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A Review of Advanced Force Torque Control Strategies for Precise Nut-to-Bolt Mating in Robotic Assembly

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ABSTRACT

Achieving precise alignment in high-precision robotic assembly is critical, where even minor misalignments can cause significant issues. Various control strategies have been developed to tackle these challenges, including passive compliance control (PCC), active control (AC), and manual teaching method (MTC). While AC is valued for its real-time adaptability, PCC and MTC offer advantages in simpler, cost-effective applications. This review evaluates these strategies, emphasizing the integration of AI and machine learning to address the limitations of traditional AC methods, such as spiral and tilt searches, which are rigid, slow, and computationally demanding, making them unsuitable for dynamic environments. Machine Learning (ML) and Artificial Intelligence (AI) offer data-driven improvements in performance and adaptability over time. Techniques like Linear Regression, Artificial Neural Networks (ANNs), and Reinforcement Learning (RL) are explored for enhancing precision and real-time adaptability in complex tasks. These AI methods are applied in real-world industries, such as automotive and electronics manufacturing. The review compares control strategies and AI techniques, analyzing trade-offs in accuracy, speed, computational efficiency, and cost. It also discusses future directions, including hybrid control systems, advanced sensor integration, and more sophisticated AI algorithms. Ethical and safety considerations are highlighted, particularly in industrial settings where reliability and human-robot interaction are critical. This comprehensive review demonstrates AI's potential to enhance precision, reduce manual intervention, and improve performance in high-precision robotic assembly while guiding the selection of appropriate methods for specific applications.

1. Introduction

Bolt and nut mechanisms are fundamental and widely used for fastening in various industries, such as automobile production [1]-[3], railway systems [4]-[7], petroleum extraction [8], and sustainable electricity generation [9], [10]. Most of these assembly operations now rely on human-machine collaboration (HMC), with operators largely using automated tightening equipment to ensure connection quality and operating efficiency [11]. In industries like automotive manufacturing and aerospace, HMC plays a vital role in tasks that require both the precision of machines and the adaptability of human operators [1], [12]. For example, in the automotive sector, robots handle heavy-duty tasks like bolt-tightening, while human operators oversee complex assemblies that require manual dexterity [1]. Despite its benefits, HMC still relies heavily on manual labor, leading to higher labor costs and inefficiencies due to large number of bolts and nuts involved. This manual dependence also introduces limitations in terms of precision and safety, especially when dealing with high-volume production environments [1].

Efficiency is a major challenge in large-scale production, as human workers often struggle to keep pace with the required speed and precision [13]. Manual processes can lead to variations in precision, increasing the risk of errors in alignment, tightening torque, or part positioning. These inconsistencies can result in poor product quality or require costly rework. Additionally, safety concerns arise due to the physical strain on workers performing repetitive tasks, increasing the likelihood of injury in high-volume environments [13]. Advanced automation systems, such as machine learning-driven robots, offer solutions to these limitations by improving consistency, reducing human error, and enhancing workplace safety through greater reliance on automation.

Various control strategies have been explored to automate the nut-to-bolt mating process, such as Passive Compliance Control (PCC), Active Control Method (AC), Manual Teaching Method (MTC), and combinations of PCC and AC techniques. Passive Compliance Control (PCC) refers to a method where the robot's movements are mechanically compliant to external forces without active feedback. PCC offers simplicity and cost-effectiveness, particularly in applications with limited degrees of freedom and predictable misalignments. However, it is limited in its effectiveness to the expected range of misalignment and force, making it less responsive to dynamic changes like misalignments or obstacles [14]-[16]. On the other hand, the Manual Teaching Method (MTC) involves human operators guiding robots through assembly tasks by physically leading or programming their movements. Once the task is recorded, the robot can replicate the process. MTC allows for greater control over complex operations but lacks the flexibility to handle component positioning or force variations, particularly in high-volume production settings [17]-[19]. Dependence on manual input increases the possibility of human error and reduces the consistency across multiple assemblies. Combinations of PCC and AC methods attempt to balance the strengths of both approaches, providing improved adaptability and control in certain situations. However, these hybrid methods often increase system complexity, require more sophisticated hardware, and need higher cost. The need for careful calibration between active and passive elements can also limit real-time adaptability, especially when unexpected changes occur [20], [21]. In contrast, Active Control (AC) involves a system that dynamically adjusts its actions based on real-time feedback from sensors, such as force-torque or visual sensors. AC stands out for its ability to leverage real-time sensor feedback to dynamically adjust robot movements, enabling continuous fine-tuning during high-precision tasks like nut-to-bolt mating. AC is particularly suited for environments where high precision and rapid adjustments are critical. However, AC systems have their drawbacks. They typically involve higher implementation costs and greater computational demands, which can be prohibitive for smaller-scale operations or low-budget applications [22]-[24]. Additionally, AC systems may require frequent recalibration and maintenance to ensure consistent performance, thereby increasing operational complexity.

Several key technologies have emerged in robotic assembly, such as computer vision technology, collision-free motion control technology, mating control technology based on a robot and coordinated bolt tightening control technology. The initial stage is to use the 2D/3D cameras and other sensors to gather and process visual data from the robot's workspace [25]. This vision system identifies the precise location and orientation of the nut and bolt by determining their depth, dimensions, and spatial position. This data is crucial for ensuring the correct alignment of components and for providing real-time feedback on the assembly environment [26]. Advanced image recognition algorithms process this data for motion planning. Next, the collision-free motion control technology ensures operational safety and efficiency by scanning the environment with complex algorithms to avoid collisions with other system components. After initially positioning, the robot evaluates the contact surface between the nut and bolt during the mating process. If misalignments are detected, the robot implements posture adjustment algorithms to reposition the components accurately [27]. Finally, the coordinated bolt tightening control technology monitors and manages torque application to meet specifications, preventing under or over-tightening that could affect assembly integrity. The system ensures consistency across multiple assemblies, minimizing the risk of under-tightening or over-tightening, which could compromise the structural integrity of the assembly. Traditional search methods with force-torque control were initially developed as a non-AI approach for precise assembly. Methods like spiral, tilt, grid, and adaptive searches use predefined patterns and force-torque feedback to find exact positions and ensure proper alignment. Force-torque control enables the robot to detect and adjust for subtle forces during the assembly process, enhancing precision and reducing errors. While these methods are reliable for basic tasks, their fixed patterns and limited adaptability have led to the exploration of Machine Learning and AI techniques, which offer greater flexibility and learning capabilities over time.

