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Condition monitoring and fault diagnosis of industrial robots: A review

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Abstract Health management of industrial robots is paramount for maintaining effective operations, ensuring consistent performance, minimizing downtime, and ultimately enhancing the safety and productivity of robotic systems. Since the invention of industrial robots, significant efforts have been dedicated to their health management. In recent years, thanks to advances in condition monitoring and fault diagnosis technologies of industrial robots, robot health management has shifted from scheduled maintenance to condition-based maintenance. This paper aims to comprehensively review the evolution of condition monitoring and fault diagnosis technologies that are critical for implementing condition-based maintenance of industrial robots. A brief introduction to robotic systems is given first to analyze the robot failure modes and their corresponding root causes. Next, the data acquisition strategies and commonly used sensors of industrial robots are investigated. Further, the development of robot condition monitoring and fault diagnosis technologies are reviewed, with an emphasis on the remarkable achievements and challenges in model-based and data-driven methods. Finally, the paper summarizes the challenges facing this research field and provides potential avenues for future advancements.

Keywords industrial robots, failure modes, data acquisition, condition monitoring, fault diagnosis

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1 Introduction

Over the past few decades, industrial robots (IRs) have made their mark in numerous sectors of modern industry, thanks to their advantages of cost-effectiveness, versatility, and efficiency. Although IRs are more reliable than humans and never get tired or bored with tedious tasks, they do go on strike occasionally due to reliability issues [1]. Scheduled maintenance is a common practice to prevent unexpected shutdowns of IRs. However, the scheduled maintenance of a large stock of IRs always results in resource wastage and even may fail to eradicate potential risks. To overcome the limitations associated with scheduled maintenance, a variety of condition monitoring and fault diagnosis technologies have been developed to realize a paradigm shift toward condition-based maintenance of IRs.

The failure modes of IRs include performance degradation of the overall systems and faults of individual components within the robotic system [2–4]. Therefore, existing studies on the condition monitoring and fault diagnosis of IRs can be categorized into two levels: system level and component level. The former concentrates on the performance evaluation of the entire robotic system, emphasizing positioning accuracy, load capacity, and stability of the overall system of IRs. The latter focuses on the health assessment of components within the robot, highlighting the faults of key components, such as electronic drives, electric motors, speed reducers, and sensors.

In the system-level condition monitoring and fault diagnosis of IRs, model-based methods are widely recognized as the most powerful tools for the detection, isolation, and identification of robot abnormalities, including body collision, driving force losses, and sensing drift [5–8]. Note that the generalized momentum observer-based method, one of

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the typical model-based methods, has been commercialized and integrated into the control systems of numerous IRs for real-time monitoring and diagnosis of robotic systems [9]. In the implementation of model-based methods for condition monitoring and fault diagnosis of IRs, the challenge mainly comes from the unmodelled uncertainties. Indeed, accurate modelling of the nonlinear behaviors of IRs, e.g., deformation, contact, impact, and friction, remains an open problem [10–12].

In the component-level condition monitoring and fault diagnosis of IRs, data-driven methods are becoming increasingly popular with most of them developed in the last five years [13–16]. Key components within IRs, such as speed reducers and electric actuators, are also common in the rotating machinery. Consequently, many studies leveraged the experience gained from fault diagnosis of rotating machinery to develop data-driven fault diagnosis methods for the rotating components in IRs [17–19]. In addition to the problems related to individual components of IRs, there are some robotic-specific challenges in condition monitoring and fault diagnosis of IRs, such as the scarcity of robotic-specific data, dynamic coupling between multiple components, and time-varying configuration of IRs [20–22].

This paper aims to provide a comprehensive overview of the development of condition monitoring and fault diagnosis of IRs and explores future opportunities and challenges in this research area. Compared with the related surveys [3,4,9,13–15,23–25], the primary contributions of this paper are as follows.

(1) This paper systematically investigates the failure modes of IRs, including the faults of robot components and body collision as noted in the existing surveys. Further, the paper discusses the behavior and root causes of the robot failures and summarizes the common faults of robot components in the existing literature.

(2) Data of faulty IRs forms the foundation of the robot health management, yet strategies for data collection are rarely discussed in the existing surveys. This paper highlights the data acquisition of faulty IRs and discusses in detail commonly used data acquisition strategies. Meanwhile, the paper introduces the proprioceptive sensors and investigates the commonly used additional sensors in data acquisition of IRs.

(3) Almost all surveys on model-based condition monitoring and fault diagnosis of IRs are over ten years old. This paper reviews the development of model-based methods in the past 30 years, including the recent advancements made in system modelling, residual generation, and decision-making.

(4) In reviewing the data-driven condition monitoring and fault diagnosis of IRs, this paper distinguishes itself from previous surveys by shifting focus from the types of data-driven methods to an examination of the data sources utilized and the faults addressed by these methods. The literature is organized into three distinct categories based on the data source: log data, proprioceptive sensor data, and additional sensor data. Such a categorization clarifies the applicability of different data sources for diagnosis of various faults of IRs.

The remainder of this paper is organized as follows. Section 2 illustrates the failure modes of IRs and common faults of robotic components and summarizes the data acquisition strategies of faulty IRs. Section 3 reviews the existing methods for condition monitoring and fault diagnosis of IRs. Further, some practical examples are provided to demonstrate the implementation of model-based and data-driven methods. Section 4 discusses the challenges facing this research field and provides potential avenues for future advancements. Section 5 concludes the paper.

2 Failure modes and data acquisition strategies of industrial robots

The scope of this paper is limited to electrically actuated IRs composed of four subsystems: mechanical system, electrical system, control system, and sensing system. The three concentric rings in Figure 1, from the innermost to the outermost, respectively present the typical mechanical structures, a concise principle of cooperation among subsystems, and some basic components of IRs. Note that the components of IRs are far more diverse than those displayed in Figure 1. The diversity of components and mechanical structures makes IRs adaptable to numerous applications but also poses a great of challenges to the condition monitoring and fault

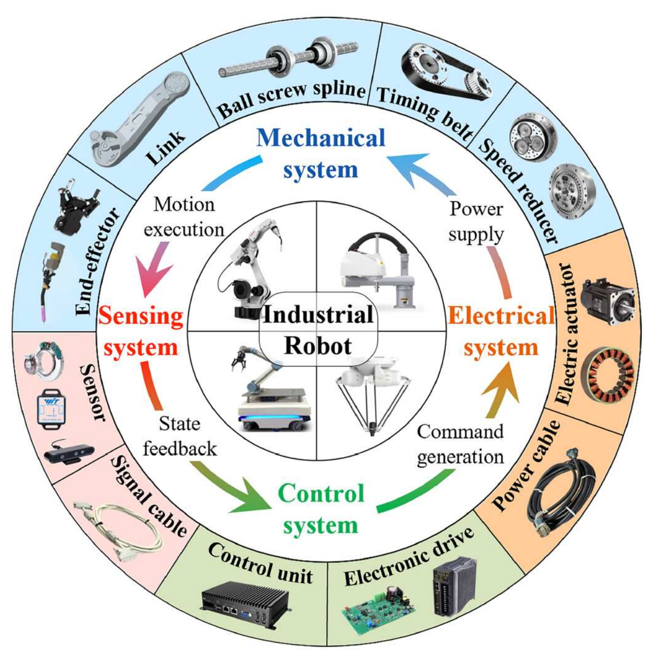

Figure 1 (Color online) System structure and basic components of industrial robots.

diagnosis of IRs. Further, the number of proprioceptive sensors in IRs is far less than the number of components, where most IRs are equipped only with essential sensors for motion control and most components in the mechanical system are sensorless. The above features of IRs make their condition monitoring and fault diagnosis a challenging task. Prior to introducing methods for condition monitoring and fault diagnosis of IRs, this section discusses in detail the failure modes and common faults of IRs, as well as data acquisition of faulty IRs.

2.1 Failure modes and common faults

In the early days of IRs, industrial control devices, such as programmable logic controllers, had just entered the digital age, and the electronic components in controllers were unreliable and subject to frequent failures [26]. At the same time, the primary cause of robot failures was the malfunction of electronic components, leading to the loss of basic functions of IRs. Therefore, the fault diagnosis of electronic components was a major concern in the design of control systems of the old-fashioned IRs [27].

Over the past fifty years, there has been a dramatic transformation in robot hardware and software technologies, significantly improving the reliability of control systems, which now integrate elementary fault diagnosis functions [2,28]. However, manual inspections of IRs are still indispensable to evaluating the health status of sensor-less mechanical systems. Further, it is well-known that the evolution process of faults in mechanical systems is always long-term, and faults in mechanical systems typically result in a degradation of the overall performance of IRs rather than an immediate loss of functions. For example, an unacceptable positioning error of the end-effector caused by faults in the mechanical system is a common failure mode in IRs used for precision machining [29–31]. Thus, failure modes of IRs include not only the loss of basic functions but also the substandard performance of the overall system.

In addition to the problems from IRs, interferences from the external environment, such as human mistakes, are also major sources of failure of IRs [32–35]. For example, IRs, especially those who frequently interact with the external environment, often fail tasks due to unexpected collisions with their surroundings. In summary, an IR is generally considered a failure if it is unable to complete user-specified tasks. The failure modes of IRs can be broadly categorized into three types: loss of basic functions, substandard performance of the overall system, and external environmental interferences.

