technique is specifically designed for a five-degree-of-freedom RV-2AJ manipulator arm. Their example study exhibited a 33% decrease in cycle time, highlighting the considerable potential of this technology to enhance productivity in industrial applications [89].

Recent studies have further advanced trajectory optimisation, namely in the field of specialised robotic systems. Su Y et al. (2021) introduced a hybrid optimisation approach that combines the hyper-heuristic whale optimisation algorithm (HHWOA) with the Gauss pseudo spectral method (GPM) to enhance the optimisation of reentry trajectories for reusable launch vehicles (RLVs). This method, which removes the requirement for user-defined beginning estimates, has demonstrated potential in spaceship design [85]. Tao Wang et al. (2022) devised a time-domain model in the realm of soft robotics to enhance the energy efficiency of a fluidic soft robotic arm. They employed the interior point approach for optimisation. Their research highlights the significance of trajectory optimisation in reducing energy consumption while maintaining mobility limitations [90]. In addition, Mousa M et al. (2024) investigated the utilisation of genetic algorithms to decrease the duration required for robotic arms to reach specified places. Their research, specifically focussing on the KUKA KR 4 R600 robot, demonstrates the superiority of genetic algorithms compared to traditional rule-based methods, resulting in dramatically improved operational efficiency [18].

Table III presents a detailed comparison of trajectory optimization algorithms used in robotic arm motion planning. It covers traditional, heuristic, and hybrid approaches, evaluating them based on advantages, limitations, computational complexity, real-time feasibility, constraint handling, robustness to disturbances, and applications. The comparison highlights the trade-offs between different optimization techniques, offering insights into their suitability for various robotic applications such as industrial automation, high-DOF manipulators, real-time motion control, and autonomous robotics.

TABLE III. COMPARATIVE ANALYSIS OF TRAJECTORY OPTIMIZATION ALGORITHMS FOR ROBOTIC ARMS

Algorithm	Approach	Advantages	Limitations	Computational Complexity	Real Time Feasibility	Constraint Handling	Robustness to Disturbances	Applications
Direct Transcription	Converts trajectory optimization into a parameterized optimization problem using full dynamic models.	Provides highly accurate set points; compatible with existing control tools.	Computationally intensive; requires detailed dynamic models.	High	Limited	Strong; considers all system constraints.	Moderate; sensitive to model inaccuracies.	Industrial robots; high-precision tasks.
Timed Elastic Band (TEB)	Adjusts a pre-planned path into a time-parameterized trajectory using optimization techniques.	Enhances computational efficiency; flexible in dynamic environments	May struggle with high degrees of freedom (DOF) systems.	Moderate	Moderate	Good; manages multiple objectives.	High; proven durability in experiments.	Visual SLAM; autonomous robotic arms.
Genetic Algorithm (GA) [91], [92]	Uses evolutionary principles (selection, mutation, crossover) to optimize trajectory parameters.	Strong global search capability; avoids local minima.	Computationally slow; convergence depends on tuning parameters.	High	Limited	Very good; can optimize multiple objectives.	Moderate; robustness depends on tuning.	Adaptive motion planning; high-complexity environments.
Particle Swarm Optimization (PSO) [84], [93]	Uses swarm intelligence to iteratively improve trajectory points.	Fast convergence; effective in high-dimensional spaces.	May get stuck in local minima; performance sensitive to hyperparameters.	Moderate to High	Moderate	Good; adaptable to various constraints.	Moderate; requires additional mechanisms for disturbance rejection.	Industrial robotics; trajectory smoothing.
Whale Optimization Algorithm (WOA) [94], [95], [96]	Inspired by the hunting behavior of whales, optimizing trajectories via encircling, spiraling, and searching strategies.	Effective at finding optimal solutions; good convergence.	Can suffer from slow convergence; parameter tuning is crucial.	Moderate	Moderate	Good; can handle trajectory constraints.	High; adaptive to changes.	Path planning for mobile and industrial robots.
Gray Wolf Optimization (GWO) [97], [98]	Mimics hierarchical hunting strategies of wolves for trajectory refinement.	Strong exploration and exploitation balance; effective for complex path planning.	Computational cost increases for large search spaces.	Moderate to High	Limited	Good; capable of multi-objective optimization.	High; resilient to disturbances.	Multi-objective trajectory optimization in robotics.
GCS (Geometric Complexity Simplification) [99]	A framework that finds better trajectories in less time by simplifying the complexity of the planning problem.	Efficient in high-dimensional complex environments; reduces computation time.	May oversimplify in certain scenarios; applicability depends on problem structure.	Low to Moderate	High	Moderate; balances simplicity and constraint handling.	High; reliable in complex settings.	Autonomous navigation; high-DOF robotic arms.
RETRO (Reactive Trajectory	Employs adaptive optimization techniques for	Generates smooth trajectories; flexible and	May require complex implementation; performance	Moderate	High	Good; integrates task-specific requirements	High; maintains performance	Real-time manipulation; dynamic environments.

Optimization) [100]	real-time motion planning in dynamic environments	adaptable; real-time applicability.	dependent on environment dynamics.			like collision avoidance.	in dynamic settings.	
LQR-RRT (Linear-Quadratic Regulator Rapidly Exploring Random Tree) [101]	Combines sampling-based planning with optimal control for kinodynamic planning.	Efficiently finds feasible trajectories; handles underactuated systems.	Requires accurate dynamic models; may be computationally intensive.	High	Limited	Good; manages dynamic constraints.	Moderate; performance depends on dynamic accuracy.	High-speed trajectory planning; autonomous systems.

The varied methods outlined in this section provide distinct benefits for computing efficiency, constraint management, and resilience to disruptions. Nevertheless, despite the ongoing advancement of these optimisation strategies, numerous enduring problems persist that affect their application in practical robotic systems.

Traditional techniques, such Direct Transcription and Timed Elastic Band (TEB), offer high-precision trajectory planning but are hindered by computing complexity and restricted real-time adaptability. Although these technologies guarantee fluid and precise movements, they frequently necessitate intricate dynamic models and encounter difficulties in managing unforeseen disturbances in highly dynamic settings. Gradient-based methods such as CHOMP and STOMP enhance trajectory refining, hence increasing smoothness and practicality. Nevertheless, they frequently exhibit sensitivity to initial conditions and may converge to local minima, hence constraining their efficacy in intricate robotic tasks.

To tackle these issues, metaheuristic and nature-inspired optimisation methods, including GA, PSO, WOA, and GWO, have been implemented. These techniques are especially efficacious in high-dimensional search spaces, offering global optimisation potential while circumventing local minima. Nonetheless, their efficacy is significantly contingent upon hyperparameter optimisation, and they may have protracted convergence, rendering them less suitable for time-critical robotic applications. Hybrid methodologies, including the Enhanced Multi-Strategy Sparrow Search Algorithm and Robotic Trajectory Planning Particle Swarm Optimisation (RTPPSO), endeavor to amalgamate the advantages of several algorithms, optimising the balance between exploration and exploitation to enhance convergence rates and resilience. Although these methods exhibit potential, their heightened processing requirements continue to hinder real-time robotic systems.

A significant concern in trajectory optimisation is the management of restrictions and disturbances. Algorithms such as KOMO (Kinematic and Optimization-Based Motion Planning) and LQR-RRT offer precise constraint management and are adept for intricate robotic systems; however, they necessitate accurate dynamic models and may incur significant computational costs when utilised for multi-objective optimisation challenges. Conversely, RETRO (Reactive Trajectory Optimisation) and GCS (Geometric Complexity Simplification) seek to reduce the complexity of motion planning, hence enhancing real-time viability. Nevertheless, these techniques may excessively simplify trajectory representations, constraining their utility in situations characterized by highly dynamic restrictions.

Future research should concentrate on hybrid trajectory optimisation methods that integrate model-based control, machine learning, and adaptive real-time re-planning strategies. Integrating reinforcement learning with neuromorphic computing may save computational overhead while preserving resilience and real-time adaptation. Moreover, trajectory planning frameworks must incorporate real-time sensor feedback loops, allowing robotic arms to adapt their movements dynamically in response to environmental alterations and unexpected disruptions. Finally, ethical and safety aspects in trajectory planning must be addressed, especially for robotic systems functioning alongside humans, to provide predictable, safe, and interpretable motion behaviour.

By surmounting these obstacles, trajectory optimisation algorithms can develop into highly autonomous, intelligent, and adaptive control systems, facilitating more efficient and reliable robotic arm applications in industrial automation, healthcare, and collaborative robotics.

V. CONTROL TECHNIQUES

The use of robotic arms encompasses a variety of methods for seamless interaction between humans and machines as shown in Fig. 8. Voice-controlled methods enable hands-free operation through spoken instructions, while vision-based methods use computer vision to interpret visual information and indicate the environment Collaboration enhances cooperation between humans and robots through power sharing and physical interaction. Additionally, brain-computer interface (BCI) techniques enable direct communication between the human brain and robotic systems, providing unprecedented independence for individuals with disabilities These different management techniques combine to provide robotic arm capabilities and applications in various industries and fields improve [102].

A. Voice Control

Integrating voice recognition technology into robotic systems is now a crucial field of study, specifically aimed at improving human-robot interaction and increasing accessibility for people with impairments. In 2009, B House, J Malkin, and J Bilmes presented the VoiceBot, a system that uses advanced voice recognition algorithms to comprehend and carry out spoken commands. Their research showcased the feasibility and reliability of VoiceBot in industrial automation and for individuals with impairments, proving its ability to greatly improve productivity and user experience through voice-activated control of robotic arms [104]. This fundamental research has laid the groundwork for additional investigation into voice-operated robotics, specifically in specialised domains like surgery and prosthetics.

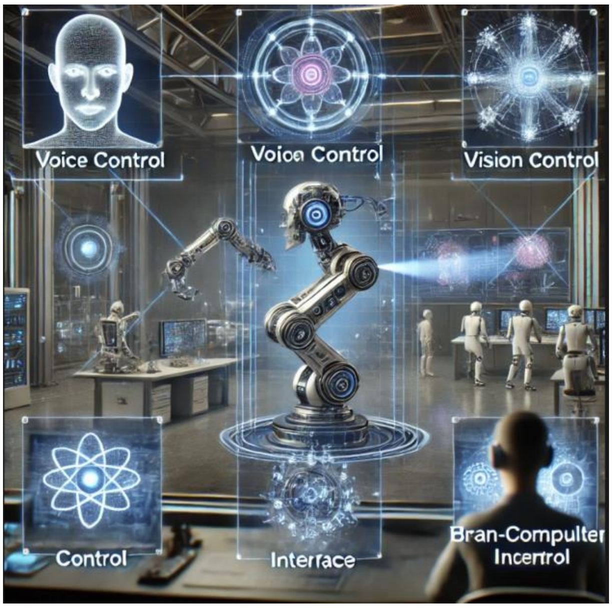

Fig. 8. Controlling techniques of robotic arms [103]

Zinchenko, Wu, and Song (2017) conducted a study to explore the practicality of utilising speech recognition for the purpose of controlling surgical robots. They proposed a system that relies on hidden Markov models to read spoken commands and translate them into actions performed by the robots. Their extensive experimentation validated the efficacy and feasibility of this strategy, indicating that speech recognition could provide surgeons with a more intuitive and efficient means of interacting with robotic equipment during procedures [105]. In a study conducted by Kateryna Zinchenko and her colleagues in 2018, they extended the use of voice control to prosthetic robot arms. They employed a highly effective modelling technique and created a system for a four-joint RRRR arm. Their approach demonstrated an 11% enhancement in voice recognition efficiency compared to current methods, underscoring the efficacy of voice commands in running prosthetic devices [106].