Relying solely on robotic vision can affect accuracy in nut-to-bolt mating. Visual systems may fail to detect physical contact between components or be obstructed by occlusions. While 2D/3D cameras provide spatial information, they cannot directly sense the forces involved during the mating process, potentially leading to misalignment or improper insertion [26]. Another significant limitation is visual occlusion, where parts of the bolt or nut are blocked from the camera's view in confined or cluttered environments. This hinders the visual system's ability to provide an accurate representation of the components. When components are partially hidden, the system struggles with location tracking, increasing collision risks and assembly errors. These visual limitations can cause misalignments, component breakage, and poor joint quality.

To address these limitations, modern systems integrate force-torque sensors with vision systems, enabling real-time measurement of forces and torques in X, Y, and Z directions. This hybrid approach enables contact force detection and immediate position adjustments. Despite advanced sensing, challenges remain in achieving precise alignment and consistent force application. The bolt’s contact surface is uniformly smooth, consistent and cylindrical, allowing for the nut to slide over the bolt with minimal resistance without a complicated alignment mechanism [28]. However, the nut’s contact surface consists of a circular hole that does not provide immediate guidance for aligning with the bolt’s surface [28]. Due to the lack of initial guiding characteristics, the nut must be precisely positioned from the start to move smoothly over the bolt.

Another challenge involves complex torque behaviors. When the nut is offset in the x-direction, torque occurs not only around the predicted y-axis but also in the x and y-directions. These unexpected torques arise from uneven contact points, reactive forces, frictional forces caused by surface defects, and structural flexibility [29]. Furthermore, the rotational forces can also be influenced by uneven insertion speed [29].As the initial contact between the nut and bolt is uneven, this produces asymmetric force distribution and increases resistance due to misalignment.

Automated nut-to-bolt mating systems in industrial settings present both safety and ethical challenges. Key concerns include system failures, human-robot interaction risks, and potential job displacement. To address these issues, implementations should incorporate redundant safety protocols, collision avoidance technologies, and comprehensive workplace training [30]. Ethical considerations can be mitigated through worker reskilling programs. Adherence to industry safety standards, such as ISO 10218, is crucial for creating a safe work environment and fostering trust in new technologies [31]. Balancing technological advancement with workforce stability remains a central challenge in the responsible deployment of these automated systems.

This paper presents a comprehensive review of sensing and control strategies for high-precision nut-to-bolt mating operations, focusing on overcoming vision-only system limitations and achieving high alignment accuracy while minimizing insertion force. The systematic analysis examines the integration of force-torque sensors with vision systems, investigating how this hybrid approach enhances assembly accuracy through real-time force measurement and position adjustment capabilities. The study addresses key challenges in achieving precise alignment during initial mating, complex force-torque interactions during assembly, and safety considerations in industrial implementation. By examining technologies used in automotive and electronics manufacturing, this review evaluates various algorithms' effectiveness in maintaining precision, enhancing adaptability in dynamic environments, and achieving 99% or higher accuracy in nut installation. Through this analysis, promising directions for future research are identified, including hybrid control systems, multi-modal sensing integration, and AI-driven adaptive control strategies, aiming to enhance precision, efficiency, and adaptability while reducing manual intervention.

2. Control Strategies for Robotic Nut-to-Bolt Mating

Various mating control technologies have been explored for precise alignment and control during bolt/nut mating processes. These technologies use sensors, visual systems, and tactile feedback to measure contact states and derive pose adjustment strategies. There are three primary algorithms, such as passive compliance control (PCC) [15], manual teaching control (MTC) [32], and active control (AC) [33]. In addition to performance and efficiency, these technologies must also address safety and ethical concerns, particularly in industrial settings where human-robot interaction poses potential risks.

2.1. Passive Compliance Control (PCC)

PCC is a fully automated technique that relies on the system's intrinsic ability to adapt to external forces without active feedback mechanisms or complex sensors [15]. It uses mechanical compliance through devices such as springs, flexures, and compliant joints to absorb alignment errors and facilitate the mating process. These elements provide compliance to compensate for minor misalignments. While PCC simplifies control and reduces sensor reliance, safety concerns, including system failures and human-robot interactions, must be addressed through features like emergency stops and passive compliance to prevent excessive force. Springs can store potential energy and release it to correct positional errors, while flexures control movement or bending, contributing to the system's ability to adjust passively [14].Compliant joints introduce flexibility into the assembly, enabling slight movements to reduce stress or misalignment during the process [14].

This control method is simple and reliable without sensor feedback or complex algorithms. This approach reduces the need for complex control algorithms and involves fewer electrical components. However, it is limited in its efficiency when dealing with significant misalignments. Its effectiveness is often constrained by the design of the compliant components, which must be carefully tuned to specific tasks to prevent over-compliance or rigidity. Additionally, environmental factors such as temperature can affect the mechanical properties of springs, flexures, and compliant joints. For example, colder temperatures may increase stiffness, reducing the system's ability to absorb misalignments, while high humidity could cause material degradation over time [34].

Based on its application, a passive wrist joint with a Push-Activate-Rotation (PAR) mechanism combined with an Inertial Measurement Unit (IMU) sensor can achieve minimal clearance and versatile application across different peg shapes, as demonstrated by T. Nishimura et al [16]. The system was tested using five peg shapes (rectangular, circular, hexagonal, and two triangular orientations) across eight peg-hole orientations. In five trials for each configuration, the system achieved 100% success for most peg shapes with initial orientation errors up to ±28°. The PAR function rotated an average of 28° ($\sigma = 1.9°$), generating 0.98 Nm torque ($\sigma = 3.0 \times 10^{-2}$ Nm). The system successfully managed a tight 0.5 mm hole clearance. Besides that, the RCC device is a passive tool used by N. Pitchandi et al. [14] to address small angular and positional misalignments during the mating process. It allows the end effector to pivot around a predefined point, enabling accurate alignment without manual adjustments. The researchers used SolidWorks 2014 for CAD modeling and MSC Adams/View for dynamic simulations. The simulations were conducted under both static and dynamic conditions, with and without compliant support. Key results showed that the introduction of viscoelastic compliant support led to a 37.92% of reduction in peak insertion forces as compared to the assembly without compliant support.