All the failure modes of IRs can be isolated to the abnormal behaviors of robot joints and links based on the well-known kinematic and dynamic models of IRs. Further, all the abnormal behaviors of robot joints and links are related to faults or abnormal behaviors of robot components, but relations between them are complex and difficult to model. Therefore, in the existing literature, the abnormal behaviors of robot joints and links are often simulated by modifying the inputs, outputs, or system parameters of IRs. The commonly simulated abnormal behaviors of robot joints and links include free-swinging joints [36], locked joints [37], partial loss of joint driving forces [38], drift in feedback data of joint displacements/speeds [39], and abnormal oscillation of joints and links [40,41].

The complex behaviors of robot joints and links, plus the diversity of robot components and faults, make the fault diagnosis of IRs challenging. Identifying the possible faults of robot components and corresponding abnormal behaviors of the overall system is helpful for the fault diagnosis of IRs, particularly for fault isolation [18–22,42–105]. Table 1 summarizes the common component faults of IRs and corresponding studies that provide experiment results of faulty IRs. Note that, in practice, the component faults of IRs go far beyond those listed in Table 1. Examples include faults of planetary gearboxes used in mobile robots [42], faults of load

Table 1 Common faults of robot components

Components	Faults[a)]	References
Servo drive	Inverter fault, capacitor fault, current sensor fault[b)]	[50–54]
Permanent magnet synchronous motor	Stator fault, rotor fault, brake fault, bearing fault	[55–66]
Harmonic reducer	Flexible spline fault, circular spline fault, wave generator fault, input shaft fault, manufacturing and assembly error, poor lubricant	[18,22,56,57,63,67–75]
Rotate vector reducer	Sun gear fault, planetary gear fault, crankshaft fault, pin gear fault, cycloidal gear fault, main bearing fault, seal fault, manufacturing and assembly error, poor lubricant	[19,20,70,76–98]
Timing belt	Belt fault, pulley fault	[75,99–101]
Bearing	Fault of support bearings in robot joints	[21,102,103]
Fastener	Bolt loosening of robot joints, bolt loosening of robot base	[104,105]

a) Faults listed in this table can be further subdivided according to their type and degree.
b) Current sensors are typically embedded in servo drives.

balancing mechanisms used in heavy-duty IRs [43], and faults of power cables [44]. Furthermore, there are lots of studies, not explicitly related to robotics, that have investigated the faults of components commonly used in IRs [45–49]. Although most of the fault diagnosis methods developed in these studies are not applicable to IRs, the fruitful experience gained from these studies advances the development of condition monitoring and fault diagnosis of IRs. For example, drawing on the experience gained from fault diagnosis of rotating machinery, many data-driven methods use vibration signals to diagnose the faults of speed reducers and electric actuators in IRs [14].

2.2 Data acquisition

Data acquisition of faulty IRs is both costly and labor-intensive due to the complexity and diversity of robot components. Further, it usually takes years to collect the full lifecycle data of an IR. In the existing studies, the following strategies are commonly used to collect data on faulty IRs: numerical simulation of faulty IRs; manual modification of inputs, outputs, or parameters of actual IRs; replacement of normal (healthy) components of IRs with faulty ones; and accelerated aging tests of IRs or their individual components. Details of these four strategies are given as follows.

(1) Numerical simulation of faulty IRs. The benefits of numerical simulation are economical, efficient, and safe, making it a preferred strategy for the development, debugging, and validation of condition monitoring and fault diagnosis methods for IRs. Since the 1990s, numerical simulation has been accepted by many studies to generate data on faulty IRs [106–109]. Nowadays, a wide range of robot simulation platforms are available, such as Gazebo, Webots, Coppeliasim, Mujoco, Isaac, and Raisim [10]. However, numerical simulation of component faults of IRs remains underdeveloped. For example, the existing studies predominantly employ simple functions such as pulses, steps, and ramps to simulate excitations generated by faulty components of IRs [77,110].

(2) Manual modifications of inputs, outputs, or parameters of actual IRs. Manually modifying robot inputs, outputs, and parameters to simulate faults of actual IRs is cost-effective and easy to implement, since it does not require any hardware modifications. Such a strategy is typically used to simulate anomalies in joint driving forces [36,111–114], anomalies in sensor feedback data [39,115–118], and external disturbances [119–123]. For example, the free-swinging actuation failure can be simulated by setting the reference torque to zero and the drift in sensor data can be simulated by introducing an additive signal to the measured data. However, it is impossible by far to simulate all component faults of IRs without hardware modifications. For example, modifications of robot inputs, outputs, and parameters are unable to simulate the stochastic excitations introduced by faults of speed reducers, which involve complex behaviors that are not yet understood thoroughly [124–126]. Further, modifications of robot inputs, outputs, and parameters could make IRs unstable and even pose risks to operators, especially in human-robot interaction scenarios [122].

(3) Replacement of normal components of IRs with faulty ones. In robotic factories, there are many substandard components of IRs retired from actual industrial lines. It is therefore cost-effective to obtain faulty IRs by replacing the components of normal IRs with substandard ones. For example, many studies employed faulty speed reducers and motors obtained from actual industrial lines to collect data on faulty IRs [20,64,65,67–69]. Fault injection is another way to obtain faulty components of IRs. The existing studies focused on fault injection of rotating machinery of IRs, including rotate vector (RV) reducers [19,79–83], harmonic reducers [70,75], and timing belts [75,99–101]. Most existing studies chose to inject faults into the rotating machinery of IRs for two main reasons: frequent impact and contact in rotating machinery make it susceptible to wear and tear, and IRs are able to work with faulty mechanical components.

(4) Accelerated aging tests of IRs or their individual components. It is time-consuming and costly to collect full lifecycle data of IRs. For example, Vallachira et al. [127] spent over four years collecting full lifecycle data of 26 IRs worked in actual industrial lines, where 13 IRs were reported with gearbox failures and the rest were normal. Accelerated aging tests are therefore usually employed to expedite the acquisition of full lifecycle data of IRs and their components. Indeed, accelerated aging tests of IRs are also time-consuming, typically taking at least three months [87,88,94,128]. In addition to accelerated aging tests of IRs, a few studies have conducted accelerated aging tests of individual components of IRs, where the test duration is significantly reduced by increasing the load of components. For example, as reported in refs. [53,129–131], accelerated aging tests of harmonic reducers and electronic drives were generally completed within a few days.

Among the above four strategies, the numerical simulation strategy is the most flexible, allowing to read any data available in the simulation model of IRs. In the remaining three strategies, the type of data that can be obtained depends on the sensors that the robot is equipped with. In most IRs, states of electric actuators obtained by proprioceptive sensors can be read through the control system. Further, additional sensors are usually employed to assist the proprioceptive sensors in acquiring data from actual IRs. One of the key issues in using additional sensors is sensor selection, where the following factors need to be considered: (i) costs of adding sensors, (ii) faults needed to be diagnosed, (iii) reliabilities of additional sensors, and (iv) operating conditions of additional sensors [87,132]. The application of additional sensors in condition monitoring and fault diagnosis of IRs is discussed in detail in subsections 3.2.3 and 3.3.2.

3 Condition monitoring and fault diagnosis technologies

The existing methods for condition monitoring and fault diagnosis of IRs can be broadly categorized into three types: knowledge-based methods, model-based methods, and data-driven methods. Expert knowledge permeates the entire lifecycle of IRs, from design and manufacturing to service and maintenance. During the design phase, a systematic analysis of failure modes and effects offers essential insights for condition monitoring and fault diagnosis of IRs [133]. The knowledge accumulated from condition monitoring and fault diagnosis is then fed back into the design and manufacturing processes to eliminate potential flaws. Expert knowledge of condition monitoring and fault diagnosis forms knowledge-based methods. Further, the development of both model-based and data-driven methods leverages a rich pool of expert knowledge, effectively integrating most knowledge-based approaches. This section therefore incorporates knowledge-based methods into the review of model-based and data-driven methods.

3.1 Model-based methods

Model-based methods use analytical redundancy to replace hardware redundancy to address condition monitoring and fault diagnosis issues of practical systems [134,135]. Main tasks of model-based condition monitoring and fault diagnosis include system modelling, residual generation, and decision making.

3.1.1 System modelling

The aim of system modelling is to find a mapping between the inputs and outputs of actual systems. Typically, IRs are equipped with rotary encoders and current sensors to measure angular displacements and driving torques of electric motors, respectively. Dynamic models of IRs, that are able to characterize the relationship between angular displacements and driving torques of electric motors, are therefore common in condition monitoring and fault diagnosis of IRs. In some specific scenarios, dynamic models are not the only option for condition monitoring and fault diagnosis of IRs where the robot or its surrounding environment is equipped with additional sensors. For example, in visual servoing applications, IRs are typically equipped with vision sensors. In such cases, it is able to assess the health status of IRs using the robot kinematic models that characterize the relationship between the measurements of proprioceptive and additional sensors [136–138]. This paper focuses on the dynamic modelling of IRs, and readers interested in other models are referred to ref. [2].