Recent progress in the sector has specifically concentrated on enhancing the user-friendliness and availability of voice-controlled robotic systems for people with disabilities. Pulikottil et al. (2018) assessed the effectiveness of a voice-activated control system for assistive robotic arms, specifically the JACO2 manipulator, which was modified to be controlled by speech commands through the Robot Operating System (ROS). Usability tests conducted with individuals afflicted by neurodegenerative disorders shown a significant inclination towards the voice control system, highlighting its capacity to augment patient independence and boost quality of life [107]. In a similar vein, S. Yuvaraj et al. (2022) sought to develop a cost-effective and user-friendly robotic arm system utilising Arduino Uno, specifically tailored for those with physical limitations. The system exclusively depends on voice commands, showcasing exceptional precision and effectiveness in intricate jobs, significantly enhancing the accessibility and usefulness of voice-controlled robots in aiding persons with disabilities [108].

B. Vision Control

Computer vision and robotic manipulation have greatly enhanced assistive robotic systems, especially for disabled individuals. Hairong Jiang et al. developed an advanced object tracking, facial recognition, and gesture recognition system in 2013. This system controls a wheelchair-mounted robotic manipulator for commercial application. This specialty technology for severe spinal cord injuries (SCIs) achieved 97.5% identification accuracy for an eight-gesture lexicon. Using two Kinect cameras, the system can recognise hand motions, identify the operator's face features, and recognise objects, making it more efficient at recovering common objects. The study showed that computer vision-based solutions can help people with spinal cord injuries (SCIs) handle robotic manipulators more efficiently and effectively using gesture and facial recognition [109].

Vision-based systems have demonstrated considerable potential in the field of robotic surgery and object handling. Wang et al. (2018) proposed a technique to calibrate dual robot arms in minimally invasive surgery using visual information from endoscopic camera pictures and robot encoder data, eliminating the requirement for external tracking sensors. The validity of this approach was confirmed by testing it with the da Vinci surgical system. The results showed that camera perspective projection geometry is highly successful in properly estimating the position of surgical tools, considering the limitations of RCM-based kinematics [110]. In addition to this, Riasat Khan et al. (2022) created a robotic gripper that utilises computer vision to choose and arrange objects. Their system, employing the PixyCMU camera sensor and OpenCV, demonstrated a 100% accuracy in detecting geometric shapes and sizes, as well as an 80% accuracy in colour detection. This highlights the potential for automated sorting and manipulation tasks in diverse applications [111].

C. Human Collaboration Control

Research has focused on improving human-robot collaboration by incorporating human-like motion and interaction dynamics into humanoid robots. Kupferberg et al. (2011) investigated the effects of integrating biological motion into humanoid robots. They argued that these motions enhance the robots' similarity to humans and hence enhance their acceptance as motor partners. The study revealed that the utilisation of human-like gestures is essential for developing a sense of familiarity and comfort, which are vital for achieving successful interactions between humans and robots, particularly in environments such as healthcare and rehabilitation. This is consistent with prior studies on anthropomorphism, highlighting the significance of biological motion in enhancing the relatability and effectiveness of humanoid robots in collaborative settings [112].

In addition to these findings, later studies have examined various facets of human-robot interaction (HRI) that enhance successful collaboration. Sciutti et al. (2012) investigated motor resonance, which refers to the synchronisation of movements between humans and robots, as a measure of successful human-robot interaction (HRI). The study utilised electromyography (EMG) signals to quantify muscle activation, yielding valuable insights into the degree of involvement and effectiveness of interaction between humans and robots [113]. Psarakis, Nathanael, and Marmaras (2022) emphasised the significance of anticipatory behaviour in enhancing the collaboration between humans and robots. Their study showcased that human may improve their performance in tasks by accurately anticipating the behaviours of robots, particularly when they are supported by user-friendly and easily understandable interfaces that offer immediate updates on the robot's condition and intentions [114]. Peng Zhou et al. (2024) proposed a technique to manipulate flexible linear objects in real-time while humans and robots work together, based on these ideas. This method employs a topological latent representation and a fixed-time sliding mode controller to provide smoother interactions and more efficient management of flexible objects. As a result, it contributes to the advancement of the field of human-robot collaboration [115].

D. Brain Control

The utilisation of human brain impulses as a control signal in robotics, especially in robotic arms, is regarded as one of the most robust and cutting-edge fields of research. This technology facilitates the utilisation of robots in industries by enabling the autonomous control of robotic arms for industrial purposes. It allows for the allocation of industrial labour to other duties and the automation of production lines without requiring any modifications in the field during the manufacturing process. Manipulating brain impulses, however, advances the field of medical research by greatly improving the quality of life for individuals who are entirely incapacitated. The subsequent subsection can provide a more detailed analysis of this advancement.

VI. BRAIN CONTROLLED ROBOTIC ARM

The origin of brain-computer interfaces (BCIs) may be traced back to Hans Berger's identification of electrical activity in the human brain and the subsequent advancement of electroencephalography. EEG (electroencephalogram). In 1924, Berger pioneered the use of EEG to measure and assess human brain activity. Oscillatory activity, such as Berger's wave or the alpha wave, was identified by Berger through the examination of EEG records [116].

Music for Solo Performer, composed by Alvin Lucier, an American composer, served as an early manifestation of a brain-machine interface, predating the adoption of the phrase itself (1965). The composition employs electroencephalography (EEG) and analogue signal processing equipment to activate acoustic percussion instruments. The components include filters, amplifiers, and a mixing board. The task is accomplished by generating alpha waves, which are subsequently emitted through loudspeakers positioned in close proximity to or directly on different percussion instruments [117].

Jacques Vidal, a professor at UCLA, coined the term "BCI" and authored the initial review publications on the topic [6], [118]. Vidal is widely acknowledged in the field of brain-computer interfaces (BCIs) as the pioneer of BCIs, as demonstrated by numerous peer-reviewed publications that have investigated and discussed this topic, such as those referenced in [119], [120]. Vidal's 1973 study, as reviewed, discussed the "BCI challenge" [121] which involves the manipulation of external objects using EEG signals. Specifically, the work explores the use of Contingent Negative Variation (CNV) as a potential challenge for BCI control. Vidal's 1977 experiment marked the initial use of BCI subsequent to his 1973 BCI challenge. The task involved using noninvasive EEG to manipulate a cursor-like graphical object displayed on a computer screen, namely by utilising Visual Evoked Potentials (VEP). The demonstration resembled navigating a labyrinth [62].

In 1988, a research paper was published on the use of noninvasive EEG technology to control a physical item, specifically a robot. The study described involved the use of EEG to control multiple robot motions, including starting, stopping, and restarting, along a predetermined path marked on the floor. The default robot function was line-following, utilising both autonomous intelligence and an autonomous energy supply [122], [123]. In 1988, Stevo Bozinovski, Mihail Sestakov, and Liljana Bozinovska published the initial study on controlling robots using EEG signals [5], [124].

In 2010, recent research has shown that brain stimulation can improve synaptic effectiveness, which may allow for the restoration of functional connectivity and related behaviours [125], [126]. In light of these findings, the possibility emerged that BCI technology could also restore function in addition to enabling it.

DARPA has provided funding for BCI technology as part of the BRAIN initiative since 2013. This funding has supported various projects, including the development of a brain chip that allows a paralysed man to feel his fingers, led by the University of Pittsburgh Medical Centre in 2016 [127]. In 2017, Paradromics plans to invest $65 million to create a highly advanced, small-scale brain-computer interface. Additionally, Brown University will receive up to $19 million in 2017 to engineer the next-generation brain-computer interface, among other projects.

A. Brain Signal Acquisition Techniquies

In recent years, several technologies have emerged to evaluate the functioning of the human brain. Certain techniques monitor the fluctuation of electrical activities associated with specific brain states, whereas others measure different aspects. The existing approaches can be categorised into two groups based on their level of invasiveness: noninvasive and intrusive, as shown in Fig. 9. Invasive methods can be categorised into two main types: intra-cortical electrode array technologies and electrocorticography. ECoG stands for electrocorticography, which is a type of intracranial electroencephalography. Non-invasive methods are categorised into EEG, functional near infrared spectroscopy (fNIRS), functional magnetic resonance imaging (fMRI), and magnetoencephalography (MEG) [128].

1) Invasive Techniquies

Intra-cortical - Significant progress has been made in the study of BMIs and their ability to restore motor function. Key research has focused on understanding the processes and practical uses of this technology. In 1999, DW Moran and AB Schwartz published a groundbreaking study on the motor cortex, revealing that it employs a population code to encode both speed and direction in reaching movements. Through the observation of motor cortex neurons in monkeys engaged in reaching tasks, researchers found that although individual neurons were associated with distinct characteristics of movement, a more precise representation was obtained by considering the combined activity of populations of neurons. This discovery emphasised the significance of distributed representation in motor control, which could enhance the creation of more efficient BMIs by utilising the inherent neural coding of movement data [129]. Expanding upon this fundamental comprehension, following research has utilised these ideas to implement practical BMI applications, specifically in individuals with movement impairments. Velliste et al. (2008) proved the possibility of utilising BMIs to operate a prosthetic arm. This enabled rhesus monkeys to independently feed themselves by controlling the arm using their neurological signals. This study offered significant insights into the processes of cortical motor control and emphasised the potential of BMI technology to assist persons with motor impairments [130].

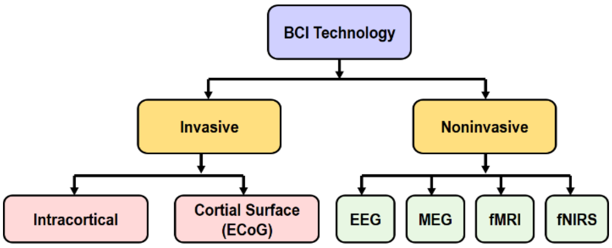

Fig. 9. Brain signals acquisition techniques [116]

In a study conducted by Hochberg et al. (2012), the researchers investigated the application of neurologically controlled robotic limbs in patients who have quadriplegia, thus making significant progress in this area. Their study shown that following the training, participants were able to utilise a robotic arm to execute activities such as grasping objects, thereby highlighting the potential of BMIs to reinstate a certain level of autonomy for individuals with profound motor impairments [131]. Collinger et al. (2013) extended these discoveries by creating a BCI that allowed a tetraplegic patient to operate a prosthetic limb with seven degrees of freedom. This demonstrated the potential of BCIs for achieving advanced motor control [132]. In addition, Bouton et al. (2016) presented a neural bypass technique that circumvents impaired sections of the spinal cord in order to restore movement by directly utilising brain impulses. This development provides a promising opportunity for persons with spinal cord injuries to regain their ability to move [133]. Collectively, these investigations signify noteworthy advancements in the advancement of BMIs and neuroprosthetics, showcasing their capacity to enhance the quality of life for persons afflicted with paralysis.

Electrocorticography (ECoG) - ECoG signals have demonstrated considerable promise in enhancing neuroprosthetic technology, specifically for patients with spinal cord injuries, in the field of BMIs. Márquez-Chin et al. (2009) showed that it is possible to use offline categorisation of ECoG signals to operate a neuroprosthesis for grasping activities. Their study yielded evidence demonstrating the successful utilisation of ECoG signals for the operation of neuroprosthetic devices. This presents a promising opportunity for enhancing motor function in individuals with spinal cord injuries [134]. This study emphasises the increasing potential of BMIs based on ECoG in restoring motor abilities that have been lost. It also implies that in the future, these technologies could have a significant impact on the quality of life for those who have severe motor impairments.