2.2. Active Control Method (AC)

AC method is another fully automated technique that uses real-time sensor data to monitor and adjust robot movements for complex assembly operations [33]. This method employs three key algorithms, such as impedance control, admittance control and hybrid position/force control. Impedance control adjusts the robot's mechanical impedance, such as stiffness, damping, and inertia, to regulate interaction forces with the environment [20]. The mathematical model for impedance control is typically defined by a second-order differential equation as shown in (1),

$$F_{ext} = M(\ddot{x} - \ddot{x}_d) + B(\dot{x} - \dot{x}_d) + K(x - x_d) \tag{1}$$

where F_{ext} is the external force, M, B, and K represent the inertia, damping, and stiffness matrices, respectively, and x and x_d represent the actual and desired position [35]. Admittance control modifies the robot's motion based on measured force/torque. In contrast to impedance control, where force is controlled by adjusting position, admittance control uses force measurements to adjust the robot's position or velocity. The control law typically takes the form as represented in (2),

$$F = m\ddot{x} + b\dot{x} + kx \tag{2}$$

where F is the external force and x is the displacement [36]. Hybrid position/force control combines position and force control, enabling the robot to follow a desired position trajectory while simultaneously applying a controlled force. The robot can switch between controlling position and force, depending on the task requirements. AC methods offer high accuracy and flexibility but have limitations. They require significant computational resources for real-time processing and depend heavily on sensor accuracy and reliability. Stability issues can arise in high-speed tasks, while implementation and maintenance costs are higher. These systems need regular calibration and can be oversensitive to minor disturbances. Safety measures like collision detection and fail-safes are crucial to prevent injuries or damage. In human-robot environments, motion planning to avoid human contact and regularly calibrated force-torque sensors help ensure safe performance. Additionally, environmental factors like temperature, humidity, and dust can negatively impact sensor performance and control algorithms. Temperature changes may cause sensor drift, while humidity and dust can interfere with optical sensors and reduce precision [37].

In practical applications, D. Li et al. [23] implemented an AC method using the Instantaneous Centre of Rotation (ICR) planning strategy for multiple peg-in-hole assembly tasks. Data was collected from multiple assembly trials (n=50) measuring 6-dimensional forces and moments using an ATI force/torque sensor. The combined use of ICR and Variable Angular Velocity Control (VAVC) resulted in a 100% success rate across all four peg-hole sets, compared to 55% for ICR alone and lower rates for baseline methods. Besides that, V. R. F. Miranda et al. [24] utilized the AC method in autonomous drone navigation. The study conducted real-world experiments with a DJI Matrice 100 drone equipped with GPS, IMU, barometer, camera, and UWB sensors. Data was collected from multiple autonomous flight trials (n=12) measuring landing accuracy and path-following performance. The mean landing error using all sensors was 0.121 m ($\sigma = 0.0641$ m), while GPS-only navigation resulted in a mean error of 1.166 m ($\sigma = 0.130$ m).

2.3. Combining Passive and Active Control Methods

Combining PCC and AC methods is a hybrid method that can enhance robotic assembly by leveraging the strengths of both approaches. However, integrating passive and AC systems requires careful design, regular calibration, and safety measures to ensure safe operation in dynamic environments. Zhang et al. [20] demonstrated a hybrid hand exoskeleton system combining PCC and AC methods for stroke rehabilitation. Their results showed precise motion tracking with errors of 0.97 ± 1.64 mm and -0.12 ± 1.04 mm in x and y directions. The system switched automatically between modes using a 0.6N force threshold: active mode when patient force was higher, and passive mode when force was lower. This dual-mode approach maintained stable performance during 5-second rehabilitation cycles despite varying patient participation levels. Besides that, Kim et al. [38] combined PCC and AC methods to enhance human-robot collision safety. Their experimental results with a 3-DOF robot arm showed the hybrid method limited maximum collision torque to 15.5 Nm, compared to over 20 Nm without safety mechanisms. The passive system provided immediate response during the controller's delay period (40-80ms), while the active system maintained precise 22N force control during wall-following tasks. This hybrid approach reduced system complexity by using passive components for initial compliance, while active control handled post-collision behaviors.

However, the integration of PCC and AC methods presents significant challenges and complexities. Coordinating mechanical passive components with electrical AC systems requires intricate design considerations and precise tuning. Both passive and active components require regular calibration and adjustments, making operations more complex and expensive. Moreover, while passive components may reduce the need for constant sensor feedback, the AC aspect still necessitates sophisticated sensors and processors, potentially keeping overall system costs high. The design process must carefully balance the trade-offs between passive and active elements to optimize performance while managing complexity. Additionally, ensuring consistent performance across various assembly scenarios and environmental conditions becomes more challenging with a hybrid system, requiring robust testing and validation protocols.

2.4. Manual Teaching Method (MTC)

MTC is a human-guided technique that involves human operators teaching robots by guiding them through tasks directly. This works well for complex jobs and variable settings that are difficult to program using traditional coding techniques. This method offers flexibility but poses safety risks from human-robot interaction, requiring safety interlocks, emergency stops, and collision avoidance. Ethical concerns include job displacement, emphasizing the need for reskilling workers. This method leverages human intuition and knowledge, allowing robots to repeat taught movements for tasks like assembly, painting, welding, and picking and placing [32]. Techniques such as direct manipulation, teach pendants, and path recording enable the robot to learn and replicate actions based on human demonstrations [17]. Direct manipulation involves physically guiding the robot's end-effector, offering intuitive programming but potentially lacking precision. Teach pendants are handheld devices for remote robot control, providing more precise input but requiring technical knowledge. Path recording captures the robot's movements as guided by the operator, efficiently creating repeatable trajectories for complex paths.

While this method is flexible and easy to use without deep technical knowledge, its success depends on operator skill, and integrating multiple tasks into a complex workflow can be challenging. Additionally, the method can be time-consuming for initial teaching, may not scale well for large-scale production, and lacks the automated optimization capabilities found in more advanced programming methods. Environmental factors affect MTC's performance. Temperature and humidity may reduce human dexterity, leading to fatigue or less precise guidance, especially in long or high-precision tasks [37]. Dust and contaminants can interfere with sensors and actuators, causing inconsistencies in the robot's recorded paths and performance [34].