The well-known rigid-body dynamic is widely used to characterize the dynamic behavior of IRs with high stiffness [139,140]. However, rigid-body dynamics often fail to characterize the dynamic behaviors of IRs with elastic joints or long arm spans, such as collaborative robots. Various rigid-flexible coupling models were introduced in existing studies to address the flexibilities of IRs [9,141,142]. The trade-off between computational efficiency and numerical accuracy is a big issue in the existing studies of flexible body modelling, where most rigid-flexible coupling models are too complicated to be both computationally efficient [143]. Further, there are many unresolved issues in the parameter identification of flexible body models [144]. Besides flexibility in IRs, modelling and parameter identification of nonlinear characteristics introduced by contact, collision, friction, and clearance between multiple components are also challenging [77,145].

Around 1990, neural networks were introduced into the dynamic modelling of robots to learn nonlinear behaviors [146]. Nevertheless, the learning abilities of early neural networks are not powerful enough to achieve the performance of traditional physical models in many scenarios. After more than twenty years of revolution, the advent of deep learning brought rapid progress to neural networks. For example, the popular physics-inspired neural networks of recent years have made significant breakthroughs in robot dynamics learning and interpretability [147–150]. However, the practical implementation of physics-informed neural networks still faces many limitations, such as their performance being highly dependent on the chosen application object, as well as the quality and quantity of training data [143]. Readers are recommended to refer to refs. [148,151] for the details of recent advances in learning-based modelling methods for robot dynamics. Furthermore, a systematic review of learning-based methods applied to the modelling and identification of general dynamic systems can be found in ref. [152].

3.1.2 Residual generation

In model-based condition monitoring and fault diagnosis, residual generation is a process of using the known nominal models to find a residual that contains information of faults on actual systems [6]. Studies on model-based condition monitoring and fault diagnosis of IRs can be classified into three categories based on their residual generation approaches: parameter identification methods, parity space methods, and state estimation methods.

(1) Parameter identification methods

Parameter identification-based residual generation methods make use of the fact that faults of actual systems often lead to changes in the values of model parameters [106,153]. The primary tasks of parameter identification-based residual generation methods include model selection and parameter identification. A necessary condition for model selection is that at least one of the identifiable parameters reflects the fault of actual systems. In practice, model selection depends on the expert knowledge of actual systems and it is usually not easy to find a model with identifiable parameters that are both sensitive to faults and robust to disturbances. One of the challenges in model selection is that most model parameters are coupled with each other and cannot be identified individually. For example, most parameters of dynamic models of IRs are not individually identifiable due to the complex robot structure and scarcity of proprioceptive sensors [154]. Further, model parameters that carry information on robot faults are typically time-varying and depend on the operating conditions of the robot. For example, the stiffness and friction coefficients of robot joints that are able to reflect faults of speed reducers are influenced by various factors, such as the spatial configuration and trajectory of the robot, and environmental conditions [77].

Parameter identification of robot models is also challenging due to unmodelled dynamics and measurement uncertainties. Common methods to cope with unmodelled dynamics and measurement uncertainties in parameter identification include extended Kalman filter [155,156], maximum likelihood estimation [157,158], set membership estimation [159,160], instrumental variable method [161,162], and semi-definite programming method with physically feasible constraints [163–166]. Among the above methods, adding reasonable constraints based on the expert knowledge of the actual robot is the only way to obtain physically feasible estimates of all model parameters [167]. However, obtaining accurate estimates of all model parameters remains by far a challenging task due to the inherent nonlinear dynamics of IRs. For example, Bittencourt et al. [94,128] used friction models to estimate the wear of robot joints, where the displacement, speed, load, and temperature of robot joints, as well as the temperature of the lubricant, have to be simultaneously recorded to determine the parameters of friction models.

In practice, parameter identification methods are more commonly used in residual generation in combination with other model-based methods than in isolation. For example, many studies employed parameter identification and state estimation methods to design adaptive observer for residual generation [110,168–171]. Indeed, since some parameters of robot models are time-varying, parameter identification methods are essential for almost all the model-based residual generation methods.

(2) Parity space methods

Parity space-based residual generation methods take advantage of the parity relations of inputs and outputs of the actual systems. Around 1980, the parity space-based residual generation methods were first introduced to linear systems in two forms: direct redundancy and temporal redundancy [172]. The direct redundancy depends on the parity relations among instantaneous inputs and outputs and the temporal redundancy depends on the parity relations among historical inputs and outputs. Based on the linear forms of parity space methods, Leuschen et al. [173,174] developed a nonlinear analytic redundancy method for the residual generation of a planar robot, where the robot model is assumed to be consistent with the actual robot. Further, Halder and Sarkar [117,175] proposed a robust nonlinear analytic redundancy method to minimize the effects of model-plant-mismatch on the generated residuals by solving a nonlinear optimization problem. Their method was verified by experiments on a PUMA 560 robot, where faults were simulated by manually modifying actuator inputs and sensor outputs. Another way to improve the robustness of the generated residuals is to increase the order of parity relations [176,177]. However, the order of parity relations is also limited by some practical issues, such as noise amplification and huge computation burden [113]. It is therefore of primary interest to generate a residual with the lowest possible order of parity relations that is able to detect faults.

Since parity space methods excel at redundancy analysis of sensor outputs, they are usually used to aid other model-based methods for designing residuals. For example, Frank et al. [107,123] employed parity space methods to design state observers for residual generation and applied the generated residual to detect the collision of robots.

(3) State estimation methods

State estimation methods are the most popular residual generation methods in condition monitoring and fault diagnosis of IRs [8,9]. The key idea of state estimation methods is to design observers or filters that reconfigure the inputs and outputs of IRs to generate residuals. Depending on the model used, state estimation methods can be classified into three categories: physical model-based methods, neural network-based methods, and hybrid model-based methods.

Physical model-based state estimation methods commonly used in the residual generation of IRs include direct estimation [178–180], time-delay estimation [8,181], recursive estimation [8,39,182–184], adaptive estimation [110,120,168,169,185–191], Kalman filter [192–194], Luenberger observer [107,195–203], high-gain observer [204], sliding mode observer [115,116,205–218], unknown input observer [115,205,206,218–220], disturbance observer [217], H-infinity based observer [221–223], energy-based observer [9,224], velocity observer [9,225–231], and momentum observer [9,141,170,197,211,223,232–236]. Among the above methods, the momentum observer method has been commercially applied to many collaborative IRs. A detailed comparison of the state estimation methods can be found in refs. [9,237,238]. Due to the difficulty in accurately modelling the inherent nonlinear characteristics of IRs, model-plant-mismatch remains one of the unsolved challenges of physical model-based state estimation methods.

Around 2000, neural networks were introduced into robot modelling, which led to the development of neural network-based state estimation methods. Since then, numerous studies used state estimation methods based on shallow neural networks, such as Hopfield network, radial basis function network, and multi-layer perceptron with one hidden layer, for residual generation of IRs [239–251]. Given the limited capability of shallow networks in learning robot dynamics, many studies developed hybrid model-based state estimation methods for the residual generation of IRs by combining neural networks with physical models [112,252–259]. In recent years, deep learning has revolutionized robotics. Deep neural networks provide better approximations of the nonlinear dynamics of IRs compared to shallow neural networks [148]. Alongside deep learning, reinforcement learning is also gaining momentum in the field of robotics. However, the application of deep learning and reinforcement learning for state estimation-based residual generation of IRs is still in its early stages with only a few relevant studies [14,15]. For example, Sacchi et al. [206] used a state estimation method based on deep reinforcement learning to design residuals for a robot with sensor faults.

3.1.3 Decision making

The process of determining the health status of IRs through residual evaluation is known as decision-making, which involves fault detection, fault isolation, and fault identification. The decision-making methods in condition monitoring and fault diagnosis of IRs can be broadly categorized as threshold-based and learning-based methods.

(1) Threshold-based methods

The basic idea of threshold-based methods is to compare the raw or post-processed residuals with specified thresholds to detect faults of IRs. In general, multiple residuals and associated thresholds are required to achieve fault isolation of IRs [153]. For example, many studies combined multiple residual generators to develop a general diagnostic framework capable of addressing multiple faults of IRs simultaneously [194,197,209,218,221,222,260]. Further, the residuals are affected by model and measurement uncertainties that vary with the operating conditions of IRs. It is therefore a challenging task to determine thresholds for numerous residuals of IRs. To address the above issues, the existing studies on residual evaluation of IRs have tried numerous methods to determine thresholds, including expert knowledge-based methods, statistics-based methods, and fuzzy logic-based methods.

Expert knowledge-based methods are typically used to determine thresholds for the IRs whose dynamics are well-understood. For example, the residual thresholds can be determined using interval estimation methods when the bounds of the model and measurement uncertainties of the robot are known [108,114,191,261]. For the IRs with unknown models and measurement uncertainties, statistics-based methods are commonly used to determine the residual thresholds. In such cases, extensive experiments on the IRs are required to figure out the statistical properties of residuals since model and measurement uncertainties vary with the operating conditions of IRs [8,39,112,171,182]. Among statistics-based methods for determining thresholds of IRs, a commonly used method is to set the threshold as the maximum of the corresponding residual. However, fixed thresholds are too conservative to detect incipient faults. Therefore, many studies introduced fuzzy logic-based methods to adaptively update the threshold according to the operating conditions of IRs [123,231,241,242]. Additionally, proper post-processing of residuals also helps avoid conservative thresholds. For example, in collision detection of IRs, high-pass filtering of residuals is able to weaken the influence of model uncertainties [9,262].