Hirata and Yoshimine (2015) highlighted the benefits of ECoG BMIs in terms of signal resolution and long-term stability, thus expanding our understanding of their potential. The participants engaged in a conversation about the capacity of ECoG BMIs to interpret intricate brain functions, like as writing and speaking, which might greatly assist people with paralysis by granting them control over their limbs and communication. Nevertheless, they also acknowledged the difficulties linked to the creation of dependable and user-friendly ECoG BMIs, such as enhancing the accuracy of signal interpretation and minimising the invasiveness of electrode placement [135]. Furthermore, Kim and Jeong (2022) examined the use of an electrocorticographic decoder employing an echo state network (ESN) and Gaussian readout to decipher arm movements for BMIs. Their methodology demonstrated greater efficacy in forecasting the paths of arm movements, suggesting that the utilisation of advanced decoding techniques could further augment the efficiency of ECoG-based Brain-Machine Interfaces [136]. These findings highlight the promise of ECoG technology in creating advanced neuroprosthetic devices that can greatly enhance the quality of life for those with neurological disorders.

2) Noninvasive Techniques

Electroencephalography (EEG) - The utilisation of EEG data for the purpose of controlling robotic prostheses has attracted considerable interest, as evidenced by numerous research that have emphasised the possibilities and difficulties associated with this method. Shedeed et al. (2013) suggested utilising EEG inputs for real-time control of robotic prostheses, highlighting the importance of accurate and dependable algorithms for efficiently analysing EEG signals. The study highlighted that the accuracy of analysing EEG data has been enhanced by improvements in machine learning and signal processing. However, it emphasised the importance of user training in order to efficiently control robotic equipment using these signals [137]. Building upon this idea, J Meng et al. (2016) investigated the practicality of utilising EEG signals to manipulate a robotic arm for the purpose of performing reach and grab tasks. Their research showed that by using a four-channel EEG helmet together with a machine-learning algorithm, they were able to precisely determine the intended movements of the participants. This allowed for the operation of assistive equipment using EEG-based technology [138].

Recent progress has been achieved in improving EEG-BCI systems to enhance the independence and physical capacities of individuals with motor disabilities. In a study conducted by R. Bousseta et al. (2018), they showed that an EEG-based BCI system was able to control a robotic arm in three dimensions with a high level of accuracy. The system achieved an average precision of 87.5% among participants who had motor impairments [139]. Jeong et al. (2020) introduced an advanced system that utilises a multi-directional Convolutional Neural Network (CNN) and Bidirectional Long Short-Term Memory (BiLSTM) network to manipulate a robotic arm using EEG signals. The system achieved an impressive precision rate of 98.33%. This system utilised the spatiotemporal components extracted from EEG data, resulting in a notable enhancement in the accuracy of categorising movement commands and enabling the robotic arm to be controlled in several directions [140]. Miao Z. et al. (2023) have recently presented LMDA-Net, a highly efficient multi-dimensional attention network that incorporates channel and depth attention modules to improve the classification of EEG data. After conducting experiments on many public datasets, LMDA-Net showed superior performance in terms of classification accuracy compared to other models. This indicates that LMDA-Net has the potential to be a flexible decoding model for EEG events, with potential applications in BCI tasks that go beyond motor control [141].

Functional near infrared spectroscopy (fNIRS) - fNIRS has demonstrated significant potential in BCI research, specifically in the non-invasive monitoring of brain activity. Coyle et al. (2007) emphasised the advantages of a simpler fNIRS system. This system uses only one source-detector pair to monitor the amount of haemoglobin in the brain, which serves as an indicator of neuronal activity. This methodology has been successfully employed in research that involve the visualisation of motions and cognitive processes, showcasing its potential for applications in brain-computer interfaces. Nevertheless, the system's actual implementation is constrained by its poor spatial resolution and vulnerability to interference from adjacent brain tissues [142]. These constraints indicate that although fNIRS has potential as a tool for BCI, additional improvements are necessary to increase its precision and practicality in real-life situations.

Canning and Scheutz (2013) suggested using fNIRS to investigate human-robot interaction (HRI) further. They contended that fNIRS has the potential to offer crucial insights into the brain mechanisms that underlie social interactions between humans and robots. By utilising fNIRS to measure brain activity during human-robot interaction (HRI) activities including collaborative attention, turn-taking, and feedback, researchers can gain a deeper understanding of how humans perceive and react to robot behaviour [143]. Zhang et al. (2017) investigated the incorporation of the common spatial pattern (CSP) algorithm, which is typically employed in EEG-based BCIs, into fNIRS-based BCIs for motor imaging. Their research showed that the implementation of the CSP algorithm enhanced the accuracy of categorising motor imagery tasks using fNIRS. This suggests that incorporating approaches from EEG-based BCIs could improve the efficiency of fNIRS-based systems as well [144]. These studies demonstrate the increasing potential of fNIRS in both BCI and human-robot interaction (HRI) research. However, they also highlight the necessity for further improvements in signal processing approaches to fully optimise the usefulness of this technology.

Functional Magnetic Resonance Imaging (fMRI) - The study of fMRI-based BCIs has provided new opportunities for helping individuals with movement limitations to operate external devices using cognitive processes. In their study, Yoo et al. (2004) provided evidence for the efficacy of fMRI-based BCIs in the domain of spatial navigation. Participants were instructed to mentally visualise travelling through a virtual environment while their brain activity was measured via fMRI scanning. The study utilised Multivariate Pattern Analysis (MVPA) to accurately decipher the imagined movements of participants. This demonstrates the potential of fMRI-based BCIs to convert mental imagery into effective commands for manipulating external equipment [145]. This method presents a hopeful resolution for people who have physical disabilities, enabling them to engage with their surroundings in novel ways by using mental imagery.

In order to make progress in this area, L. Minati et al. (2012) and Cohen et al. (2014) conducted research on the utilisation of fMRI signals to manipulate robotic systems. Their findings showcased the capability of non-invasive brain imaging techniques in controlling robots. In a proof-of-concept experiment, Minati et al. (2012) enabled participants to operate a robotic arm by picturing the movement of their hands. The robot's actions were guided by fMRI signals [146]. In a study conducted by Cohen et al. (2014), it was demonstrated that people can control a robot arm in a way that resembles human movement by mentally imagining their own arm movements. This study established a significant connection between the signals in the motor cortex of the brain, as measured by functional magnetic resonance imaging (fMRI), and the movements of the robot arm [147]. These studies emphasise the potential of fMRI-based BCIs in prosthetics and rehabilitation. However, they also emphasise the necessity for enhancements in the accuracy, speed, and ethical aspects of this developing technology.

Magnetoencephalography (MEG) - BCI technology has recently made significant progress by utilising MEG as it offers excellent temporal resolution and the capability to capture intricate brain activity. McClay et al. (2015) introduced a novel real-time BCI system that utilises MEG data and interactive 3D visualisation to offer instant feedback on cognitive processes. The system employs the Hadoop ecosystem to manage the vast amount of data produced by MEG, facilitating real-time analysis and visualisation. Their proof-of-concept study on visual attention confirmed the system's feasibility, highlighting its capacity to accurately detect real-time changes in brain activity [148].

Fukuma et al. (2016) investigated the application of MEG signals to enable real-time control of neuroprosthetic limbs for patients with amyotrophic lateral sclerosis (ALS), building upon the existing capabilities of MEG in BCIs. The study showcased the efficacy of MEG in capturing brain signals linked to imagined hand movements. This enables individuals with severe paralysis to exert accurate and precise control over a neuroprosthetic hand. The discovery highlights the capacity of MEG-based systems to enhance motor function in patients with motor deficits, especially in cases of extreme paralysis [149]. Rathee et al. (2021) made a significant contribution to the area by developing a detailed MEG dataset that is specifically tailored for applications of BCIs that involve motor and cognitive imagery. The dataset, comprising more than 500 trials, has been openly released on the OpenNeuro platform, serving as a valuable asset for future study and advancement in MEG-based BCIs [150].

B. Brain Signal Classification Techniquies

The primary focus of BCI research is to precisely extract the relevant features from EEG data and improve the speed of classification and identification. Support Vector Machine (SVM), K-Nearest Neighbour (KNN), Artificial Neural Networks (ANN), and Linear Discriminant Analysis (LDA) are frequently used classification techniques in Brain-Computer Interface (BCI) systems [151].

Upon analysing the content of Table IV, which presents a compilation of research focused on classifying brain signals for the purpose of automating control of different types of robots, such as auxiliary devices or robotic arms, one can gain insights into the most prevalent and extensively employed classification techniques. These methods offer a diverse array of classification options and demonstrate exceptionally high accuracy in their classification outcomes.

1) Emotional EEG Brain Signal Classification

Significant progress has been made in utilising Electroencephalography (EEG) data for emotion identification. Numerous studies have investigated various approaches to improve accuracy and practicality. In their study, Bhardwaj et al. (2015) utilised EEG signals in combination with Independent Component Analysis (ICA) and machine learning methods, including Support Vector Machine (SVM) and Linear Discriminant Analysis (LDA), to classify emotions into seven distinct moods. Their research showed that EEG can be used as a reliable measure of authentic emotions by directly examining brain activity. Support Vector Machine (SVM) achieved an average accuracy of 74.13%, while Linear Discriminant Analysis (LDA) achieved 66.50% [166]. In addition, Z.-T. Liu et al. (2019) employed the DEAP dataset and introduced a technique that relies on Valance and Arousal. They utilised K-nearest neighbour and support vector networks to accurately categorise emotional states. Their method attained an impressive detection accuracy of 86.46%, especially when using EEG data obtained within a single temporal frame. This underscores the potential for real-time emotion recognition in human-robot interaction systems [167].

Recent developments in EEG-based emotion recognition have primarily concentrated on enhancing accuracy by employing more advanced models and algorithms. In their study, T. Song et al. (2020) proposed the use of a dynamical graph convolutional neural network (DGCNN) for the purpose of classifying emotions based on multichannel EEG data. This approach employed graph structures to more accurately depict the connections between EEG channels, resulting in enhanced accuracy in recognising emotions. Through their investigation of the DREAMER and SEED datasets, they found that the suggested DGCNN model performed better than previous approaches, obtaining an accuracy of 79.95% in subject-independent cross-validation and 90.4% in subject-dependent trials [168]. In a study conducted by S. K. Khare et al. (2020), an adaptive adjustable Q wavelet transform was proposed. The researchers used grey wolf optimisation to fine-tune the parameters of the transform. As a consequence, they achieved a classification accuracy of 95.70% for identifying four basic emotions. The combination of nonparametric techniques and machine learning technology has the potential to improve EEG-based emotion identification, as demonstrated by this method [169].

Recent research has been expanding the limits of emotion identification using EEG, by investigating novel structures and potential uses. In their 2021 study, S. Issa et al. proposed a method that employs the Broad Learning System (BLS) to accurately categorize emotions based on EEG data, eliminating the need for user-specific information. Their methodology exhibited strong and reliable performance, with accuracies of around 93.1% and 94.4% on the DEAP and MAHNOB-HCI databases, respectively. Additionally, the training time required was remarkably low [170]. In addition, Chowdary MK et al. (2022) investigated the application of recurrent neural network structures, such as LSTM, GRU, and RNN, for the purpose of emotion recognition using EEG inputs. Each model achieved impressive accuracy rates of 95%, 97%, and 96% correspondingly [171]. Chen J. et al. (2024) conducted a recent study where they used EEG technology to investigate emotions in simulated driving situations. They utilised graph neural networks (GNN) to analyse brain data and categorize panic responses and accident-avoidance skills. Their approach yielded a binary classification accuracy of 91.5% and demonstrated the efficacy of deep learning algorithms in capturing emotional states during high-stress scenarios [172], [173].