To enhance flexibility and precision, MTC can be combined with other control methods. This includes combining MTC with sensor-based feedback systems for improved accuracy and adaptability, using machine learning to improve taught paths and using hybrid approaches that merge MTC with traditional programming for complex tasks. These combinations can fix some MTC limitations while potentially introducing additional complexity in system design and implementation.

3. Traditional Search Method with Force-Torque Control

The search method is a non-AI approach for precise robotic assembly that helps find exact positions in a two-dimensional space. This strategy is particularly effective when initial misalignment may cause serious problems in the whole assembly process. This method reduces the possibility of jamming and damage to the components, offering a smooth assembly operation. There are several search methods for precise assembly tasks, such as the spiral search method, tilt search method, grid search method, random search method, adaptive search method, concentric circle search method and line search method. These techniques use predefined patterns and force-torque feedback to correctly align components, identify holes, and achieve perfect placement.

In high-precision assembly tasks, the traditional search method is commonly used to ensure the accurate alignment and placement of components. The common application is bolt-to-nut or nut-to-bolt assembly, where the spiral search method is used to systematically cover the area around the target component to ensure the accurate alignment of the bolts or nuts. Fig. 1 shows the flowchart of the spiral search method. Based on the research, Chen et al. [39] used the spiral search method combined with vision-based position correction and force feedback to find the correct position in a two-dimensional space. The study evaluated the method through both simulation (100 tests) and physical experiments (20 tests) using a CR5 robotic arm, Robotiq gripper, FT sensor and realsense camera. The vision-based correction reduced positioning errors by 0.2mm in simulation and 1mm on the physical platform. Force and torque data were analyzed during spiral search and post-search correction to improve assembly success rates. Park et al. [40] developed an improved Partial Spiral Force Trajectory (PSFT) method for precision nut-to-bolt mating. The study employed both simulation and physical experiments to evaluate the method's performance. Simulations were conducted using the MuJoCo robotics simulator, with 250 trials for each parameter set, comparing PSFT to the traditional Spiral Force Trajectory (SFT). Physical experiments utilized an eight-joint manipulator with square, circular, and triangular peg-in-hole setups, each tested 20 times. Data collection included position, velocity, and orientation measurements of the peg, recorded at 300 Hz. Performance metrics analyzed were success rate, mean elapsed time, and standard deviation of elapsed time. Statistical analysis revealed that PSFT achieved a tolerance of 0.01mm, reduced mean elapsed time by up to 30.8%, and decreased standard deviation of elapsed time by up to 91.7% compared to SFT.

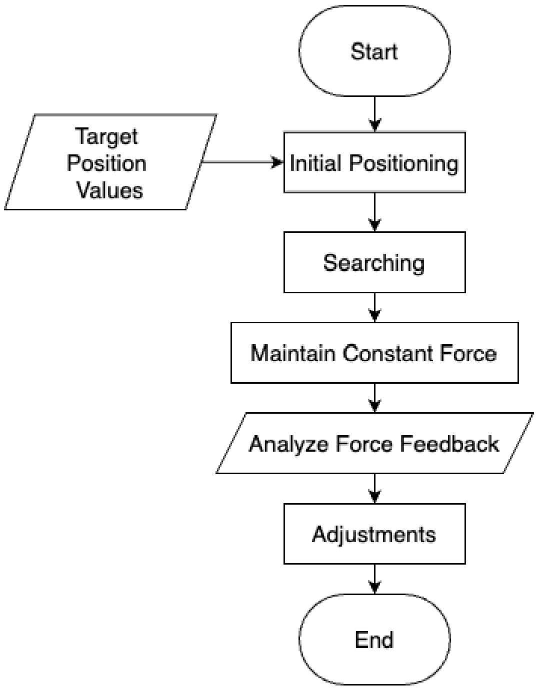

Fig. 1. Flowchart of spiral search method

Besides that, the tilt search method is applied by adjusting the bolt or nut’s orientation. This method can mate the bolt and nut without jamming by detecting the change in force-torque feedback and making necessary adjustments. Based on research, Unten et al. [41] guided the peg into the hole by tilting the peg slightly and using transient force response data for alignment. The study employed a 6-DOF industrial manipulator with a 6-axis force sensor, conducting experiments on two fittings with different clearances. Data analysis included success rate evaluation over 10 trials at various initial positions, hole direction estimation accuracy comparison with baseline methods, and insertion time analysis. The proposed method achieved overall success rates of 94.4% and 95.6% for the two fittings, respectively. It demonstrated superior efficiency with an average insertion time of 5.71 seconds compared to the traditional spiral search method's 13.86 seconds, showcasing significantly improved performance in high-precision assembly tasks. Additionally, the combined tilt and spiral search method by Chen et al. [42] enhanced the accuracy and efficiency of the peg-in-hole operation by using the tilt method for initial alignment and the spiral search for fine-tuning. The study used a dual-arm UR3 robot equipped with Robotiq 85 grippers. Experiments were conducted on six different objects, including a complex 15-pair connector and five common industrial connectors. The method achieved an average assembly time of around 30 seconds per task and effectively handled positional and rotational errors. Wang et. al [43] primarily used the spiral search method by making an outward spiral motion with constant pressure to find the hole, followed by tilting the peg by a small angle to improve the success rate and simplify pose adjustment. The study used a variable compliance center and displacement sensor implemented on a 6-DOF UR5 robot with a custom elastic device. The study conducted experiments with a 0.1 mm clearance peg-hole pair. The results show that the variable compliance center method for peg-in-hole assembly achieved faster completion times (7 seconds vs 25-35 seconds) and higher success rates (nearly 100% vs 60%) compared to traditional spiral and random search techniques, especially for large initial misalignments of up to 8mm.

Additionally, the grid search method is normally used in electronic component placement by checking all potential positions and ensuring that components are placed accurately and reliably [44]-[46]. For robotic surgery, the adaptive search strategy is especially useful. It modifies the search pattern in real-time depending on sensor data, ensuring accurate tool placement in a dynamic and possibly unpredictable environment [47]-[50].

4. Machine Learning (ML) and Artificial Intelligence (AI) in Force-Torque Control

Force-torque control is an important aspect of robot operation, particularly high-precision assembly tasks. While traditional search methods have been widely used for precise component alignment and placement, they have significant drawbacks that make them unsuitable for more complex and dynamic situations.