(2) Learning-based methods

Learning-based methods address decision-making as a classification problem. They are capable of learning the features of different faults from the raw residuals of IRs, avoiding the difficulties associated with the post-processing of residuals and determination of numerous thresholds. However, machine learning-based methods also have limitations, such as they typically require a comprehensive fault dataset for training the classifier.

Numerous studies have shown that the traditional learning-based method, such as learning methods based on radial basis function networks, multilayer perceptron, support vector machines and k-nearest neighbours, achieve high accuracy in residual classification of IRs [207,239,240,246,247,249–251,254,263,264]. The primary reason for this success is that the residual generation incorporates extensive expert knowledge of the robot faults, along with preliminary treatment of the model and measurement uncertainties of the robot. This makes the generated residuals sensitive to faults, enabling learning-based methods to effectively extract features of faults from the raw residuals.

Terra and Tinós [246] compared a learning method based on radial basis function networks and a threshold-based method for the actuator fault diagnosis of a robot. Their experimental results demonstrated that the learning method based on radial basis function networks is more robust to perturbations than the threshold-based method. Park et al. [265] used a learning method based on support vector machines and convolutional neural networks to classify momentum residuals of a robot to detect collisions. The results showed that the learning method based on convolutional neural networks outperformed the learning method based on support vector machines when the number of training samples was sufficient. Considering the high cost of collecting robot fault data, Park et al. [266] introduced unsupervised learning for residual classification to reduce the dependence on large amounts of labelled fault data. Additionally, Kim et al. [267] employed a transfer learning method for residual classification to facilitate the sharing of fault data and knowledge across multiple robots.

3.2 Data-driven methods

The data obtained from proprioceptive sensors, event logs from the control system and maintenance logs are typically available for condition monitoring and fault diagnosis of IRs. However, log data and proprioceptive sensor data are obviously insufficient for the condition monitoring and fault diagnosis of all components of IRs. Adding sensors to IRs is therefore a common practice to enhance data acquisition of their components, particularly for the sensorless components. Based on the available data for IRs, three categories of data-driven condition monitoring and fault diagnosis methods have been developed: methods based on log data, methods based on proprioceptive sensor data, and methods based on additional sensor data.

3.2.1 Methods based on log data

Robot log data mainly includes event information such as warnings and alarms from controllers and electronic drives. In practice, robot maintenance experts often begin their troubleshooting with the above log data, leveraging expert knowledge to investigate the causes of faults. They further enrich their expert knowledge based on collected historical log data and maintenance records. Manually refining expert knowledge is time-consuming and labour-intensive, prompting many studies to use techniques like natural language processing to refine knowledge from log data and maintenance records. Knowledge graphs, known for their powerful information organization and association abilities, are particularly favoured for the refinement and management of fault diagnosis knowledge of IRs [268]. For example, Wang et al. [269–271] utilized deep learning methods to extract semantic entities and relationships from log data, maintenance records, and repair manuals of IRs. They constructed a fault diagnosis knowledge graph for the robot fault isolation and maintenance decision-making. Due to the difficulty of fault isolation caused by the rich semantic relations in the knowledge graph, Li et al. [272,273] integrated methods like fuzzy decision-making into the fault diagnosis knowledge graph to analyze the root causes of faults of IRs.

Given the lower sampling frequency of log data compared to proprioceptive sensor data, log data is generally used for fault isolation and cause analysis in fault diagnosis, while proprioceptive sensor data is mainly used for online fault detection. For example, the predictive maintenance system for welding robots developed by Wang et al. [60] first extracts fault characteristics from proprioceptive sensor data to identify the robot's health status. When a fault is detected, the log data is recorded and input into the fault diagnosis knowledge graph for fault isolation, cause analysis, and maintenance decision-making.

3.2.2 Methods based on proprioceptive sensor data

The proprioceptive sensor data can be accessed through the control system of IRs at sampling frequencies ranging from 1 Hz to 7000 Hz [274]. The proprioceptive sensor data of IRs typically includes angular displacements, angular speeds, currents, and torques of electric motors. In recent years, numerous data-driven methods based on proprioceptive sensor data have been developed for condition monitoring and fault diagnosis of IRs.

One of the most intuitive data-driven methods is to directly compare proprioceptive sensor data from normal and faulty IRs. Such methods are generally applicable to IRs that perform repetitive tasks [275]. For example, Izagirre et al. [55] achieved the fault diagnosis of a robot by comparing joint torques under identical motion trajectories. They validated their method on a heavy-duty IR that unexpectedly shut down on a production line. Upon disassembly, it was discovered that the shutdown was due to a significant increase in joint torques caused by a fault in the motor brake. Xiao et al. [276,277] detected the abnormal vibrations or noise of different robot joints by comparing the proprioceptive sensor data from normal and faulty IRs under the same motion trajectory. They also investigated the effect of data sampling frequency on fault detection. Their experiment results show that the classification accuracy of faults in the robot joints remains high even at a sampling frequency of 0.1 Hz. Chen et al. [56,57,63,64,278] collected proprioceptive sensor data from IRs with single and compound faults by replacing faulty motors and speed reducers with normal ones. They demonstrated that faults in electric motors and speed reducers of IRs can be diagnosed using data-driven methods based on deep learning and the proprioceptive sensor data with a sampling frequency of 1 Hz. Yang et al. [72] utilized proprioceptive sensor data from an IR under a single-joint reciprocating motion to identify abnormal vibrations induced by the harmonic reducer in the robot joint. Similarly, Hsu et al. [100] employed proprioceptive sensor data from an IR under a single-joint reciprocating motion to detect the timing belt looseness in the robot joint.

Considering the difference between online operating trajectories and offline test trajectories, Oh et al. [20] implemented fault diagnosis of IRs using transfer learning and proprioceptive sensor data under multiple trajectories for both reciprocating motions of a single-joint and those of multiple joints. Heo et al. [279] used deep learning and proprioceptive sensor data to detect the collision of a robot that executes randomly generated motion trajectories, where the robot is required to repeatedly follow these trajectories. In summary, existing data-driven condition monitoring and fault diagnosis methods necessitate robots repeatedly executing specific motion trajectories. When it comes to a new trajectory, most data-driven algorithms require fine-tuning or even retraining based on the proprioceptive sensor data of the new trajectory.

3.2.3 Methods based on additional sensor data

One of the advantages of data-driven methods based on additional sensor data is that sensors can be customized to the specific faults of IRs. Due to the diversities of faults of IRs, a variety of sensors have potential applications in condition monitoring and fault diagnosis of IRs. Table 2 summarizes the additional sensors that are commonly used in the existing studies of IRs, with most of the references published within the last five years [18,19,21,22,34,44,61,62,65–70,73–76,78–92,95,97–99,102–105,118,185,205,262,280–305]. As shown in Table 2, accelerometers are the most frequently used additional sensors in data acquisition of IRs, followed by current sensors and inertial measurement units (IMUs). The popularity of accelerometers is due to two main reasons: mechanical systems of IRs have many rotating components and accelerometers are widely accepted for condition monitoring and fault diagnosis of rotating machinery [17]. Current sensors are also popular for condition monitoring and fault diagnosis of rotating machinery driven by electric motors [274]. Although the proprioceptive sensors of IRs include current sensors, the stator currents obtained by them are generally not publicly accessible. Therefore, many studies added current sensors to IRs to collect stator currents of electric motors. In the following sections, all current sensors refer to additional current sensors unless otherwise specified. IMUs added to IRs are usually used to estimate motion states of links, such as spatial poses, speeds, and accelerations [2]. With the motion states of links, it is thereby able to evaluate the overall performance of entire systems of IRs, as well as to estimate the motion states of robot joints by solving inverse kinematics problems [136]. In addition to accelerometers, current sensors and IMUs, some studies have employed other sensors, such as cameras, acoustic emission (AE) sensors, microphones, and laser trackers, to estimate the states of IRs. A detailed discussion of applications of the additional sensors in condition monitoring and fault diagnosis of IRs is given in the sequel.

(1) Accelerometers

As shown in Table 2, accelerometers are the most used additional sensors in condition monitoring and fault diagnosis of IRs. They are typically mounted on the robot joints and links to acquire vibration data of the rotating components at sampling frequencies greater than 1 kHz.

Numerous studies have employed the vibration data obtained by accelerometers to diagnose faults in mechanical power transmission components of IRs. For example, Nentwich et al. [88,281,283] mounted accelerometers on IRs to collect the full life cycle data under accelerated wear. They analyzed the effects of temperature and mounting position on the vibration data obtained by accelerometers and verified the feasibility of using vibration data to diagnose faults of gearboxes in the robot joints. He et al. [18,67–69] fixed an accelerometer on each link of a 6-degrees-of-freedom (DOF) IR to collect vibration data and used deep learning methods to diagnose artificial faults of harmonic reducers at different operating speeds of the robot joints. Yang et al. [22,73,74,282] orthogonally mounted three unidirectional accelerometers at the end-effector of a 6-DOF IR and achieved abnormal vibration detection of harmonic reducers

Table 2 Additional sensors commonly used in IRs

Sensors	Advantages	Disadvantages	References
Accelerometer	• Sensitive to faults of rotary machine	• Trajectory dependent • Placement dependent	[18,19,21,22,61,67–69,73–76,78,81–83,85–88,91,98,99,102–104,262,280–290]
Current sensor	• Low cost • Easy to install • Sensitive to faults of electric motors, electronic drives, proprioceptive current sensors, and power cables	• Trajectory dependent • Friction dependent	[44,62,65,70,78,87,99,102,105,291–293]
IMU	• Sensitive to faults of rotary machine • Able to track the pose of IRs	• Calibration required for pose tracking • Prone to drift	[79,80,84,89,90,92,95,185,294,295]
Camera	• Images are intuitive and interpretable	• Light dependent • Calibration required for pose tracking	[34,66,118,205,296–301]
AE sensor	• Sensitive to incipient faults of machinery	• High cost • Placement dependent • Extremely high sampling frequency	[97,102,302,303]
Microphone	• Large measurement range	• Sensitive to noise • Trajectory dependent	[19,304]
Laser tracker	• High-accuracy pose measurement of IRs	• Extremely high cost • Stringent measurement conditions required	[305]

in three joints close to the end-effect. Pu et al. [76,81,85,86] mounted an accelerometer on a link of a 6-DOF IR and used deep learning methods to detect artificial faults of an RV reducer connected to the link. Note that although the above studies using accelerometers for fault diagnosis of IRs achieve high accuracy close to 100%, most of them require the robot to follow specific motion trajectories [20].