VII. Critical Analysis and Final Revision

Control of robotic arms has shown substantial progress, incorporating conventional kinematic modelling, AI-based optimisation, and brain-computer interfaces (BCI) [174]. Every method exhibits distinct advantages; nonetheless, obstacles remain. Classical control approaches encounter difficulties with complicated, high-degree-of-freedom systems, whereas heuristic and AI-based solutions enhance adaptability but frequently require substantial processing resources. Trajectory optimisation methods, such as Genetic Algorithms (GA), Particle Swarm Optimisation (PSO), and hybrid models, have improved motion efficiency and constraint management; nonetheless, real-time applicability and robustness continue to be limiting constraints. BCI-controlled robotic arms offer transformative applications but encounter challenges including subpar signal quality, prolonged calibration durations, and ethical issues related to brain data protection.

TABLE IV. BRIEF VIEW OF BRAIN SIGNAL DIFFERENT CLASSIFICATION TECHNIQUES

Classification technique	Reference	Signal acquisition technique	Robot	Accuracy percentage
Support Vector Machine (SVM)	2014 [152]	EEG	Robot arm	95 %
	2016 [153]	EEG	Mobile robot	59 to 68 %
	2017 [154]	EEG	Mobile robot	> 75 %
	2018 [139]	EEG	Dual-arm robot	69 %
	2020 [7]	EEG	Quadcopter	75 %
K-Nearest Neighbor (KNN)	2007 [155]	MEG	Visuomotor	97 %
	2015 [156]	EEG	Quadcopter	75 %
	2020 [157]	EEG	-------	95.7 %
Artificial Neural Networks (ANN)	2013 [158]	MEG and EEG	7-DOF robotic arm	94 %
	2014 [159]	EEG	Wheelchair	86.5 %
	2016 [160]	EEG	Quadcopter	98 %
	2020 [161]	EEG	Tractor driving robot	93 %
Linear Discriminant Analysis (LDA)	2011 [162]	EEG	Industrial arm	78 to 92 %
	2015 [163]	EEG-NIRS	Quadcopter	78 to 90 %
Hybrid	2019 [164]	EEG	Exoskeleton robot	95 %
	2022 [165]	EEG	--------	98 %

Notwithstanding these developments, other hurdles must be surmounted to attain completely autonomous and adaptive control of robotic arms. Real-time execution continues to be a constraint, as several optimisation strategies necessitate substantial processing capacity. Scalability and adaptability remain constrained, as task-specific control techniques necessitate regular human modifications. Furthermore, as robotic arms assimilate into human settings, it will be essential to guarantee safe human-robot collaboration, the interpretability of AI-generated choices, and the ethical implications associated with automation and brain-computer interface technologies. Addressing these concerns will be crucial for the broader use of industrial, medical, and assistive robotics.

Future research ought to concentrate on hybrid AI and physics-based control, harmonizing data-driven adaptability with deterministic stability. Real-time, low-latency trajectory optimisation is essential for dynamic situations, whereas developments in BCI must emphasise user accessibility and signal dependability. As robotic systems advance in intelligence and societal integration, the focus must transition to explainable AI, ethical automation, and human-centered design. Addressing these difficulties would enhance robotic arm control, making it more efficient, safe, and intelligent, thereby influencing the future of automation, healthcare, and human enhancement.

VIII. CONCLUSION

This review paper presents a thorough examination of the fully controlled robotic arm process, including essential elements like kinematic analysis, path planning, trajectory optimisation, control approaches, brain signal acquisition, and brain signal classification. This study synthesizes current research findings, emphasizing both progress and ongoing obstacles, so providing significant insights for researchers, engineers, and practitioners in robotics and neuro-engineering.

Notwithstanding considerable advancements, some persistent problems impede the extensive implementation of robotic arm technologies. The implementation of real-time systems continues to be a significant challenge, especially in dynamic contexts where external disturbances, sensor errors, and processing inefficiencies impact performance. The computational demands of optimisation methods and AI-based control models restrict their real-time use, necessitating the development of energy-efficient, low-latency algorithms as a focal point for future study. Furthermore, developing resilient, adaptable, and scalable control techniques that can generalize across diverse robotic configurations and situations continues to be a significant research issue.

In addition to technical constraints, the ethical and sociological ramifications of robotic arm technology require thorough scrutiny. The incorporation of brain-computer interfaces (BCIs) has advanced neuroprosthetics and assistive robots, although also raises issues related to data security, privacy, and the possible exploitation of neurological signals. Furthermore, the growing automation of industrial and manual jobs prompts concerns regarding workforce displacement and social inequality, highlighting the necessity for regulatory frameworks that reconcile technological advancement with societal welfare. Prioritizing safety issues in human-robot interaction is essential to avert mishaps and foster user trust in intelligent robotic systems.

Future progress will necessitate interdisciplinary collaborations across robotics, neuroscience, artificial intelligence, and computational engineering to tackle these difficulties. Future innovations must prioritize the creation of energy-efficient, adaptive, and socially responsible robotic arm systems, facilitating their smooth integration into healthcare, industrial automation, and daily applications. Addressing these unresolved difficulties will advance the field of robotic arm control towards more intelligent, human-compatible, and ethically responsible inventions that serve the broader society.

REFERENCES

[1] S. Kucuk and Z. Bingul, “The inverse kinematics solutions of industrial robot manipulators,” in *Proceedings of the IEEE International Conference on Mechatronics, 2004. ICM ’04., IEEE*, pp. 274–279, 2004, doi: 10.1109/ICMECH.2004.1364451.

[2] L. Carbonari, M.-C. Palpacelli, and M. Callegari, “Inverse Kinematics of a Class of 6R Collaborative Robots with Non-Spherical Wrist,” *Robotics*, vol. 12, no. 2, 2023, doi: 10.3390/robotics12020036.

[3] A. Pozo *et al*., “Vision-Driven Assembly Robot,” 2013. Accessed: Jan. 08, 2024. [Online]. Available: http://his.diva-portal.org/smash/get/diva2:1803111/FULLTEXT01.pdf

[4] L. Bi, X.-A. Fan, and Y. Liu, "EEG-Based Brain-Controlled Mobile Robots: A Survey," *IEEE Trans Hum Mach Syst*, vol. 43, no. 2, pp. 161–176, 2013, doi: 10.1109/TSMCC.2012.2219046.

[5] M. A. Lebedev and M. A. L. Nicolelis, "Brain-Machine Interfaces: From Basic Science to Neuroprostheses and Neurorehabilitation," *Physiol Rev*, vol. 97, no. 2, pp. 767–837, 2017, doi: 10.1152/physrev.00027.2016.

[6] J. J. Vidal, "Toward Direct Brain-Computer Communication," *Annu Rev Biophys Bioeng*, vol. 2, no. 1, pp. 157–180, 1973, doi: 10.1146/annurev.bb.02.060173.001105.

[7] J. Choi and S. Jo, "Application of Hybrid Brain-Computer Interface with Augmented Reality on Quadcopter Control," in *2020 8th International Winter Conference on Brain-Computer Interface (BCI)*, pp. 1–5, 2020, doi: 10.1109/BCI48061.2020.9061659.

[8] V. A. Knights, O. Petrovska, and J. G. Kljusurić, "Nonlinear Dynamics and Machine Learning for Robotic Control Systems in IoT Applications," *Future Internet*, vol. 16, no. 12, Nov. 2024, doi: 10.3390/fi16120435.

[9] Z. Yan *et al*., "Deep Learning-Driven Robot Arm Control Fusing Convolutional Visual Perception and Predictive Modeling for Motion Planning," *Journal of Organizational and End User Computing*, vol. 36, no. 1, pp. 1–29, Sep. 2024, doi: 10.4018/JOEUC.355191.

[10] Y. Dou, E. Prempain, and T. O. Ting, "Enhancing Robotic Arm Trajectory Tracking via Hybrid Weightless Swarm Algorithm and Iterative Learning Control (WSA-ILC)," in *2024 10th International Conference on Control, Decision and Information Technologies (CoDIT), IEEE*, pp. 2821–2826, Jul. 2024, doi: 10.1109/CoDIT62066.2024.10708100.

[11] S. M. Megahed, "Inverse Kinematics of Spherical Wrist Robot Arms: Analysis and Simulation," *J Intell Robot Syst*, vol. 5, pp. 211–227, 1992, doi: 10.1007/BF00247418.

[12] S. Asif and P. Webb, "Kinematics Analysis of 6-DoF Articulated Robot with Spherical Wrist," *Math Probl Eng*, pp. 1–7, 2021, doi: 10.1155/2021/6647035.

[13] M. S. Elhadidy, W. S. Abdalla, A. A. Abdelrahman, S. Elnaggar, and M. Elhosseini, "Assessing the accuracy and efficiency of kinematic analysis tools for six-DOF industrial manipulators: The KUKA robot case study," *AIMS Mathematics*, vol. 9, no. 6, pp. 13944–13979, 2024, doi: 10.3934/math.2024678.

[14] K. Raza, T. A. Khan, and N. Abbas, "Kinematic analysis and geometrical improvement of an industrial robotic arm," *Journal of King Saud University - Engineering Sciences*, vol. 30, no. 3, pp. 218–223, Jul. 2018, doi: 10.1016/j.jksues.2018.03.005.

[15] D. R. Isenberg, "Analytical Inverse Kinematic Solutions for End-Effector Positioning and Pointing Applied to Revolute Manipulators with Spherical Wrists," in *SoutheastCon 2021, IEEE*, pp. 1–8, Mar. 2021, doi: 10.1109/SoutheastCon45413.2021.9401896.

[16] L.-H. Ma, Y.-B. Zhong, G.-D. Wang, and N. Li, "The Kinematic and Dynamic Modeling and Numerical Calculation of Robots with Complex Mechanisms Based on Lie Group Theory," *Math Probl Eng*, vol. 2021, pp. 1–34, Oct. 2021, doi: 10.1155/2021/6014256.

[17] P. T. Lin, E. Shahabi, K.-A. Yang, Y.-T. Yao, and C.-H. Kuo, "Parametrically Modeled DH Table for Soft Robot Kinematics: Case Study for A Soft Gripper," *Advances in Mechanism and Machine Science: Proceedings of the 15th IFToMM World Congress on Mechanism and Machine Science 15*, pp. 617–625, 2019, doi: 10.1007/978-3-030-20131-9_62.

[18] M. A. A. Mousa, A. T. Elgohr, and H. A. Khater, "Trajectory Optimization for a 6 DOF Robotic Arm Based on Reachability Time," *Annals of Emerging Technologies in Computing*, vol. 8, no. 1, pp. 22–35, Jan. 2024, doi: 10.33166/AETiC.2024.01.003.

[19] I. Journal, T. P. Singh, P. Suresh, and S. Chandan, "Forward and Inverse Kinematic Analysis of Robotic Manipulators," *International Research Journal of Engineering and Technology (IRJET)*, vol. 4, no. 2, pp. 1459–1469, 2017.

[20] R. Singh, V. Kukshal, and V. S. Yadav, "A Review on Forward and Inverse Kinematics of Classical Serial Manipulators," in *Advances in Engineering Design*, pp. 417–428, 2021, doi: 10.1007/978-981-33-4018-3_39.

[21] Z. Fu, W. Yang, and Z. Yang, "Solution of Inverse Kinematics for 6R Robot Manipulators With Offset Wrist Based on Geometric Algebra," *J Mech Robot*, vol. 5, pp. 310081–310087, Jun. 2013, doi: 10.1115/1.4024239.