Traditional search methods are limited to predefined patterns, making them less responsive to dynamic changes in the environment. This limitation is problematic for varying conditions requiring real-time adjustments. Although high precision is achieved in the controlled setting, its precision depends heavily on the specific application, which leads to reduced efficiency of complex tasks. Furthermore, these approaches lack learning capabilities, relying solely on rigid rules and do not improve over time with experience. Scalability is a concern with traditional search methods as they struggle to handle large, complex datasets effectively, which contrasts sharply with the needs of modern robotics. Machine Learning (ML) and Artificial Intelligence (AI) offer promising solutions by learning from data and optimizing performance. They provide high adaptability, flexibility, and scalability, making them ideal for enhancing force-torque control in robotics. However, implementing these ML and AI techniques requires comprehensive safety measures, including accurate sensor calibration, continuous system validation, and robust error handling mechanisms, ensuring reliable human-robot interaction while maintaining high-performance metrics in industrial settings.

To better understand the different ML and AI approaches in force-torque control, Table 1 provides a comparative analysis of Linear Regression, Neural Networks, and Reinforcement Learning methods. Linear Regression offers computational efficiency and simple implementation, it struggles with complex dynamics and adaptability. Neural Networks excel at handling non-linear relationships and offer high accuracy, though they require significant computational resources and large training datasets. Reinforcement Learning provides excellent adaptability through continuous learning and handles uncertain conditions well but faces challenges with training stability and resource-intensive scaling. Future research should focus on scaling these ML and AI approaches for large-scale industrial applications and collaborative robots (cobots), while exploring the integration of force-torque control with multiple sensory inputs like vision and tactile feedback to enhance robotic assembly capabilities.

Table 1. Comparison of different ML and AI approaches in force-torque control

Aspects	Linear Regression	Neural Networks	Reinforcement Learning
Strengths	Computationally efficient Fast implementation Simple to train	Excellent non-linear handling Complex pattern learning High accuracy	Learns through trial and error Environment adaptive Handles uncertain conditions
Weaknesses	Limited to linear relationships Poor with complex dynamics Less adaptable to changes	High computational needs Large training datasets required Complex to implement	Extensive training needed Training can be unstable Complex to implement
Accuracy	Limited in complex scenarios	Higher accuracy	Higher accuracy
Adaptability	Limited to train scenarios Fixed model parameters	Highly adaptive to new situations Can handle varying conditions	Excellent through continuous learning
Scalability	Good for small-scale tasks Simple to deploy	Good system scalability Validated in industry	Challenging due to training needs Resource-intensive scaling

4.1. Linear Regression Analysis

Linear regression analysis is a vital tool in the field of robotics for fine-tuning a robot's movements based on force and torque data collected during operation. This statistical technique finds connections between independent variables (force and torque readings) and dependent variables (robot movements). Multivariate linear regression is used when there are two or more dependent variables influenced by one or more independent variables [51]. This is crucial for predicting multiple outcomes simultaneously, as described by (3).

$$\begin{aligned} y_1 &= \beta_{10} + \beta_{11}x_1 + \beta_{12}x_2 + \beta_{13}x_3 + \cdots + \beta_{1n}x_n + \epsilon_1 \\ y_2 &= \beta_{20} + \beta_{21}x_1 + \beta_{22}x_2 + \beta_{23}x_3 + \cdots + \beta_{2n}x_n + \epsilon_2 \\ &. \\ &. \\ &. \\ y_m &= \beta_{m0} + \beta_{m1}x_1 + \beta_{m2}x_2 + \beta_{m3}x_3 + \cdots + \beta_{mn}x_n + \epsilon_m \end{aligned} \tag{3}$$

Ordinary Least Squares (OLS) regression is a widely used method to estimate the coefficients by minimizing the error between predicted and actual results. The OLS regression equation is shown in (4).

$$\beta = \left(X^T X \right)^{-1} X^T y \tag{4}$$

In this equation, β is the vector of the estimated coefficient, X^T is the transpose matrix of variable X, and y is the vector value of the response variable. OLS regression can be applied to all the types of regression analyses. By applying it to the graph, OLS finds the best-fit lines according to the criterion of least squares.

The force-torque feedback integration in robotic assembly involves real-time data processing and control mechanisms. The force-torque sensor data first undergoes signal conditioning and noise filtering before transformation into the robot's coordinate frame. Linear regression techniques are then applied to establish relationships between measured forces/torques and required position adjustments. The system samples force-torque measurements in a closed-loop structure, using regression models to generate immediate position corrections. These corrections are computed using Ordinary Least Squares regression to minimize positioning errors, while multiple linear regression accounts for various force and torque components simultaneously. The adaptive control system updates the regression parameters continuously, enabling the robot to refine its movements based on accumulated sensor data, particularly during the critical initial contact phase of nut-to-bolt mating.

While linear regression models offer computational efficiency and interpretability for force-torque control, they have limitations in handling complex, non-linear dynamics common in robotic assembly. For instance, when dealing with varying friction coefficients, material deformations, or complex contact geometries, linear models may oversimplify these relationships. More advanced ML techniques, such as neural networks and reinforcement learning, can capture these non-linear dynamics more accurately by learning complex patterns from large datasets of force-torque interactions. However, they require more computational resources and training data compared to linear regression approaches.

Practical applications of these regression techniques have been demonstrated in various fields. For instance, Song et al. [51] employed multivariate linear regression to analyze heavy metal distribution in vegetables, using data from 35 sampling sites along the Changjiang River delta with a systematic collection of vegetables, soil, irrigation water, and fertilizers. Their analysis, combining ICP-MS chemical testing with PCA and CA statistical methods, revealed that fertilizer contributed 38.5-65.25% of heavy metals in vegetables, while soil and irrigation water significantly contributed to As (44.58%) and Hg (66.97%) levels respectively. Hesamian et al. [52] developed a soft multiple linear regression model using machine learning to handle fuzzy predictors and responses. Their approach minimizes the absolute distance between predicted and observed data under specific constraints. The model's effectiveness was tested through simulations and real-world examples, achieving a RMSE of 0.46, MARE of 0.47, and MSM of 0.77, demonstrating improved prediction accuracy and robustness in dealing with uncertainty and imprecise data. Similarly, other researchers have applied these methods to urban planning and management, particularly in analyzing domestic water demand in Seville, Spain.