Considering the effect of time-varying operating conditions on the vibration response of IRs, Kim et al. [98] used the joint velocities obtained by proprioceptive sensors to split the vibration data obtained by accelerometers. Further, they analyzed the spectral characteristics of the vibration data under the uniform motion of the robot joint to diagnose the faults of the RV reducer. Qiao et al. [78] combined accelerometers and current sensors to synchronously collect vibrations and stator currents in a robot joint. They achieved fault diagnosis of RV reducers at time-varying speeds and loads using nonlinear response spectrum analysis of current and vibration data. In addition to fault diagnosis of speed reducers, vibration signals from accelerometers had also been applied to fault diagnosis of electric motors [61], timing belts [75], and bolts [104,284], as well as collision detection of links [262,285].

(2) Current sensors

The primary advantage of adding current sensors to IRs is the ease of installation. Most Hall current sensors allow the power cable of the robot to pass through for measuring the stator currents of electric motors. This enables the use of current data obtained by current sensors to diagnose faults of power cables [44]. The stator currents measured through the power cable serve as both the output of the electronic drive and the input to the electric motor, making them useful for diagnosing faults of electronic drives [54,306,307] and electric motors [62,291]. Furthermore, additional current sensors provide hardware redundancy with the proprioceptive current sensors within the electronic drive and can be used for fault diagnosis of sensors. In fact, faults of proprioceptive current sensors can also be identified by current signature analysis even without hardware redundancy since the three-phase stator windings of an electric motor are typically symmetrical [306,307].

Due to the compact structure of IRs, the torsional characteristics of the speed reducers also affect the dynamic response of the electric motors. Consequently, the stator current data of the motor are often used to diagnose faults of speed reducers in the robot joints [293]. For example, Liu et al. [77] developed a dynamic model of IRs to analyze the effects of faults and nonlinear behaviors of RV reducers on motor performance. They further demonstrated the feasibility of using motor currents or torques for long-term health monitoring of RV reducers in robot joints. Additionally, many data-driven methods have employed motor currents obtained by additional current sensors to diagnose faults of harmonic reducers and RV reducers [70]. Since motor current reflects the health state of speed reducers primarily through torsional characteristics, this method is insensitive to partial faults of speed reducers and susceptible to frictional perturbations. Therefore, some studies have proposed fault diagnosis methods that integrate multiple sources of data, such as current, vibration, and acoustic emission, to identify the health status of speed reducers in robot joints [78,102]. In fact, in a robot joint, the dynamic response of the motor is affected by many factors other than faults of speed reducers, such as loose bolts and lubricant leakage. For example, Xu et al. [105] verified the feasibility of using motor currents obtained by additional current sensors to identify bolt loosening of a robot joint.

(3) IMUs

In condition monitoring and fault diagnosis of IRs, IMUs that consist of accelerometers, gyroscopes, and magnetometers are generally fixed to the robot links to acquire their linear acceleration, angular velocity, and orientation at a sampling frequency of less than 1 kHz [308]. Given that the robot links are driven by robot joints, the fault diagnosis of components in robot joints can be performed using the motion data of links. For example, many studies mounted IMUs on the robot links to collect their motion data and utilized the link motion data to diagnose faults of the RV reducer connected to the link [79,80,84,89,90,92]. These studies employed deep learning methods to extract fault features of RV reducers from the link motion data where the robot is required to follow specific motion trajectories.

In addition to fault diagnosis of components, IMUs are also common in collision detection and system performance evaluation of IRs. For example, Birjandi et al. [294] mounted an IMU at the end-effector of a 6-DOF robot and performed collision detection of links by fusing data obtained from the IMU and proprioceptive sensors. In their work, the precise calibration of the position of the IMU relative to the robot link is required to accurately estimate the collision force. Similarly, the calibration of IMUs is also crucial for estimating the end-effector positioning errors of IRs [295,309,310].

(4) Cameras

Cameras are common in visual-servoing applications and environmental monitoring of IRs. There are two configurations of IRs and cameras, namely the eye-in-hand configuration and the eye-to-hand configuration [2]. The camera-based condition monitoring and fault diagnosis of IRs usually performed in the eye-to-hand configuration where cameras are fixed in the robot workspace to capture the image of IRs and their surroundings. For example, Peng and Chen [298] utilized images captured by cameras fixed in the workspace of IRs to estimate their actual positions and compare the actual positions with the desired/commended ones to detect malfunctions of the robot. At the same time, the images captured by cameras can also be used to detect anomalies of other objects in the robot workspace [296,311]. In addition to 2D images, depth cameras, such as structured light cameras, are able to produce depth data that can be used to estimate distance between two entities in 3D space. Typical applications of depth cameras in condition monitoring and fault diagnosis of IRs include collision detection [312], positioning error evaluation [118,297,299–301], and fault diagnosis of actuators and sensors [205]. Note that the calibration of cameras is required for almost all applications, especially for the positioning error evaluation of high-accuracy IRs.

(5) AE sensors

Thanks to the ability to detect transient elastic stress waves generated by the deformation of materials, AE sensors are more sensitive to incipient faults of machinery compared to accelerometers, current sensors, IMUs, and cameras [49]. In the condition monitoring and fault diagnosis of IRs, AE sensors are typically used to detect faults of bearings and speed reducers [97,102,302,303]. The frequency of acoustic emissions produced by speed reducers in IRs can reach hundreds of kilohertz, necessitating a high sample frequency for AE sensors and resulting in a significant computational burden for signal processing.

(6) Microphones

In the manual maintenance of IRs, experienced engineers identify the health status of speed reducers by listening to the sounds they make during operation. Inspired by this practice, some studies used microphones to collect sounds produced by IRs for condition monitoring and fault diagnosis. For example, Qiao et al. [19] used a microphone and an accelerometer to diagnose the faults of an RV reducer in single joint robot, where the microphone was fixed near the RV reducer and the accelerometer was fixed on the RV reducer. They discovered that combining sound and vibration data for fault diagnosis of RV reducers yields better results than using either data source alone. Yun et al. [304] attached microphones to the links of a six-DOF IR to identify abnormal noises caused by overloading. In their experiment setup, the microphones were securely fixed to the link surfaces to minimize external sound interference. Similar to accelerometers, the condition monitoring and fault diagnosis of IRs using microphones generally require the robot to respectively execute specific trajectories.

(7) Other sensors

In addition to the six commonly used sensors mentioned above, other types of sensors such as temperature sensors and voltage sensors have also been used in condition monitoring and fault diagnosis of IRs. For example, Sabry et al. [313] added voltage and current sensors to a robot's electronic drive to monitor power consumption, which in turn was used to diagnose the actuator and sensor faults of the robot. Temperature sensors were usually used to help monitor the wear of speed reducers of IRs [94,128].

Although there are abundant sensors available for condition monitoring and fault diagnosis of IRs, sensors capable of accurately measuring the pose of the robot end-effector online are scarce. The commonly used sensors for the pose measurement of IRs include laser trackers, draw-line encoders, IMUs, and cameras. While laser trackers and draw-line encoders offer high-accuracy pose measurement, their stringent measurement conditions and high costs make them impractical for online pose measurement of most IRs in real-production lines [314]. IMUs and cameras are not as accurate as laser trackers and draw-line encoders for position measurement, but they are cost-effective. Applications of IMUs and cameras in online pose measurement of IRs are also challenging due to their inherent drawbacks, such as drift of IMUs, and the light-dependency of cameras.

3.3 Practical examples

This subsection presents some practical examples to briefly demonstrate the implementation of model-based and data-driven methods for condition monitoring and fault diagnosis of IRs. In the demonstration of the model-based methods, the dynamic model of IRs is first introduced followed by the implementation of parameter identification methods, parity space methods, and state estimation methods. The demonstration of data-driven methods is organized into two parts: (1) data acquisition and (2) data analysis.