[22] M. Wenz and H. Worn, "Solving the inverse kinematics problem symbolically by means of knowledge-based and linear algebra-based methods," in *IEEE International Conference on Emerging Technologies and Factory Automation, ETFA*, pp. 1346–1353, Jun. 2007, doi: 10.1109/EFTA.2007.4416937.

[23] I. Zaplana, H. Hadfield, and J. Lasenby, "Closed-form solutions for the inverse kinematics of serial robots using conformal geometric algebra," *Mech Mach Theory*, vol. 173, p. 104835, 2022, doi: 10.1016/j.mechmachtheory.2022.104835.

[24] K. Arikawa, "Symbolic Computation of Inverse Kinematics for General 6R Manipulators Based on Raghavan and Roth's Solution," in *Volume 10: 44th Mechanisms and Robotics Conference (MR), American Society of Mechanical Engineers*, Aug. 2020, doi: 10.1115/DETC2020-22231.

[25] H. Shen, Y. Zhao, J. Li, G. Wu, and D. Chablat, "A novel partially-decoupled translational parallel manipulator with symbolic kinematics, singularity identification and workspace determination," *Mech Mach Theory*, vol. 164, p. 104388, Oct. 2021, doi: 10.1016/j.mechmachtheory.2021.104388.

[26] A. A. Saad, "An Efficient Full-Numerical Solution for The Inverse Kinematics of The 6-DOF Full-Articulated Manipulator," *The International Conference on Applied Mechanics and Mechanical Engineering*, vol. 18, pp. 3–5, 2018.

[27] R. Iakovlev, A. Denisov, and R. Prakapovich, "Iterative Method for Solving the Inverse Kinematics Problem of Multi-link Robotic Systems with Rotational Joints," *Proceedings of 14th International Conference on Electromechanics and Robotics "Zavalishin's Readings" ER (ZR) 2019*, pp. 237–251, 2019, doi: 10.1007/978-981-13-9267-2_20.

[28] Y. Quiñonez, O. Zatarain, C. Lizarraga, R. Aguayo, and J. Mejía, "Numerical Method Using Homotopic Iterative Functions Based on the via Point for the Joint-Space Trajectory Generation," *Applied Sciences*, vol. 13, no. 2, Jan. 2023, doi: 10.3390/app13021142.

[29] S. Horvath and H. Neuner, "Introduction of a Framework for the Integration of a Kinematic Robot Arm Model in an Artificial Neural Network - Extended Kalman Filter Approach," *J Intell Robot Syst*, vol. 110, no. 4, p. 137, Sep. 2024, doi: 10.1007/s10846-024-02164-6.

[30] Y. Hamida El Naser, D. Karayel, M. S. Demirsoy, M. S. Sarıkaya, and N. Y. Peker, "Robotic Arm Trajectory Tracking Using Image Processing and Kinematic Equations," *Black Sea Journal of Engineering and Science*, vol. 7, no. 3, pp. 436–444, May 2024, doi: 10.34248/bsengineering.1445455.

[31] M. Restrepo, C. A. Cañizares, J. W. Simpson-Porco, P. Su, and J. Taruc, "Optimization- and Rule-based Energy Management Systems at the Canadian Renewable Energy Laboratory microgrid facility," *Appl Energy*, vol. 290, May 2021, doi: 10.1016/j.apenergy.2021.116760.

[32] N. Gunantara, "A review of multi-objective optimization: Methods and its applications," *Cogent Eng*, vol. 5, no. 1, p. 1502242, Jan. 2018, doi: 10.1080/23311916.2018.1502242.

[33] A. B. Hashemi and M. R. Meybodi, "Cellular PSO: A PSO for Dynamic Environments," *Advances in Computation and Intelligence: 4th International Symposium, ISICA 2009 Huangshi, China, Ocotober 23-25, 2009 Proceedings 4*, pp. 422–433, 2009, doi: 10.1007/978-3-642-04843-2_45.

[34] M. Alkayyali and T. A. Tutunji, "PSO-based Algorithm for Inverse Kinematics Solution of Robotic Arm Manipulators," *2019 20th International Conference on Research and Education in Mechatronics (REM)*, pp. 1–6, 2019.

[35] A. Singh, A. Sharma, S. Rajput, A. Bose, and X. Hu, "An Investigation on Hybrid Particle Swarm Optimization Algorithms for Parameter Optimization of PV Cells," *Electronics (Basel)*, vol. 11, no. 6, Mar. 2022, doi: 10.3390/electronics11060909.

[36] H. Deng and C. Xie, "An Improved Particle Swarm Optimization Algorithm for Inverse Kinematics Solution of Multi-DOF Serial Robotic Manipulators," *Soft Comput.*, vol. 25, no. 21, pp. 13695–13708, Nov. 2021, doi: 10.1007/s00500-021-06007-6.

[37] H. Danaci, L. A. Nguyen, T. L. Harman, and M. Pagan, "Inverse Kinematics for Serial Robot Manipulators by Particle Swarm

Optimization and POSIX Threads Implementation," *Applied Sciences*, vol. 13, no. 7, Apr. 2023, doi: 10.3390/app13074515.

[38] M. Kumar, M. Husian, N. Upreti, and D. Gupta, "Genetic Algorithm: Review and Application," *International Journal of Information Technology and Knowledge Management*, vol. 2, no. 2, pp. 451–454, 2010, doi: 10.2139/ssrn.3529843.

[39] C.-Y. Chen, M.-G. Her, Y.-C. Hung, and M. Karkoub, "Approximating a Robot Inverse Kinematics Solution Using Fuzzy Logic Tuned by Genetic Algorithms," *The International Journal of Advanced Manufacturing Technology*, vol. 20, no. 5, pp. 375–380, Sep. 2002, doi: 10.1007/s001700200166.

[40] R. Köker, "A genetic algorithm approach to a neural-network-based inverse kinematics solution of robotic manipulators based on error minimization," *Inf Sci (N Y)*, vol. 222, pp. 528–543, 2013, doi: 10.1016/j.ins.2012.07.051.

[41] Z. Zhou, H. Guo, Y. Wang, Z. Zhu, J. Wu, and X. Liu, "Inverse kinematics solution for robotic manipulator based on extreme learning machine and sequential mutation genetic algorithm," *Int J Adv Robot Syst*, vol. 15, no. 4, Jul. 2018, doi: 10.1177/1729881418792992.

[42] J. Hernandez-Barragan, G. Martinez-Soltero, J. D. Rios, C. Lopez-Franco, and A. Y. Alanis, "A Metaheuristic Optimization Approach to Solve Inverse Kinematics of Mobile Dual-Arm Robots," *Mathematics*, vol. 10, no. 21, Nov. 2022, doi: 10.3390/math10214135.

[43] N. Courty and E. Arnaud, "Inverse Kinematics Using Sequential Monte Carlo Methods," in *Perales, F.J., Fisher, R.B. (eds) Articulated Motion and Deformable Objects. AMDO*, Jun. 2008, doi: 10.1007/978-3-540-70517-8_1.

[44] A. Martín-Barrio, A. Barrientos, and J. Cerro, "The Natural-CCD Algorithm, a Novel Method to Solve the Inverse Kinematics of Hyper-redundant and Soft Robots," *Soft Robot*, vol. 5, Jun. 2018, doi: 10.1089/soro.2017.0009.

[45] M. Soleimani Amiri and R. Ramli, "Intelligent Trajectory Tracking Behavior of a Multi-Joint Robotic Arm via Genetic–Swarm Optimization for the Inverse Kinematic Solution," *Sensors*, vol. 21, no. 9, May 2021, doi: 10.3390/s21093171.

[46] A. Sheelwant, P. M. Jadhav, and S. K. R. Narala, "ANN-GA based parametric optimization of Al-TiB2 metal matrix composite material processing technique," *Mater Today Commun*, vol. 27, Jun. 2021, doi: 10.1016/j.mtcomm.2021.102444.

[47] A.-V. Duka, "Neural Network based Inverse Kinematics Solution for Trajectory Tracking of a Robotic Arm," *Procedia Technology*, vol. 12, pp. 20–27, 2014, doi: 10.1016/j.protcy.2013.12.451.

[48] M. Soylak, T. Oktay, and İ. Turkmen, "A simulation-based method using artificial neural networks for solving the inverse kinematic problem of articulated robots," *Proceedings of the Institution of Mechanical Engineers, Part E: Journal of Process Mechanical Engineering*, vol. 231, no. 3, pp. 470–479, 2017, doi: 10.1177/0954408915608755.

[49] J. Lu, T. Zou, and X. Jiang, "A Neural Network Based Approach to Inverse Kinematics Problem for General Six-Axis Robots," *Sensors*, vol. 22, no. 22, p. 8909, Nov. 2022, doi: 10.3390/s22228909.

[50] M. R. A. Refaai, "An Improved Inverse Kinematics Solution for a Robot Arm Trajectory Using Multiple Adaptive Neuro-Fuzzy Inference Systems," *Advances in Materials Science and Engineering*, vol. 2023, 2022, doi: 10.1155/2022/1413952.

[51] J. Narayan and A. Singla, "ANFIS based kinematic analysis of a 4-DOFs SCARA robot," in *2017 4th International Conference on Signal Processing, Computing and Control (ISPCC), IEEE*, pp. 205–211, Sep. 2017, doi: 10.1109/ISPCC.2017.8269676.

[52] D. Deshmukh, D. K. Pratihar, A. K. Deb, H. Ray, and A. Ghosh, "ANFIS-Based Inverse Kinematics and Forward Dynamics of 3 DOF Serial Manipulator," in *Hybrid Intelligent Systems. HIS*, vol. 1375, pp. 144–156, 2021, doi: 10.1007/978-3-030-73050-5_15.

[53] J. Demby's, Y. Gao, and G. N. DeSouza, "A Study on Solving the Inverse Kinematics of Serial Robots using Artificial Neural Network and Fuzzy Neural Network," in *2019 IEEE International Conference on Fuzzy Systems (FUZZ-IEEE), IEEE*, pp. 1–6, Jun. 2019, doi: 10.1109/FUZZ-IEEE.2019.8858872.

[54] R. Singh, Ankur, A. Agrawal, A. Mishra, P. K. Arya, and A. Sharma, "Application of Deep Learning Model for Analysis of Forward Kinematics of a 6-Axis Robotic Hand for a Humanoid," in *2024 3rd International Conference on Artificial Intelligence and Autonomous Robot Systems (AIARS), IEEE*, pp. 1–6, Jul. 2024, doi: 10.1109/AIARS63200.2024.00006.

[55] M. Kashkash, A. El Saddik, and M. Guizani, "Optimizing 7-DOF Robot Manipulator Path Using Deep Reinforcement Learning Techniques," in *2024 IEEE International Symposium on Robotic and Sensors Environments (ROSE), IEEE*, pp. 1–7, Jun. 2024, doi: 10.1109/ROSE62198.2024.10591186.

[56] A. Serat and B. Djebbar, "Integrating artificial immune systems and multi-layer perceptron-biogeography-based optimization for enhanced inverse kinematics in robotic arm," *IAES International Journal of Robotics and Automation (IJRA)*, vol. 13, no. 4, pp. 401–409, Dec. 2024, doi: 10.11591/ijra.v13i4.pp401-409.

[57] O. Aydogmus and G. Boztas, "Implementation of singularity-free inverse kinematics for humanoid robotic arm using Bayesian optimized deep neural network," *Measurement*, vol. 229, Apr. 2024, doi: 10.1016/j.measurement.2024.114471.

[58] W. Ma, Q. Du, R. Zhu, W. Han, D. Chen, and Y. Geng, "Research on Inverse Kinematics of Redundant Robotic Arms Based on Flexibility Index," *IEEE Robot Autom Lett*, vol. 9, no. 8, pp. 7262–7269, Aug. 2024, doi: 10.1109/LRA.2024.3420704.