4.2. Neural Networks

Neural networks are computational models inspired by the human brain's ability to process information. It is widely used in various fields, including medical imaging for disease diagnosis, financial forecasting, object recognition, facial identification, and voice recognition systems [53]. They are made up of linked nodes, or neurons, that are organized into three layers, which are an input layer, one or more hidden layers, and an output layer. Each connection is assigned a weight, and each neuron has an activation function that determines its output. There are diverse types of neural networks customized for distinct sorts of tasks and data, such as Artificial Neural Networks (ANNs), Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs) and Generative Adversarial Networks (GANs).

Artificial Neural Networks (ANNs) are neural networks that can perform several tasks such as regression, classification, and pattern recognition. ANNs are ideal for predicting coordinates X and Y from forces and torques in different directions because of their effectiveness at modelling complicated, nonlinear relationships. Based on Fig. 2, the architecture diagram of ANN consists of an input layer, hidden layers and an output layer. The input receives force and torque data, the hidden layers are intermediate layers that apply weights and activation functions, and the output layer produces the final predictions, which are the X and Y coordinates. Each neuron in a layer is linked to neurons in the next layer, and the strength of these connections is modified during training via a process known as backpropagation. This entails minimizing a loss function, which calculates the difference between projected outputs and actual objectives.

Fig. 3 shows the flowchart that describes the iterative process of training an ANN, which includes input data, parameter setup, forward pass through the network, loss computation, backpropagation for weight updates, and lastly, model evaluation and prediction.

ANNs are good at capturing and modelling the non-linear correlations between input pressures, torques, and output coordinates, which is critical for jobs involving complicated and non-linear dynamics like robotic movement [54]. Additionally, it can learn detailed patterns and relationships in data using different activation functions such as ReLU, Sigmoid, and Tanh, which classic linear models cannot do. In robotic applications, ANN can induce new and unknown situations from training data, which enables the robot to work effectively in a changeable and unpredictable environment [55]. Furthermore, ANNs are very useful in supervised learning contexts, in which the training process enables the network to recognize underlying patterns and generate accurate predictions [56]. However, ANNs require large amounts of high-quality training data to achieve reliable performance, which can be challenging and costly to obtain in many robotic applications. Moreover, the internal decision-making processes of ANNs are often difficult to interpret and explain, which poses challenges for safety-critical robotic systems where transparency and explainability are essential.

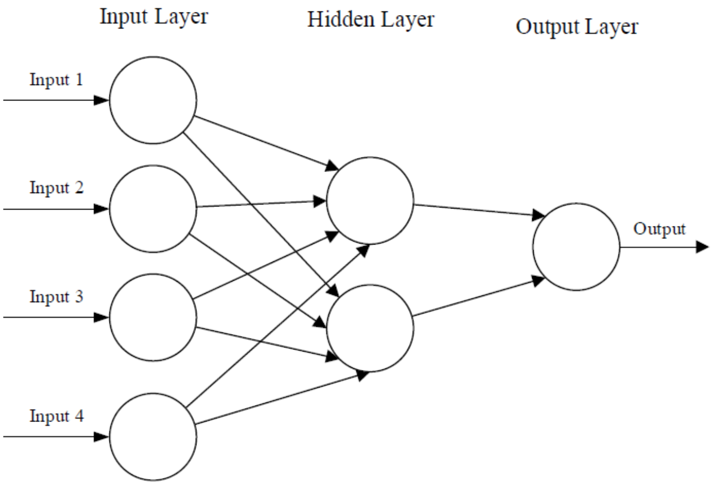

Fig. 2. Architecture diagram of ANN

Neural networks in robotic assembly employ task-specific architectures, typically featuring a 6-dimensional force/torque sensor input layer (Fx, Fy, Fz, Tx, Ty, Tz) [57], followed by 2-3 hidden layers (first layer: 64-128 neurons, second layer: 32-64 neurons) with ReLU, Sigmoid, or Tanh activation functions, and an output layer for position corrections or joint configurations [58]. The system requires significant computational resources, including real-time processing at 1kHz sampling rate with position tracking precision of 10^{-5} meters [58], GPU acceleration for training, and deployment needs encompassing network weight storage, real-time force-to-position conversion, and minimum 100Hz sampling frequency for stable control [57].

Based on the research, Serbest et al. [54] applied ANNs to predict joint torques using comprehensive data collection and standardized metrics. They collected data from 20 participants across different BMI groups using motion capture (Sony Handycam, 1920×1080, 30 Hz) with six anatomical markers. Their four-layer neural network (22 inputs, 9-11-15-4 neurons) was trained using Levenberg-Marquardt algorithm with a 70-15-15 split for training-testing-validation. Performance was evaluated consistently using MEP, RMSE, and R^2, achieving R^2 values of 1.0 for ankle, knee, and neck torques, and 0.99999 for hip torques. The model demonstrated practical application in clinical settings for analyzing sit-to-stand movements, with potential use in rehabilitation assessment. Bobka et al. [59] applied ANN to predict and compensate for assembly deviations in a pick-and-place process for planar objects. Their experimental setup collected 1000 pick-and-place trials using a SCARA robot with ±0.01mm repeatability, where 800 trials were used for training and 200 for validation. Using a deep feedforward neural network with 6 layers (45 neurons total), they processed positional data from two cameras - a 5.04-megapixel camera for detection and a 10.55-megapixel camera for measurement. The implementation reduced assembly deviations significantly, with X-axis dispersion improving from 12.40mm to 0.63mm and Y-axis dispersion from 5.31mm to 0.59mm.