3.3.1 Model-based methods

In general, the dynamic models of a *n*-degrees-of-freedom robot can be written as a set of second-order differential equations of the form [274]:

$$\mathbf{M}(\mathbf{q},\mathbf{p})\ddot{\mathbf{q}}+\mathbf{C}(\mathbf{q},\dot{\mathbf{q}},\mathbf{p})\dot{\mathbf{q}}+\mathbf{g}(\mathbf{q},\mathbf{p})+\mathbf{f}(\mathbf{q},\dot{\mathbf{q}},\mathbf{p})=\boldsymbol{\tau}, \tag{1}$$

where $\mathbf{q}, \dot{\mathbf{q}}, \ddot{\mathbf{q}} \in \mathbb{R}^n$ are generalized position, velocity, and acceleration vectors, respectively. $\mathbf{p}$ is a vector of model parameters that collects geometric parameters, inertial parameters, friction parameters, and so on. $\boldsymbol{\tau} \in \mathbb{R}^n$ is a vector of applied forces. $\mathbf{M}(\mathbf{q},\mathbf{p}) \in \mathbb{R}^{n\times n}$ is a symmetric and positive-defined matrix of inertia terms. $\mathbf{C}(\mathbf{q},\dot{\mathbf{q}},\mathbf{p})\dot{\mathbf{q}}$ is a vector of the Coriolis and centrifugal force terms with $\mathbf{C} \in \mathbb{R}^{n\times n}$ and $\dot{\mathbf{M}} = \mathbf{C}+\mathbf{C}^{\mathrm{T}}$. $\mathbf{g}(\mathbf{q},\mathbf{p}) \in \mathbb{R}^n$ is a vector of gravitational terms. $\mathbf{f}(\mathbf{q},\dot{\mathbf{q}},\mathbf{p}) \in \mathbb{R}^n$ is a vector of force terms that account for any other forces acting on the system other than those in $\boldsymbol{\tau}$ (e.g., friction forces, disturbances generated by speed reducers and electric actuators). It is well-known that $\mathbf{f}(\mathbf{q},\dot{\mathbf{q}},\mathbf{p})$ is typically challenging to model accurately. Therefore, implementing model-based methods requires extensive attention to address the modelling errors associated with $\mathbf{f}(\mathbf{q},\dot{\mathbf{q}},\mathbf{p})$.

In most IRs, $\mathbf{q}$ and $\boldsymbol{\tau}$ are measurable. $\dot{\mathbf{q}}$ and $\ddot{\mathbf{q}}$ can be obtained by numerically differentiating the measured $\mathbf{q}$ once and twice. Note that special attentions are always required to address the noise in $\ddot{\mathbf{q}}$ and $\boldsymbol{\tau}$.

(1) Parameter identification methods

Combining the robot dynamic equations of K samples yields a set of nonlinear equations of $\mathbf{p}$. The estimates of model parameters are then obtained by solving the nonlinear equations of $\mathbf{p}$. Such a process is known as the parameter identification. Define a simple residual based on parameter identification as

$$\mathbf{r}_{\mathrm{PI}} = \left|\hat{\mathbf{p}} - \mathbf{p}_0\right|, \tag{2}$$

where $\mathbf{p}_0$ and $\hat{\mathbf{p}}$ are the nominal values and current estimates of model parameters, respectively.

In the fault-free case, $\mathbf{r}_{\mathrm{PI}}$ is expected to be zero. However, the unmodelled dynamics and measurement uncertainties of real IRs always make $\mathbf{r}_{\mathrm{PI}}$ greater than zero. Therefore, in fault detection of IRs, a lot of experiments are required to determine robust thresholds for each term in $\mathbf{r}_{\mathrm{PI}}$. Further, the fault isolation and fault identification of IRs are also possible by examining each term in $\mathbf{r}_{\mathrm{PI}}$. A detailed illustration of parameter identification-based fault diagnosis methods can be found in ref. [106] and a review of parameter identification methods can be found in ref. [167].

(2) Parity space methods

Parity space methods rely on past measurement and input data from the actual system, making them primarily applicable to discrete-time dynamic systems. Additionally, determining the parity vector in these methods requires the state space equations of the actual system. Define the state variables of the robot as

$$\mathbf{x} = \begin{bmatrix} \mathbf{q} \\ \dot{\mathbf{q}} \end{bmatrix}. \tag{3}$$

The state space equations of the dynamic model of a n-degrees-of-freedom robot are given by

$$\dot{\mathbf{x}} = \mathbf{A}_{\mathrm{c}}\mathbf{x} + \mathbf{B}_{\mathrm{c}}\boldsymbol{\tau} + \mathbf{h}_{\mathrm{c}} + \boldsymbol{\eta}_{\mathrm{c}} \tag{4}$$

with

$$\mathbf{A}_{\mathrm{c}} = \begin{bmatrix} 0_{n\times n} & 1_{n\times n} \\ 0_{n\times n} & 0_{n\times n} \end{bmatrix}, \mathbf{B}_{\mathrm{c}} = \begin{bmatrix} 0_{n\times n} \\ \mathbf{M}^{-1}(\mathbf{x}, \hat{\mathbf{p}}) \end{bmatrix},$$

$$\mathbf{h}_{\mathrm{c}} = \begin{bmatrix} 0_{n\times n} \\ \mathbf{M}(\mathbf{x}, \hat{\mathbf{p}})^{-1}\mathbf{N}(\mathbf{x}, \hat{\mathbf{p}}) \end{bmatrix}, \mathbf{N}(\mathbf{x}, \hat{\mathbf{p}}) = \mathbf{C}(\mathbf{x}, \hat{\mathbf{p}})\dot{\mathbf{q}} + \mathbf{g}(\mathbf{x}, \hat{\mathbf{p}}) + \mathbf{f}(\mathbf{x}, \hat{\mathbf{p}}).$$

In eq. (4), $\boldsymbol{\eta}_{\mathrm{c}} \in \mathbb{R}^{2n}$ denotes the modelling uncertainties. According to the first order forward Euler's method, the discrete-time form of eq. (4) with a fixed time step T can be written as

$$\mathbf{x}(k+1) = \mathbf{A}\mathbf{x}(k) + \mathbf{B}(k)\boldsymbol{\tau}(k) + \mathbf{h}(k) + \boldsymbol{\eta}(k) \tag{5}$$

with

$$\mathbf{A} = \begin{bmatrix} 1_{n\times n} & T1_{n\times n} \\ 0_{n\times n} & 1_{n\times n} \end{bmatrix}, \mathbf{B}(k) = \begin{bmatrix} 0_{n\times n} \\ T\mathbf{M}^{-1}(\mathbf{x}(k), \hat{\mathbf{p}}) \end{bmatrix},$$

$$\mathbf{h}(k) = \begin{bmatrix} 0_{n\times n} \\ T\mathbf{M}^{-1}(\mathbf{x}(k), \hat{\mathbf{p}})\mathbf{N}(\mathbf{x}(k), \hat{\mathbf{p}}) \end{bmatrix}, \boldsymbol{\eta}(k) = T\boldsymbol{\eta}_{\mathrm{c}}(k) + \boldsymbol{\rho}(k),$$

where $\boldsymbol{\rho}(k)$ represents the discretization errors due to the truncation of the series.

Introducing the actuator faults and sensor faults into the robot dynamics yields

$$\begin{aligned}\bar{\mathbf{x}}(k+1) = {} & \mathbf{A}\bar{\mathbf{x}}(k) + \mathbf{B}(k)\left(\bar{\boldsymbol{\tau}}(k) + \mathbf{f}_{\mathrm{a}}(k)\right) \\ & + \mathbf{h}(k) + \boldsymbol{\eta}(k) + \mathbf{f}_{\mathrm{s}}(k),\end{aligned} \tag{6}$$

where $\bar{\mathbf{x}}(k)$ and $\bar{\boldsymbol{\tau}}(k)$ are the actual values of $\mathbf{x}(k)$ and $\boldsymbol{\tau}(k)$ of faulty robots, respectively. $\mathbf{f}_{\mathrm{a}}(k) \in \mathbb{R}^{2n}$ and $\mathbf{f}_{\mathrm{s}}(k) \in \mathbb{R}^{2n}$ are vectors account for the effects of actuator faults and sensor faults on the robot dynamics.

Combining eq. (6) of K samples yields

$$\bar{\mathbf{x}}_{\mathrm{K}} = \mathbf{A}_{\mathrm{K}}\bar{\mathbf{x}}(1) + \mathbf{B}_{\mathrm{K}}\left(\bar{\boldsymbol{\tau}}_{\mathrm{K}} + \mathbf{f}_{\mathrm{a,K}}\right) + \mathbf{C}_{\mathrm{K}}\left(\mathbf{h}_{\mathrm{K}} + \boldsymbol{\eta}_{\mathrm{K}} + \mathbf{f}_{\mathrm{s,K}}\right) \tag{7}$$

with

$$\bar{\mathbf{x}}_{\mathrm{K}} = \begin{bmatrix} \bar{\mathbf{x}}(2) \\ \bar{\mathbf{x}}(3) \\ \vdots \\ \bar{\mathbf{x}}(K) \end{bmatrix}, \bar{\boldsymbol{\tau}}_{\mathrm{K}} = \begin{bmatrix} \bar{\boldsymbol{\tau}}(1) \\ \bar{\boldsymbol{\tau}}(2) \\ \vdots \\ \bar{\boldsymbol{\tau}}(K-1) \end{bmatrix},$$

$$\mathbf{f}_{\mathrm{a,K}} = \begin{bmatrix} \mathbf{f}_{\mathrm{a}}(1) \\ \mathbf{f}_{\mathrm{a}}(2) \\ \vdots \\ \mathbf{f}_{\mathrm{a}}(K-1) \end{bmatrix}, \mathbf{h}_{\mathrm{K}} = \begin{bmatrix} \mathbf{h}(1) \\ \mathbf{h}(2) \\ \vdots \\ \mathbf{h}(K-1) \end{bmatrix},$$