[59] M. Fazilat, N. Zioui, and J. St-Arnaud, "A novel quantum model of forward kinematics based on quaternion/Pauli gate equivalence: Application to a six-jointed industrial robotic arm," *Results in Engineering*, vol. 14, Jun. 2022, doi: 10.1016/j.rineng.2022.100402.

[60] A. Gasparetto, P. Boscariol, A. Lanzutti, and R. Vidoni, "Path Planning and Trajectory Planning Algorithms: A General Overview," *Mechanisms and Machine Science*, vol. 29, pp. 3–27, Mar. 2015, doi: 10.1007/978-3-319-14705-5_1.

[61] M. Ali and M. Mailah, "Path Planning and Control of Mobile Robot in Road Environments Using Sensor Fusion and Active Force Control," *IEEE Trans Veh Technol*, vol. 68, no. 3, pp. 2176-2195, Jan. 2019, doi: 10.1109/TVT.2019.2893878.

[62] J. Yi, Q. Yuan, R. Sun, and H. Bai, "Path planning of a manipulator based on an improved P_RRT* algorithm," *Complex & Intelligent Systems*, vol. 8, no. 3, pp. 2227–2245, 2022, doi: 10.1007/s40747-021-00628-y.

[63] J.-Y. Kim, U.-J. Yang, and K. Park, "Design, motion planning and control of frozen shoulder rehabilitation robot," *International Journal of Precision Engineering and Manufacturing*, vol. 15, no. 9, pp. 1875–1881, 2014, doi: 10.1007/s12541-014-0541-4.

[64] R. Soltani Zarrin, A. Zeiaee, R. Langari, and N. Robson, "Reference path generation for upper-arm exoskeletons considering scapulohumeral rhythms," in *2017 International Conference on Rehabilitation Robotics (ICORR)*, pp. 753–758, 2017, doi: 10.1109/ICORR.2017.8009338.

[65] Q. Meng, H. Shao, L. Wang, and H. Yu, "Task-Based Trajectory Planning for an Exoskeleton Upper Limb Rehabilitation Robot," *International Conference on Man-Machine-Environment System Engineering (MMESE)*, vol. 527, pp. 141–149, Jan. 2019, doi: 10.1007/978-981-13-2481-9_18.

[66] C. Wang et al., "Kinematic Redundancy Analysis during Goal-Directed Motion for Trajectory Planning of an Upper-Limb Exoskeleton Robot," in *2019 41st Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC)*, pp. 5251–5255, 2019, doi: 10.1109/EMBC.2019.8857716.

[67] G. Li, Q. Fang, T. Xu, J. Zhao, H. Cai, and Y. Zhu, "Inverse kinematic analysis and trajectory planning of a modular upper limb rehabilitation exoskeleton," *Technology and Health Care*, vol. 27, pp. 123–132, 2019, doi: 10.3233/THC-199012.

[68] Z. Li, W. Zuo, and S. Li, "Zeroing dynamics method for motion control of industrial upper-limb exoskeleton system with minimal potential energy modulation," *Measurement*, vol. 163, p. 107964, 2020, doi: https://doi.org/10.1016/j.measurement.2020.107964.

[69] M. A. A. Mousa, A. Elgohr, and H. Khater, "Path Planning for a 6 DoF Robotic Arm Based on Whale Optimization Algorithm and Genetic Algorithm," *Journal of Engineering Research*, vol. 7, no. 5, pp. 160–168, Nov. 2023, doi: 10.21608/erjeng.2023.237586.1256.

[70] R. K. Malhan, S. Thakar, A. M. Kabir, P. Rajendran, P. M. Bhatt, and S. K. Gupta, "Generation of Configuration Space Trajectories Over Semi-Constrained Cartesian Paths for Robotic Manipulators," *IEEE*

Transactions on Automation Science and Engineering, vol. 20, no. 1, pp. 193–205, Jan. 2023, doi: 10.1109/TASE.2022.3144673.

[71] J.-C. Chung, C.-H. Huang, H.-C. Chou, and C.-H. Kuo, "Trajectory Planning of a Redundant Manipulator from Investigations of Upper Limb Motions of Human Beings," *IFAC Proceedings Volumes*, vol. 45, no. 2, pp. 538–543, 2012.

[72] E. Sabbaghi, M. Bahrami, and S. S. Ghidary, "Learning of gestures by imitation using a monocular vision system on a humanoid robot," *2014 Second RSI/ISM International Conference on Robotics and Mechatronics (ICRoM)*, pp. 588–594, 2014, doi: 10.1109/ICRoM.2014.6990966.

[73] J. Garrido, W. Yu, and X. Li, "Robot trajectory generation using modified hidden Markov model and Lloyd's algorithm in joint space," *Eng Appl Artif Intell*, vol. 53, pp. 32–40, Aug. 2016, doi: 10.1016/j.engappai.2016.03.006.

[74] C. Lauretti *et al*., "Learning by Demonstration for Motion Planning of Upper-Limb Exoskeletons," *Front Neurorobot*, vol. 12, 2018, doi: 10.3389/fnbot.2018.00005.

[75] S. S. Naghibi, A. Fallah, A. Maleki, and F. Ghassemi, "Elbow angle generation during activities of daily living using a submovement prediction model," *Biol Cybern*, vol. 114, no. 3, pp. 389–402, 2020.

[76] F. Tao *et al*., "Trajectory Planning of Upper Limb Rehabilitation Robot Based on Human Pose Estimation," *2020 17th International Conference on Ubiquitous Robots (UR)*, pp. 333–338, Jun. 2020, doi: 10.1109/UR49135.2020.9144771.

[77] A. Duburcq, Y. Chevaleyre, N. Bredeche, and G. Boeris, "Online Trajectory Planning Through Combined Trajectory Optimization and Function Approximation: Application to the Exoskeleton Atalante," in *2020 IEEE International Conference on Robotics and Automation (ICRA)*, pp. 3756–3762, 2020, doi: 10.1109/ICRA40945.2020.9196633.

[78] S. Zhang, Q. Xia, M. Chen, and S. Cheng, "Multi-Objective Optimal Trajectory Planning for Robotic Arms Using Deep Reinforcement Learning," *Sensors*, vol. 23, no. 13, Jun. 2023.

[79] A. Gasparetto, P. Boscariol, A. Lanzutti, and R. Vidoni, "Trajectory Planning in Robotics," *Mathematics in Computer Science*, vol. 6, no. 3, pp. 269–279, Sep. 2012, doi: 10.1007/s11786-012-0123-8.

[80] F. G. Flores and A. Kecskeméthy, "Time-Optimal Path Planning Along Specified Trajectories," in *Multibody System Dynamics, Robotics and Control, H. Gattringer and J. Gerstmayr, Eds., Vienna: Springer Vienna*, pp. 1–16, 2013, doi: 10.1007/978-3-7091-1289-2_1.

[81] H. Liu, X. Chen, and C. Li, "Path Planning Optimization for Obstacle Avoidance in Unknown Environment," in *2024 36th Chinese Control and Decision Conference (CCDC)*, pp. 5601–5606, 2024, doi: 10.1109/CCDC62350.2024.10588054.

[82] A. Gasparetto and V. Zanotto, "A new method for smooth trajectory planning of robot manipulators," *Mech Mach Theory*, vol. 42, no. 4, pp. 455–471, 2007, doi: 10.1016/j.mechmachtheory.2006.04.002.

[83] M. Ratiu and M. Adriana Prichici, "Industrial robot trajectory optimization- a review," in *MATEC Web of Conferences, EDP Sciences,* Oct. 2017. doi: 10.1051/matecconf/201712602005.

[84] Y. Chen, L. Chen, and J. Ding, "Adaptive Genetic Algorithm Based Particle Swarm Optimization for Industrial Robotic Arm Obstacle Avoidance Trajectory Optimization," in *2022 International Conference on Automation, Robotics and Computer Engineering (ICARCE)*, pp. 1–4, 2022, doi: 10.1109/ICARCE55724.2022.10046592.

[85] Y. Su, Y. Dai, and Y. Liu, "A hybrid hyper-heuristic whale optimization algorithm for reusable launch vehicle reentry trajectory optimization," *Aerosp Sci Technol*, vol. 119, p. 107200, Dec. 2021, doi: 10.1016/j.ast.2021.107200.

[86] A. Heim and O. Von Stryk, "Trajectory optimization of industrial robots with application to computer-aided robotics and robot controllers," *Optimization*, vol. 47, no. 3–4, pp. 407–420, Jan. 2000.

[87] C. Rösmann, W. Feiten, T. Wösch, F. Hoffmann, and T. Bertram, "Efficient trajectory optimization using a sparse model," in *2013 European Conference on Mobile Robots*, pp. 138–143, 2013, doi: 10.1109/ECMR.2013.6698833.

[88] G. Kahn *et al*., "Active exploration using trajectory optimization for robotic grasping in the presence of occlusions," in *2015 IEEE International Conference on Robotics and Automation (ICRA)*, pp. 4783–4790, 2015, doi: 10.1109/ICRA.2015.7139864.

[89] R. Benotsmane, L. Dudás, and G. Kovács, "Trajectory Optimization of Industrial Robot Arms Using a Newly Elaborated 'Whip-Lashing' Method," *Applied Sciences*, vol. 10, no. 23, p. 8666, Dec. 2020, doi: 10.3390/app10238666.

[90] T. Wang, S. Yao, and S. Zhu, "Energy-saving trajectory optimization of a fluidic soft robotic arm," *Smart Mater Struct*, vol. 31, no. 11, p. 115011, 2022, doi: 10.1088/1361-665X/ac9768.

[91] N. Yokoyama and S. Suzuki, "Modified genetic algorithm for constrained trajectory optimization," *Journal of Guidance, Control, and Dynamics*, vol. 28, no. 1, pp. 139–144, 2005, doi: 10.2514/1.3042.

[92] S. Števo, I. Sekaj, and M. Dekan, "Optimization of Robotic Arm Trajectory Using Genetic Algorithm," *19th IFAC World Congress*, vol. 47, no. 3, pp. 1748–1753, 2014, doi: 10.3182/20140824-6-ZA-1003.01073.

[93] R. Wu, Y. Yang, X. Yao, and N. Lu, "Optimal Trajectory Planning for Robotic Arm Based on Improved Dynamic Multi-Population Particle Swarm Optimization Algorithm," *International Journal of Advanced Computer Science and Applications*, vol. 15, no. 5, 2024, doi: 10.14569/IJACSA.2024.0150571.

[94] M. A. A. Mousa, A. T. Elgohr, and H. A. Khater, "Whale-Based Trajectory Optimization Algorithm for 6 DOF Robotic Arm," *Annals of Emerging Technologies in Computing (AETiC)*, vol. 8, no. 4, pp. 99–114, Oct. 2024, doi: 10.33166/AETiC.2024.04.005.

[95] T. Wang, Z. Xin, H. Miao, H. Zhang, Z. Chen, and Y. Du, "Optimal Trajectory Planning of Grinding Robot Based on Improved Whale Optimization Algorithm," *Math Probl Eng*, vol. 2020, p. 3424313, 2020, doi: 10.1155/2020/3424313.

[96] Y. Dai, J. Yu, C. Zhang, B. Zhan, and X. Zheng, "A novel whale optimization algorithm of path planning strategy for mobile robots," *Applied Intelligence*, vol. 53, no. 9, pp. 10843–10857, 2023, doi: 10.1007/s10489-022-04030-0.