Cao et al. [57] demonstrated an industrial application of ANN for high-precision robotic assembly using a 7-DOF Franka Emika Panda arm equipped with an ATI Gamma force/torque sensor. Their system combined ANN-based force/torque calibration (using a 6-32-32-6 neural network) with constrained optimization and surface-based spherical tree representation to handle 6D uncertainties. Testing on complex multi-peg-in-hole assemblies achieved 100% success rate across 80 experimental trials, with clearances under 0.015 rad (orientation) and 1.5 mm (position), completing assemblies within 13 seconds using standardized velocity (0.5 m/s) and acceleration (0.1 m/s²) parameters. This demonstrated practical viability for tight-tolerance industrial assembly tasks. Gao et al. [58] demonstrated the industrial implementation of ANN for force feedback control in dual-arm robotic assembly, using a three-layer neural network trained on six-dimensional force/torque sensor data from a JR3 sensor. Testing on automotive headlight assembly validated the system's performance with standardized metrics: position tracking errors within 4×10^{-5} meters for both arms and near-zero contact forces along the assembly direction. The system achieved high-speed, precise assembly using a 7-DOF redundant dual-arm robot with force-based online error correction, demonstrating practical applicability for complex industrial tasks. Lastly, Luis et al. [60] demonstrated the industrial implementation of Fuzzy ARTMAP neural networks for peg-in-hole assembly using a KUKA KR16 robot with JR3 force/torque sensor feedback. Their pattern selection criterion autonomously determined when to learn new patterns, achieving a 27.86% reduction in corrective movements (from 23 to 14 movements) between first and second insertions with 1mm initial misalignment. Testing with real assembly operations validated the system's adaptability and precision, preventing overtraining while maintaining low contact forces and successfully handling initial position uncertainties without human intervention.

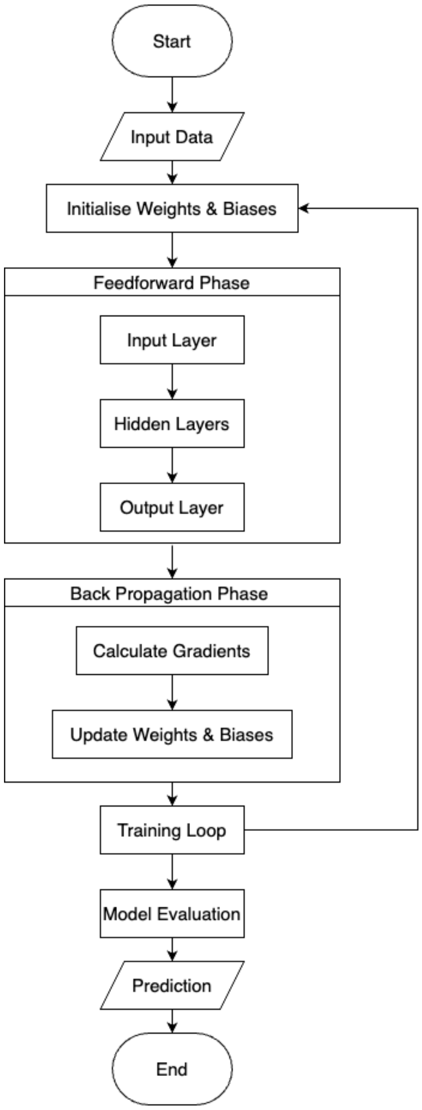

Fig. 3. Flowchart describing the iterative process of training an ANN

4.3. Reinforcement Learning

Reinforcement Learning (RL) is a machine learning approach where an agent learns to make decisions by interacting with its environment to maximize cumulative rewards [61]. In contrast to supervised learning, which relies on labelled input-output pairs, RL is based on trial and error, with the agent exploring different behaviors to identify the most rewarding strategies. RL is usually applied in game playing [62], [63], robotics [64]-[68], autonomous vehicles [69], [70] and finance [71]-[73]. The key components of RL and their relationships can be understood through their interactions. The Environment is the external system the agent interacts with and uses for decision-making. The State (S) shows the current situation of the environment as observed by the gent. The Agent is the learner or decision-maker who interacts with the environment to maximize the cumulative rewards. Actions (A) are decisions made by the agent based on its policy that have an impact on the environment and future states. The Reward (R) is feedback from the environment, which guides the agent to take action. The Policy (π) is referred by agent to take action based on current state and maximize the rewards. The Value Function (V) calculates the predicted cumulative reward from a given state, which informs policy and helps the agent make better decisions.

Fig. 4 shows the flowchart of repeated procedures that allow an agent to learn optimum behaviors through interaction with its environment. Initially, the agent initializes a policy (π) and value functions (V or Q). Next, the agent observes the current state (S) of the environment. Based on the state (S) and policy (π), the agent takes action (A) that can maximize the predicted reward (R). During the Execution and Transition phase, action (A) is taken and leads the environment to a new state (S'). Next, the environment gives feedback and updates the reward (R). The updated reward (R) and the new state (S') are used by the agent to fine-tune its policy (π) and value functions (V) to make better future decisions. Next, different strategies are applied, such as Q-Learning, SARSA, Deep Q-Networks and Policy Gradient Methods. Q-Learning is an off-policy algorithm that updates the Q-value using Bellman equation as shown in (5).

$$\mathrm{Q}(\mathrm{s},\mathrm{a}) \leftarrow \mathrm{Q}(\mathrm{s},\mathrm{a}) + \alpha[\mathrm{r} + \gamma \max_{\mathrm{a}'} \mathrm{Q}(\mathrm{s}',\mathrm{a}') - \mathrm{Q}(\mathrm{s},\mathrm{a})] \tag{5}$$

SARSA is an on-policy algorithm that updates the Q-value based on policy (π) using (6).

$$\mathrm{Q}(\mathrm{s},\mathrm{a}) \leftarrow \mathrm{Q}(\mathrm{s},\mathrm{a}) + \alpha[\mathrm{r} + \gamma \mathrm{Q}(\mathrm{s}',\mathrm{a}') - \mathrm{Q}(\mathrm{s},\mathrm{a})] \tag{6}$$

Deep Q-Networks update the Q-value using neural networks, while Policy Gradient Methods directly optimize the policy by adjusting parameters to maximize expected rewards. During the interaction cycle, the agent continuously refines its policy (π) based on collected experience. Throughout the iterative process, the agent must balance Exploration and Exploitation. The ε-greedy approach and Upper Confidence Bound (UCB) are excellent techniques for managing this equilibrium.

Reinforcement learning implementation in robotic assembly requires specific network architecture and computational resources. The system uses 6-DOF force/torque readings with joint positions for state space [64], [65], and a policy network containing 3-4 layers (256-512 neurons per layer) for PPO implementation [68]. Training requires a lot of computation, exemplified by ILTSFC's 100-iteration requirement [74] and PEARL's simulation-based pre-training approach [64]. Real-time deployment requires 1kHz force/torque data sampling, continuous policy updates, and sufficient memory for network parameters. The process typically starts with simulation training before real-world implementation, incorporating safety constraints and performance validation across various assembly scenarios.