$$\mathbf{f}_{\mathrm{s,K}} = \begin{bmatrix} \mathbf{f}_{\mathrm{s}}(1) \\ \mathbf{f}_{\mathrm{s}}(2) \\ \vdots \\ \mathbf{f}_{\mathrm{s}}(K-1) \end{bmatrix}, \boldsymbol{\eta} = \begin{bmatrix} \boldsymbol{\eta}(1) \\ \boldsymbol{\eta}(2) \\ \vdots \\ \boldsymbol{\eta}(K-1) \end{bmatrix},$$

$$\mathbf{A}_{\mathrm{K}} = \begin{bmatrix} \mathbf{A} \\ \mathbf{A}^2 \\ \vdots \\ \mathbf{A}^{K-1} \end{bmatrix}, \mathbf{C}_{\mathrm{K}} = \begin{bmatrix} 1_{2n\times n} & 0_{2n\times n} & \cdots & 0_{2n\times n} \\ \mathbf{A} & 1_{2n\times n} & \cdots & 0_{2n\times n} \\ \vdots & \vdots & \ddots & \vdots \\ \mathbf{A}^{K-2} & \mathbf{A}^{K-3} & \cdots & 1_{2n\times n} \end{bmatrix},$$

$$\mathbf{B}_{\mathrm{K}} = \begin{bmatrix} \mathbf{B}(1) & 0_{2n\times n} & \cdots & 0_{2n\times n} \\ \mathbf{A}\mathbf{B}(1) & \mathbf{B}(2) & \cdots & 0_{2n\times n} \\ \vdots & \vdots & \ddots & \vdots \\ \mathbf{A}^{K-2}\mathbf{B}(1) & \mathbf{A}^{K-3}\mathbf{B}(2) & \cdots & \mathbf{B}(K-1) \end{bmatrix}.$$

Define the residual as

$$\begin{aligned}\mathbf{r}_{\mathrm{PS}} &= \mathbf{V}\left(\bar{\mathbf{x}}_{\mathrm{K}} - \mathbf{A}_{\mathrm{K}}\bar{\mathbf{x}}(1) - \mathbf{B}_{\mathrm{K}}\bar{\boldsymbol{\tau}}_{\mathrm{K}} - \mathbf{C}_{\mathrm{K}}\mathbf{h}_{\mathrm{K}}\right) \\ &= \mathbf{V}\left(\mathbf{B}_{\mathrm{K}}\mathbf{f}_{\mathrm{a,K}} + \mathbf{C}_{\mathrm{K}}\boldsymbol{\eta}_{\mathrm{K}} + \mathbf{C}_{\mathrm{K}}\mathbf{f}_{\mathrm{s,K}}\right)\end{aligned} \tag{8}$$

with

$$\mathbf{r}_{\mathrm{PS}} = \begin{bmatrix} r_{\mathrm{PS},1} \\ r_{\mathrm{PS},2} \\ \vdots \\ r_{\mathrm{PS},s} \end{bmatrix}, \mathbf{V} = \begin{bmatrix} \mathbf{v}_1^{\mathrm{T}} \\ \mathbf{v}_2^{\mathrm{T}} \\ \vdots \\ \mathbf{v}_s^{\mathrm{T}} \end{bmatrix},$$

where $\mathbf{v}_i \in \mathbb{R}^{2n(K-1)} (i = 1, 2, \cdots, s)$ is known as the parity vector.

In the actuator fault diagnosis, $\mathbf{v}_i$ is expected to satisfy

$$\mathbf{v}_i\mathbf{B}_{\mathrm{K}} \neq 0,\ \mathbf{v}_i\mathbf{C}_{\mathrm{K}} = 0. \tag{9}$$

In practice, it is impossible to find $\mathbf{v}_i$ that always satisfies eq. (9). The above desired property can be weakened to the following statement: finding a set of vector $\mathbf{v}_i$, such that $\|\mathbf{v}_i\mathbf{B}_{\mathrm{K}}\|$ is far more than $\|\mathbf{v}_i\mathbf{C}_{\mathrm{K}}\|$. Such a statement means that the residual is much more sensitive to actuator faults than to modelling errors and sensor faults.

In the sensor fault diagnosis, $\mathbf{v}_i$ is expected to satisfy

$$\mathbf{v}_i\mathbf{B}_{\mathrm{K}} = 0,\ \mathbf{v}_i\mathbf{C}_{\mathrm{K}} \neq 0,\ \mathbf{v}_i\mathbf{C}_{\mathrm{K}}\boldsymbol{\eta}_{\mathrm{K}} = 0. \tag{10}$$

Similarly, the above desired property can also be weakened to the following statement: finding a set of vector $\mathbf{v}_i$, such that $\|\mathbf{v}_i\mathbf{C}_{\mathrm{K}}\|$ is far more than $\|\mathbf{v}_i\mathbf{B}_{\mathrm{K}}\|$ and $\|\mathbf{v}_i\mathbf{C}_{\mathrm{K}}\boldsymbol{\eta}_{\mathrm{K}}\|$. Readers who are interested in the implementation of other forms of parity space methods are suggested to refer to refs. [117,315].

(3) State estimation methods

The design of state observers is key to the implementation of state estimation-based fault diagnosis methods. According to ref. [8], the general structure of state observer for the robot dynamics given in eq. (6) can be written as

$$\begin{aligned}\hat{\mathbf{x}}(k+1) = {} & \mathbf{A}\hat{\mathbf{x}}(k) + \mathbf{B}(k)\bar{\boldsymbol{\tau}}(k) + \mathbf{h}(k) \\ & + \hat{\boldsymbol{\eta}}(k) + \mathbf{K}_{\mathrm{o}}\mathbf{e}(k)\end{aligned} \tag{11}$$

with

$$\mathbf{e}(k) = \bar{\mathbf{x}}(k) - \hat{\mathbf{x}}(k),\ \mathbf{K}_{\mathrm{o}} = \begin{bmatrix} \mathbf{K}_1 & T1_{n\times n} \\ 0_{n\times n} & \mathbf{K}_2 \end{bmatrix},$$

where $\mathbf{K}_1 \in \mathbb{R}^{n\times n}$ and $\mathbf{K}_2 \in \mathbb{R}^{n\times n}$ are positive definite diagonal matrices and are also called the gain matrices.

In eq. (11), $\hat{\mathbf{x}}(k)$ is the estimate of state variable $\mathbf{x}(k)$ and $\hat{\boldsymbol{\eta}}(k)$ is the estimate of modelling error $\boldsymbol{\eta}(k)$. The recursive equations for $\mathbf{e}(k)$ is given by

$$\begin{aligned}\mathbf{e}(k+1) &= \bar{\mathbf{x}}(k+1) - \hat{\mathbf{x}}(k+1) \\ &= \mathbf{F}_{\mathrm{o}}\mathbf{e}(k) + \tilde{\boldsymbol{\eta}}(k) + \mathbf{B}(k)\mathbf{f}_{\mathrm{a}}(k) + \mathbf{f}_{\mathrm{s}}(k),\end{aligned} \tag{12}$$

where $\tilde{\boldsymbol{\eta}}(k) = \boldsymbol{\eta}(k) - \hat{\boldsymbol{\eta}}(k)$ and $\mathbf{F}_{\mathrm{o}} = \mathbf{A} - \mathbf{K}_{\mathrm{o}}$.

Define a residual as

$$\begin{aligned}r_{\mathrm{SO}}(k+1) &= \mathbf{e}(k+1) - \mathbf{F}_{\mathrm{o}}\mathbf{e}(k) \\ &= \tilde{\boldsymbol{\eta}}(k) + \mathbf{B}(k)\mathbf{f}_{\mathrm{a}}(k) + \mathbf{f}_{\mathrm{s}}(k).\end{aligned} \tag{13}$$

It is clear that $r_{\mathrm{SO}}(k+1)$ is affected by the estimation error of the modelling error $\boldsymbol{\eta}(k)$. The typical estimation methods for $\boldsymbol{\eta}(k)$ can be found in refs. [8,238]. Note that regardless of how $\boldsymbol{\eta}(k)$ is estimated, only fault detection can be achieved using $r_{\mathrm{SO}}(k+1)$. A further process of $r_{\mathrm{SO}}(k+1)$ is required to achieve fault isolation and fault identification. Such a limitation can be addressed by combining the state estimation methods and parity space methods, e.g., using the parity space methods to design a transformation matrix for $r_{\mathrm{SO}}(k+1)$. Furthermore, the state observer given in eq. (11) has an inherent limitation: the requirement to calculate the inverse of the inertia matrix $\mathbf{M}(\mathbf{q}, \hat{\mathbf{p}})$. Such a limitation was addressed by Luca and Mattone [234], where they proposed the well-known momentum observer based on the property of robot dynamics $\dot{\mathbf{M}}(\mathbf{q}, \mathbf{p}) = \mathbf{C}(\mathbf{q}, \dot{\mathbf{q}}, \mathbf{p}) + \mathbf{C}^{\mathrm{T}}(\mathbf{q}, \dot{\mathbf{q}}, \mathbf{p})$. Readers are recommended to refer to refs. [9,313] for the details of the implementation of momentum observer and other observers in fault diagnosis of IRs.