[97] S. Ziamanesh, H. S. Salimi, A. Tavana, and A. A. Ghavifekr, "Parameter Tuning of Discontinues Lyapunov Based Controller Based on the Gray Wolf Optimization Algorithm Applied to a Robotic Manipulator," in *2022 8th Iranian Conference on Signal Processing and Intelligent Systems (ICSPIS)*, pp. 1–6, 2022, doi: 10.1109/ICSPIS56952.2022.10043942.

[98] A. Pawlowski, S. Romaniuk, Z. Kulesza, and M. Petrovic, "Trajectory optimization using learning from demonstration with meta-heuristic grey wolf algorithm," *IAES International Journal of Robotics and Automation (IJRA)*, vol. 11, no. 4, pp. 263–277, Dec. 2022, doi: 10.11591/ijra.v11i4.pp263-277.

[99] Z. Wang, X. Zhou, C. Xu, and F. Gao, "Geometrically Constrained Trajectory Optimization for Multicopters," *IEEE Transactions on Robotics*, vol. 38, no. 5, pp. 3259–3278, Oct. 2022, doi: 10.1109/TRO.2022.3160022.

[100] A. Dastider, H. Fang, and M. Lin, "RETRO: Reactive Trajectory Optimization for Real-Time Robot Motion Planning in Dynamic Environments," in *2024 IEEE International Conference on Robotics and Automation (ICRA)*, pp. 8764–8770, 2024, doi: 10.1109/ICRA57147.2024.10610542.

[101] K. Wei, Y. Chu, and H. Gan, "An improved Rapidly-exploring Random Tree Approach for Robotic Dynamic Path Planning," in *2021 11th International Conference on Intelligent Control and Information Processing (ICICIP)*, pp. 181–187, 2021, doi: 10.1109/ICICIP53388.2021.9642182.

[102] Sam Cubero, Industrial Robotics: Theory, Modelling and Control. Russia: Pro Literatur Verlag, Germany / ARS, Austria, 2006. doi: 10.5772/44.

[103] Q. V. Doan, A. T. Vo, T. D. Le, H.-J. Kang, and N. H. A. Nguyen, "A Novel Fast Terminal Sliding Mode Tracking Control Methodology for Robot Manipulators," *Applied Sciences*, vol. 10, no. 9, p. 3010, Apr. 2020, doi: 10.3390/app10093010.

[104] B. House, J. Malkin, and J. Bilmes, "The VoiceBot: A Voice Controlled Robot Arm," in *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems, in CHI '09. New York, NY, USA: Association for Computing Machinery*, pp. 183–192, 2009, doi: 10.1145/1518701.1518731.

[105] K. Zinchenko, C.-Y. Wu, and K.-T. Song, "A Study on Speech Recognition Control for a Surgical Robot," *IEEE Trans Industr Inform*, vol. 13, no. 2, pp. 607–615, 2017, doi: 10.1109/TII.2016.2625818.

[106] K. Gundogdu, S. Bayrakdar, and I. Yucedag, "Developing and modeling of voice control system for prosthetic robot arm in medical systems," *Journal of King Saud University - Computer and Information Sciences*, vol. 30, no. 2, pp. 198–205, 2018, doi: 10.1016/j.jksuci.2017.04.005.

[107] T. B. Pulikottil, M. Caimmi, M. G. D'Angelo, E. Biffi, S. Pellegrinelli, and L. M. Tosatti, "A Voice Control System for Assistive Robotic Arms: Preliminary Usability Tests on Patients," in *2018 7th IEEE International Conference on Biomedical Robotics and Biomechatronics (Biorob)*, pp. 167–172, 2018, doi: 10.1109/BIOROB.2018.8487200.

[108] S. Yuvaraj, A. Badholia, P. William, K. Vengatesan, and R. Bibave, "Speech recognition based robotic arm writing," in *Proceedings of International Conference on Communication and Artificial Intelligence: ICCAI 2021*, pp. 23-33, 2022.

[109] H. Jiang, J. P. Wachs, and B. S. Duerstock, "Integrated vision-based robotic arm interface for operators with upper limb mobility impairments," in *2013 IEEE 13th International Conference on Rehabilitation Robotics (ICORR)*, pp. 1–6, 2013, doi: 10.1109/ICORR.2013.6650447.

[110] Z. Wang *et al*., "Vision-Based Calibration of Dual RCM-Based Robot Arms in Human-Robot Collaborative Minimally Invasive Surgery," *IEEE Robot Autom Lett*, vol. 3, no. 2, pp. 672–679, 2018, doi: 10.1109/LRA.2017.2737485.

[111] A. Noman, A. Eva, T. Yeahyea, and R. Khan, "Computer Vision-based Robotic Arm for Object Color, Shape, and Size Detection," *Journal of Robotics and Control (JRC)*, vol. 3, pp. 180–186, Jul. 2022, doi: 10.18196/jrc.v3i2.13906.

[112] A. Kupferberg, S. Glasauer, M. Huber, M. Rickert, A. Knoll, and T. Brandt, "Biological movement increases acceptance of humanoid robots as human partners in motor interaction," *AI Soc*, vol. 26, no. 4, pp. 339–345, 2011, doi: 10.1007/s00146-010-0314-2.

[113] A. Sciutti *et al*., "Measuring Human-Robot Interaction Through Motor Resonance," *Int J Soc Robot*, vol. 4, no. 3, pp. 223–234, 2012.

[114] L. Psarakis, D. Nathanael, and N. Marmaras, "Fostering short-term human anticipatory behavior in human-robot collaboration," *Int J Ind Ergon*, vol. 87, p. 103241, 2022, doi: 10.1016/j.ergon.2021.103241.

[115] P. Zhou *et al*., "Reactive human–robot collaborative manipulation of deformable linear objects using a new topological latent control model," *Robot Comput Integr Manuf*, vol. 88, Aug. 2024, doi: 10.1016/j.rcim.2024.102727.

[116] M. A. A. Mousa, A. T. Elgohr, and H. A. Khater, "A Novel Hybrid Deep Neural Network Classifier for EEG Emotional Brain Signals," *International Journal of Advanced Computer Science and Applications*, vol. 15, no. 6, 2024, doi: 10.14569/IJACSA.2024.01506107.

[117] V. Straebel and W. Thoben, "Alvin Lucier's Music for Solo Performer : Experimental music beyond sonification," *Organised Sound*, vol. 19, no. 1, pp. 17–29, Apr. 2014.

[118] J. J. Vidal, "Real-time detection of brain events in EEG," *Proceedings of the IEEE*, vol. 65, no. 5, pp. 633–641, 1977, doi: 10.1109/PROC.1977.10542.

[119] J. R. Wolpaw, N. Birbaumer, D. J. McFarland, G. Pfurtscheller, and T. M. Vaughan, "Brain–computer interfaces for communication and control," *Clinical Neurophysiology*, vol. 113, no. 6, pp. 767–791, 2002, doi: 10.1016/S1388-2457(02)00057-3.

[120] B. Z. Allison, E. W. Wolpaw, and J. R. Wolpaw, "Brain–computer interface systems: progress and prospects," *Expert Rev Med Devices*, vol. 4, no. 4, pp. 463–474, 2007, doi: 10.1586/17434440.4.4.463.

[121] S. Bozinovski and L. Bozinovska, "Brain–Computer Interface in Europe: the thirtieth anniversary," *Automatika*, vol. 60, no. 1, pp. 36–47, 2019, doi: 10.1080/00051144.2019.1570644.

[122] S. Bozinovski, "Controlling Robots Using EEG Signals, Since 1988," in *ICT Innovations 2012, M. Markovski Smile and Gusev, Ed., Berlin, Heidelberg: Springer Berlin Heidelberg*, pp. 1–11, 2013.

[123] J. Cao, S. Q. Xie, R. Das, and G. L. Zhu, "Control strategies for effective robot assisted gait rehabilitation: The state of art and future prospects," *Med Eng Phys*, vol. 36, no. 12, pp. 1555–1566, Dec. 2014, doi: 10.1016/j.medengphy.2014.08.005.

[124] M. Lebedev, "Augmentation of Sensorimotor Functions with Neural Prostheses," *Opera Med Physiol*, vol. 2, no. 3, pp. 211–227, 2016, doi: 10.20388/OMP.003.0035.

[125] R. A. Miranda et al., "DARPA-funded efforts in the development of novel brain–computer interface technologies," *J Neurosci Methods*, vol. 244, pp. 52–67, 2015, doi: 10.1016/j.jneumeth.2014.07.019.

[126] M. Jacobs, A. Premji, and A. J. Nelson, "Plasticity-Inducing TMS Protocols to Investigate Somatosensory Control of Hand Function," *Neural Plast*, vol. 2012, p. 350574, 2012, doi: 10.1155/2012/350574.

[127] M. Fox, "Using Brain Machine Interface in Medicine and Comparative Analysis of EEG and ECoG," *International Research Journal of Modernization in Engineering Technology and Science*, vol. 4, no. 10, pp. 216–223, Oct. 2022, doi: 10.56726/irjmets30428.

[128] A. T. Elgohr, M. S. Elhadidy, M. Elazab, R. Ahmed Hegazii, and M. M. El Sherbiny, "Multi-Classification Model for Brain Tumor Early Prediction Based on Deep Learning Techniques," *Journal of Engineering Research*, vol. 8, p. 2024, 2024.

[129] D. W. Moran and A. B. Schwartz, "Motor Cortical Representation of Speed and Direction During Reaching," *J Neurophysiol*, vol. 82, no. 5, pp. 2676–2692, Nov. 1999, doi: 10.1152/jn.1999.82.5.2676.

[130] M. Velliste, S. Perel, M. C. Spalding, A. S. Whitford, and A. B. Schwartz, "Cortical control of a prosthetic arm for self-feeding," *Nature*, vol. 453, no. 7198, pp. 1098–1101, 2008, doi: 10.1038/nature06996.

[131] L. R. Hochberg *et al*., "Reach and grasp by people with tetraplegia using a neurally controlled robotic arm," *Nature*, vol. 485, no. 7398, pp. 372–375, 2012, doi: 10.1038/nature11076.

[132] J. L. Collinger *et al*., "High-performance neuroprosthetic control by an individual with tetraplegia," *The Lancet*, vol. 381, no. 9866, pp. 557–564, Feb. 2013, doi: 10.1016/S0140-6736(12)61816-9.

[133] C. E. Bouton *et al*., "Restoring cortical control of functional movement in a human with quadriplegia," *Nature*, vol. 533, no. 7602, pp. 247–250, 2016, doi: 10.1038/nature17435.

[134] C. Márquez-Chin, M. R. Popovic, T. Cameron, A. M. Lozano, and R. Chen, "Control of a neuroprosthesis for grasping using off-line classification of electrocorticographic signals: case study," *Spinal Cord*, vol. 47, no. 11, pp. 802–808, 2009, doi: 10.1038/sc.2009.41.

[135] M. Hirata and T. Yoshimine, "Electrocorticographic Brain–Machine Interfaces for Motor and Communication Control," in *Clinical Systems Neuroscience*, pp. 83–100, 2015, doi: 10.1007/978-4-431-55037-2_5.

[136] H.-H. Kim and J. Jeong, "An electrocorticographic decoder for arm movement for brain–machine interface using an echo state network and Gaussian readout," *Appl Soft Comput*, vol. 117, p. 108393, 2022, doi: https://doi.org/10.1016/j.asoc.2021.108393.

[137] H. A. Shedeed, M. F. Issa, and S. M. El-sayed, "Brain EEG signal processing for controlling a robotic arm," in *2013 8th International Conference on Computer Engineering & Systems (ICCES)*, pp. 152–157, 2013, doi: 10.1109/ICCES.2013.6707191.