Based on the research, Luo et al. [64], [65] demonstrated the industrial application of deep reinforcement learning for peg insertion tasks using a UR5 robot equipped with a Robotiq FT300 force/torque sensor. Their system combined a neural network (4 layers, 128 neurons each) with admittance control to handle deformable materials, achieving 100% success rate for 5mm offsets and 60% for 10mm offsets during 20-minute training sessions. Testing on a challenging case where the peg diameter (25mm) exceeded the hole diameter (20mm) validated the method's practical applicability for manufacturing tasks requiring precise force control. Schoettler et al. [66] demonstrated industrial applications of meta-reinforcement learning for precision assembly using a Sawyer robot. Their PEARL algorithm trained on randomized simulated tasks (±5mm position offsets, 13-15mm clearances) before adapting to real-world electrical connector and gear insertions, achieving 100% success rate within 20 trials compared to 80-84% for standard spiral search methods. Testing with industrial components validated the system's robustness, completing insertions in 5.3-8.2 seconds even with 2-3mm goal perturbations, outperforming traditional methods that required 13.6-26.6 seconds. Luo et. al [68] developed a robotic assembly method combining reinforcement learning with operational space force control, testing it on a Rethink Robotics Sawyer robot operating at 20 Hz. Using iterative Linear-Quadratic-Gaussian (iLQG) control and force/torque feedback, their approach achieved 100% success rates on peg-in-hole tasks and gear-shaft insertions with sub-millimeter precision. The results were validated through systematic testing with four roll-outs per training iteration, though the method required 3-5 iterations to achieve reliable performance.

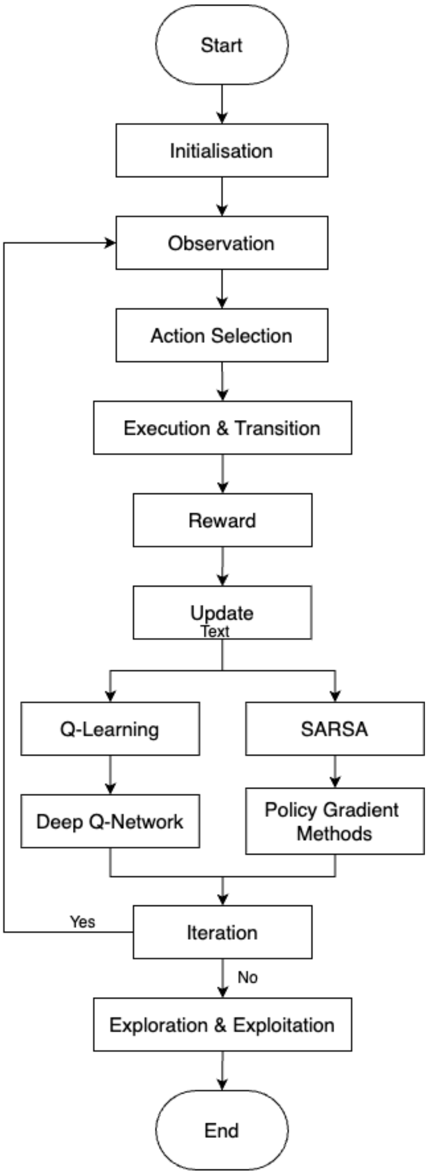

Fig. 4. Flowchart of repeated procedures for reinforcement learning (RL)

Furthermore, the tilt search method combined with reinforcement learning (RL) was implemented in [75] for battery pack assembly. While their approach achieved an impressive 99.54%

success rate across 13,500 real-world assemblies, demonstrating strong industrial viability, the assembly time of 11 seconds per unit (with only 4 seconds for actual insertion) was still slower than human operators who could complete the task in 3 seconds. The method required the robot to operate within specific constraint regions and relied on careful parameter tuning for reliable operation. Bos et al. [74] developed Iteratively Learned and Temporally Scaled Force Control (ILTSFC), which combines two coupled iterative learning controllers - one for increasing assembly speed and another for adjusting reference trajectories to reduce contact forces. Using an ABB YuMi robot for peg-in-hole assembly tasks, their method achieved a 40% reduction in task duration while simultaneously reducing contact forces by 50% and increasing operational speed by a factor of 1.8 after 100 iterations. The system demonstrated robustness against environmental disturbances without compromising assembly performance.

While reinforcement learning demonstrates effectiveness in robotic assembly, several practical implementation challenges exist. The requirement for extensive training data is evident from ILTSFC [74], needing 100 iterations to achieve optimal performance. This extensive training process demands significant computational resources, particularly for deep RL methods like PEARL [64] and PPO [68] that process complex force-torque sensor data in real-time. Additionally, systems face overfitting risks and challenges in balancing exploration versus exploitation [64], [65], while the transition from simulation to real-world application remains difficult [64]. While RL systems demonstrate impressive initial performance in robotic assembly tasks, sustained reliability requires periodic retraining, sensor recalibration, and continuous monitoring to maintain effectiveness over time.

5. Conclusion

The review of traditional search methods and their application in high-precision robotic assembly tasks highlights both their strengths and limitations. Traditional search methods, such as spiral and tilt search techniques, while effective in controlled environments, demonstrate significant limitations in modern manufacturing settings. These methods are constrained by rigid programming structures, show limited adaptability, and lack the ability to learn from experience, making them increasingly inadequate for contemporary manufacturing needs that require flexibility and real-time adaptation to changing conditions.

Machine Learning (ML) and artificial intelligence (AI) methodologies provide increased flexibility, strength, robustness, and scalability by enabling systems to learn from data and adapt to changing environments, greatly improving the precision and reliability of high-precision assembly tasks. These advanced approaches have demonstrated remarkable improvements, including success rates of up to 95-100%, significant reductions in assembly time and contact forces, and enhanced adaptability to varying conditions. While implementation challenges exist, such as computational requirements and initial setup complexity, the integration of ML and AI technologies in robotic assembly represents a significant advancement in manufacturing automation, offering improved precision, reduced manual intervention, and enhanced performance in dynamic environments.

Future research should focus on developing hybrid systems that combine traditional methods' reliability with AI's adaptability, improving transfer learning capabilities for faster adaptation to new tasks, and creating more efficient training methods requiring less data. Additionally, emphasis should be placed on simplifying deployment procedures, reducing computational requirements, and developing cost-effective solutions that maintain high-performance standards, making these technologies more accessible for industrial applications.

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