[138] J. Meng, S. Zhang, A. Bekyo, J. Olsoe, B. Baxter, and B. He, "Noninvasive Electroencephalogram Based Control of a Robotic Arm for Reach and Grasp Tasks," *Sci Rep*, vol. 6, no. 1, p. 38565, 2016, doi: 10.1038/srep38565.

[139] R. Bousseta, I. El Ouakouak, M. Gharbi, and F. Regragui, "EEG Based Brain Computer Interface for Controlling a Robot Arm Movement Through Thought," *IRBM*, vol. 39, no. 2, pp. 129–135, 2018, doi: 10.1016/j.irbm.2018.02.001.

[140] J. H. Jeong, K. H. Shim, D. J. Kim, and S. W. Lee, "Brain-Controlled Robotic Arm System Based on Multi-Directional CNN-BiLSTM Network Using EEG Signals," *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, vol. 28, no. 5, pp. 1226–1238, May 2020, doi: 10.1109/TNSRE.2020.2981659.

[141] Z. Miao, M. Zhao, X. Zhang, and D. Ming, "LMDA-Net:A lightweight multi-dimensional attention network for general EEG-based brain-computer interfaces and interpretability," *Neuroimage*, vol. 276, Aug. 2023, doi: 10.1016/j.neuroimage.2023.120209.

[142] S. M. Coyle, T. E. Ward, and C. M. Markham, "Brain–computer interface using a simplified functional near-infrared spectroscopy system," *J Neural Eng*, vol. 4, no. 3, p. 219, 2007.

[143] C. Canning and M. Scheutz, "Functional Near-Infrared Spectroscopy in Human-Robot Interaction," *J. Hum.-Robot Interact*., vol. 2, no. 3, pp. 62–84, Sep. 2013, doi: 10.5898/JHRI.2.3.Canning.

[144] S. Zhang *et al*., "Application of a common spatial pattern-based algorithm for an fNIRS-based motor imagery brain-computer

interface," *Neurosci Lett*, vol. 655, pp. 35–40, 2017, doi: 10.1016/j.neulet.2017.06.044.

[145] S.-S. Yoo *et al*., "Brain–computer interface using fMRI: spatial navigation by thoughts," *Neuroreport*, vol. 15, no. 10, pp. 1591–1595, 2004, doi: 10.1097/01.wnr.0000133296.39160.fe.

[146] L. Minati, A. Nigri, C. Rosazza, and M. G. Bruzzone, "Thoughts turned into high-level commands: Proof-of-concept study of a vision-guided robot arm driven by functional MRI (fMRI) signals," *Med Eng Phys*, vol. 34, no. 5, pp. 650–658, 2012, doi: 10.1016/j.medengphy.2012.02.004.

[147] O. Cohen *et al*., "fMRI-Based Robotic Embodiment: Controlling a Humanoid Robot by Thought Using Real-Time fMRI," *Presence*, vol. 23, no. 3, pp. 229–241, 2014, doi: 10.1162/PRES_a_00191.

[148] W. McClay, N. Yadav, Y. Ozbek, A. Haas, H. Attias, and S. Nagarajan, "A Real-Time Magnetoencephalography Brain-Computer Interface Using Interactive 3D Visualization and the Hadoop Ecosystem," *Brain Sci*, vol. 5, no. 4, pp. 419–440, Sep. 2015, doi: 10.3390/brainsci5040419.

[149] R. Fukuma *et al*., "Real-Time Control of a Neuroprosthetic Hand by Magnetoencephalographic Signals from Paralysed Patients," *Sci Rep*, vol. 6, no. 1, p. 21781, 2016, doi: 10.1038/srep21781.

[150] D. Rathee, H. Raza, S. Roy, and G. Prasad, "A magnetoencephalography dataset for motor and cognitive imagery-based brain-computer interface," *Sci Data*, vol. 8, no. 1, p. 120, 2021, doi: 10.1038/s41597-021-00899-7.

[151] A. Malki, C. Yang, N. Wang, and Z. Li, "Mind guided motion control of robot manipulator using EEG signals," in *2015 5th International Conference on Information Science and Technology (ICIST)*, pp. 553–558, 2015, doi: 10.1109/ICIST.2015.7289033.

[152] S. Bhattacharyya, A. Konar, and D. N. Tibarewala, "Motor imagery, P300 and error-related EEG-based robot arm movement control for rehabilitation purpose," *Med Biol Eng Comput*, vol. 52, no. 12, pp. 1007–1017, 2014, doi: 10.1007/s11517-014-1204-4.

[153] D. H. Krishna, I. A. Pasha, and T. S. Savithri, "Autonomuos robot control based on EEG and cross-correlation," in *2016 10th International Conference on Intelligent Systems and Control (ISCO)*, pp. 1–4, 2016, doi: 10.1109/ISCO.2016.7727098.

[154] I. Sakamaki, C. E. P. del Campo, S. A. Wiebe, M. Tavakoli, and K. Adams, "Assistive technology design and preliminary testing of a robot platform based on movement intention using low-cost brain computer interface," in *2017 IEEE International Conference on Systems, Man, and Cybernetics (SMC)*, pp. 2243–2248, 2017, doi: 10.1109/SMC.2017.8122954.

[155] M. Besserve, K. Jerbi, F. Laurent, S. Baillet, J. Martinerie, and L. Garnero, "Classification methods for ongoing EEG and MEG signals," *Biol Res*, vol. 40, no. 4, pp. 415–437, 2007.

[156] T. Shi, H. Wang, and C. Zhang, "Brain Computer Interface system based on indoor semi-autonomous navigation and motor imagery for Unmanned Aerial Vehicle control," *Expert Syst Appl*, vol. 42, no. 9, pp. 4196–4206, 2015, doi: 10.1016/j.eswa.2015.01.031.

[157] P. Kant, S. H. Laskar, J. Hazarika, and R. Mahamune, "CWT Based Transfer Learning for Motor Imagery Classification for Brain computer Interfaces," *J Neurosci Methods*, vol. 345, p. 108886, Nov. 2020, doi: 10.1016/j.jneumeth.2020.108886.

[158] W. Ouyang, K. Cashion, and V. K. Asari, "Electroencephelograph based brain machine interface for controlling a robotic arm," in *2013 IEEE Applied Imagery Pattern Recognition Workshop (AIPR)*, pp. 1–7, 2013, doi: 10.1109/AIPR.2013.6749312.

[159] M. H. Alomari, A. Samaha, and K. Alkamha, "Automated Classification of L/R Hand Movement EEG Signals using Advanced Feature Extraction and Machine Learning," *(IJACSA) International Journal of Advanced Computer Science and Applications*, vol. 4, no. 6, 2013.

[160] M. Plechawska-Wojcik, P. Wolszczak, R. Cechowicz, and K. Łygas, "Construction of neural nets in brain-computer interface for robot arm steering," in *2016 9th International Conference on Human System Interactions (HSI)*, pp. 348–354, 2016, doi: 10.1109/HSI.2016.7529656.

[161] W. Lu, Y. Wei, J. Yuan, Y. Deng, and A. Song, "Tractor Assistant Driving Control Method Based on EEG Combined With RNN-TL Deep Learning Algorithm," *IEEE Access*, vol. 8, pp. 163269–163279, 2020, doi: 10.1109/ACCESS.2020.3021051.

[162] P. Horki, T. Solis-Escalante, C. Neuper, and G. Müller-Putz, "Combined motor imagery and SSVEP based BCI control of a 2 DoF artificial upper limb," *Med Biol Eng Comput*, vol. 49, no. 5, pp. 567–577, 2011, doi: 10.1007/s11517-011-0750-2.

[163] M. J. Khan, K.-S. Hong, N. Naseer, and M. R. Bhutta, "Hybrid EEG-NIRS based BCI for quadcopter control," in *2015 54th Annual Conference of the Society of Instrument and Control Engineers of Japan (SICE)*, pp. 1177–1182, 2015, doi: 10.1109/SICE.2015.7285434.

[164] J. Lee, K. Cha, H. Kim, J. Choi, C. Kim, and S. Lee, "Hybrid MI-SSSEP Paradigm for classifying left and right movement toward BCI for exoskeleton control," in *2019 7th International Winter Conference on Brain-Computer Interface (BCI)*, pp. 1–3, 2019, doi: 10.1109/IWW-BCI.2019.8737319.

[165] B. Chakravarthi, S. C. Ng, M. R. Ezilarasan, and M. F. Leung, "EEG-based emotion recognition using hybrid CNN and LSTM classification," *Front Comput Neurosci*, vol. 16, Oct. 2022, doi: 10.3389/fncom.2022.1019776.

[166] A. Bhardwaj, A. Gupta, P. Jain, A. Rani, and J. Yadav, "Classification of human emotions from EEG signals using SVM and LDA Classifiers," in *2015 2nd International Conference on Signal Processing and Integrated Networks (SPIN)*, pp. 180–185, 2015, doi: 10.1109/SPIN.2015.7095376.

[167] Z.-T. Liu, Q. Xie, M. Wu, W.-H. Cao, D.-Y. Li, and S.-H. Li, "Electroencephalogram Emotion Recognition Based on Empirical Mode Decomposition and Optimal Feature Selection," *IEEE Trans Cogn Dev Syst*, vol. 11, no. 4, pp. 517–526, Dec. 2019, doi: 10.1109/TCDS.2018.2868121.

[168] T. Song, W. Zheng, P. Song, and Z. Cui, "EEG Emotion Recognition Using Dynamical Graph Convolutional Neural Networks," *IEEE Trans Affect Comput*, vol. 11, no. 3, pp. 532–541, Jul. 2020, doi: 10.1109/TAFFC.2018.2817622.

[169] S. K. Khare, V. Bajaj, and G. R. Sinha, "Adaptive Tunable Q Wavelet Transform-Based Emotion Identification," *IEEE Trans Instrum Meas*, vol. 69, no. 12, pp. 9609–9617, Dec. 2020, doi: 10.1109/TIM.2020.3006611.

[170] S. Issa, Q. Peng, and X. You, "Emotion Classification Using EEG Brain Signals and the Broad Learning System," *IEEE Trans Syst Man Cybern Syst*, vol. 51, no. 12, pp. 7382–7391, Dec. 2021, doi: 10.1109/TSMC.2020.2969686.

[171] M. K. Chowdary, J. Anitha, and D. J. Hemanth, "Emotion Recognition from EEG Signals Using Recurrent Neural Networks," *Electronics (Basel)*, vol. 11, no. 15, Jul. 2022, doi: 10.3390/electronics11152387.

[172] J. Chen, X. Lin, W. Ma, Y. Wang, and W. Tang, "EEG-based emotion recognition for road accidents in a simulated driving environment," *Biomed Signal Process Control*, vol. 87, no. 8, Jan. 2024, doi: 10.1016/j.bspc.2023.105411.

[173] A. Elbrashy, A. Elgohr, A. Elshennawy, M. Rashad, and M. El-fakharany, "Modeling of Heat Transfer and Airflow Inside Evacuated Tube Collector With Heat Storage Media: Experimental Validation Powered by Artificial Neural Network," *Heat Transfer*, Nov. 2024, doi: 10.1002/htj.23215.

[174] O. H. Hassan, M. S. Elhadidy, A. T. Elgohr, A. O. Ali, M. H. El-Mahdy, and M. Zaki, "Performance Evaluation of a Standalone Solar-Powered Irrigation System in Desert Regions Using PVsyst: A Comprehensive Analysis," in *2024 25th International Middle East Power System Conference (MEPCON)*, pp. 1–6, 2024, doi: 10.1109/MEPCON63025.2024.10850121.