In practice, the combination of the above three categories of model-based methods is common in the condition monitoring and fault diagnosis of IRs. The advantages of combing parameter identification methods, parity space methods, and state estimation methods are as follows. (i) Model parameters can be continuously updated using parameter identification methods to account for the time-varying terms in robot dynamics, in particular the force term $\mathbf{f}(\mathbf{q}, \dot{\mathbf{q}}, \mathbf{p})$ in eq. (1); (ii) Parity space methods can be employed to design the state observer-based residuals that are sensitive to faults and robust to disturbances; (iii) Residual generation can be performed online using state estimation methods to ensure a numerically stable and efficient computation.

3.3.2 Data-driven methods

(1) Data acquisition

In this subsection, a six-degrees-of-freedom serial robot is taken as an example to demonstrate the acquisition of log data, proprioceptive sensor data, and additional sensor data. The experiment setup of the robot is presented in Figure 2. All joints of the robot are driven by electric motors equipped with two types of proprioceptive sensors: the high-resolution encoders and the phase current sensors. The proprioceptive encoders and proprioceptive current sensors are used to measure the positions and stator currents of electric motors, respectively. All the proprioceptive sensor data is fed back to the robot control unit to enable close-loop control of electric motors. Meanwhile, the log data is also recorded in the robot control unit. Note that the maximum sample frequency of proprioceptive sensor data is 1000 Hz and the log data is event-triggered data.

In addition to the proprioceptive sensor, two types of additional sensors, accelerometers and current sensors, are added to the robot. As shown in Figure 2, accelerometers are fixed on the robot links to collect vibration data. The additional current sensors are employed to measure the stator currents of electric motors with the power cable of the robot passing through the current sensors. Further, a multi-source data acquisition device is required to collect the additional sensor data at adjustable sample frequencies. The determination of sample frequency of additional sensor data depends

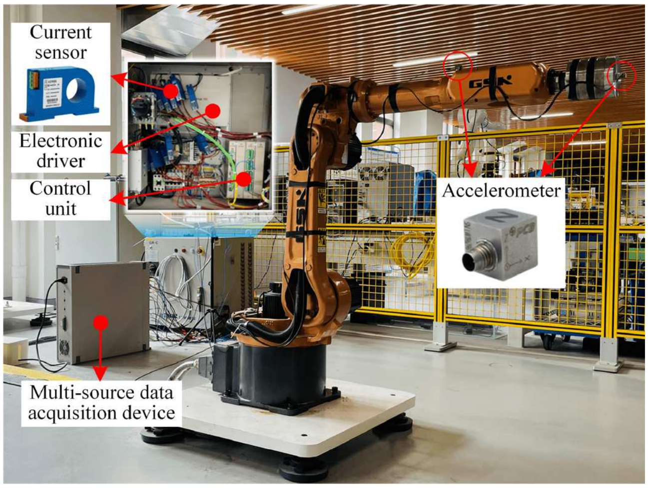

Figure 2 (Color online) Experimental setup of a six-degrees-of-freedom robot for data acquisition.

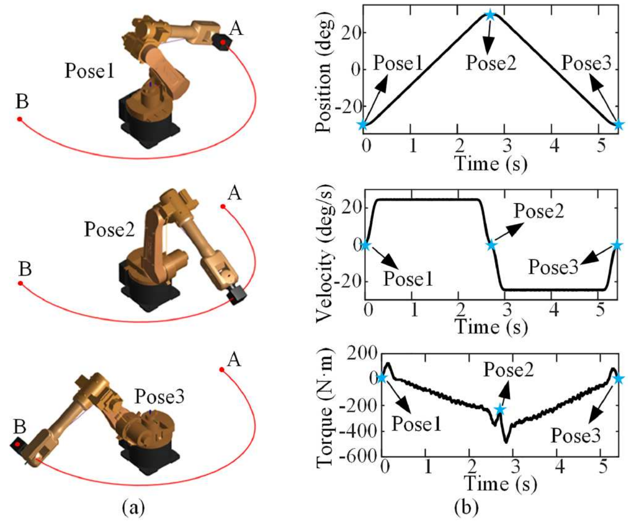

Figure 3 (Color online) Exciting trajectory of a six-degrees-of-freedom robot. (a) The robot end moves back and forth between point A and point B; (b) the output positions, velocities, and torques of joint 2.

on many practical requirements, where the following factors need to be carefully considered: (i) fault excitation bandwidth; (ii) sensor bandwidth; (iii) computation and storage requirements; and (iv) associated costs.

In addition to the sensor selection, the choice of exciting trajectories is also a key issue in the data acquisition of IRs. Different from the traditional rotating machinery, the choice of exciting trajectories of IRs must account for numerous physical constraints, such as the position limits of robot joints. As depicted in Figure 3, these physical constraints necessitate frequent acceleration and deceleration of the robot joints during operation, resulting in significant variations in the joint positions, velocities, and torques. Further, the robot configuration, i.e., the poses of robot joints and links, also varies with the motion of the robot. Note that the time-varying configuration of robots not only has great influences on the joint torques but also alters the pose of additional sensors fixed on the robot links. All the above characteristics of IRs pose a great of challenges to data acquisition and analysis. Consequently, the existing studies on condition monitoring and fault diagnosis of IRs often require IRs to follow specific motion trajectories.

(2) Data analysis

The data analysis of IRs typically involves three main procedures: (i) data pre-processing; (ii) feature extraction; and (iii) fault diagnosis. The key issues in the implantation of these procedures are discussed as follows.

The synchronization of multi-source data, including proprioceptive sensor data, log data, and additional sensor data, is of paramount importance in the data pre-processing of IRs. As displayed in Figure 2, the additional sensor data is collected by a multi-source data acquisition device, while the proprioceptive sensor data and log data are collected by the robot control unit. The synchronization between the robot control unit and the multi-source data acquisition device is therefore required to allow the data acquisition of proprioceptive and additional sensors to begin at the same time. In practice, the robot control unit can be programmed to send a digital trigger signal to the multi-source data acquisition device when data collection begins and stops. Further, parts of the multi-source data can also be synchronized through data analysis [316].

The main challenge in feature extraction of robot data comes from the time-varying operation conditions of IRs. One approach to address this challenge is to extract the stationary data when the robot joint velocity is constant. Once stationary data is obtained, typical signal processing techniques can be employed to extract features in the time domain, frequency domain, and time-frequency domain [17]. Another common approach is using neural networks to extract features from data of IRs with time-varying operation conditions. Note that the features extracted by neural networks lack clear physical interpretation and are usually not generalized across different trajectories of IRs [20]. In other words, when the robot executes a new trajectory, the neural network used for feature extraction needs to be retrained with data from the new trajectory.

The fault diagnosis of IRs consists of three key tasks: fault detection, fault isolation, and fault identification. Generally, fault detection is easy to be achieved through data analysis when the robot follows a specific trajectory. For example, it is able to detect the faults of components in the robot joint by comparing the proprioceptive sensor data obtained from the normal and faulty robots. An example is depicted in Figure 4, where the robot follows the exciting trajectory displayed in Figure 3(a). It is obvious that the joint torques of normal and faulty robots are quite different, where notable periodic fluctuations can be found in the joint torque of the faulty

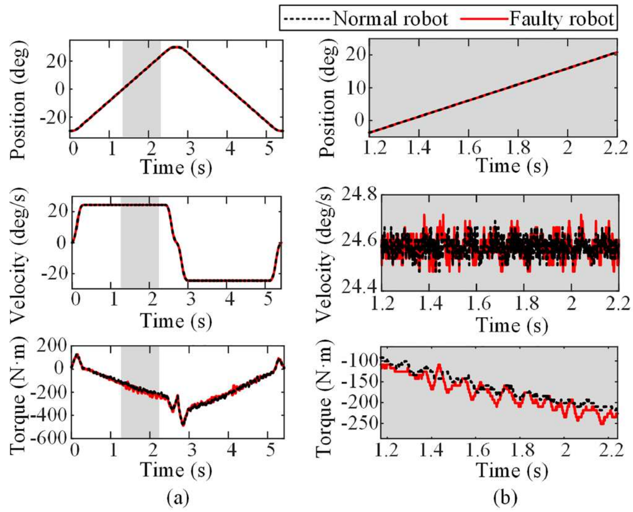

Figure 4 (Color online) Comparison of proprioceptive sensor data obtained from the normal and faulty robots. (a) The output positions, velocities, and torques of joint 2; (b) local view of the output positions, velocities, and torques of joint 2.

robot. The periodic fluctuations are generated by the faults of the RV reducer in joint 2. Therefore, the faults of the RV reducer in joint 2 can be detected by comparing the joint torques of normal and faulty robots.

In the implementation of fault isolation, fusion of multi-source data is generally essential since there are numerous exciting sources in IRs. The fusion approaches of multi-source data can be broadly classified into the following categories: (i) data-level fusion; (ii) feature-level fusion; and (iii) decision-level fusion. The data-level fusion approaches require synchronization and alignment of data streams and are often applied to the sensors that measure the same or complementary phenomena. For example, the fusion of vibration data obtained by multiple accelerometers fixed on the robot links. The feature-level fusion approaches reduce the dimensionality of multi-source data, focusing on key information. For example, the fusion of frequency-domain features of data measured by multiple accelerometers and current sensors. The decision-level fusion approaches allow for the integration of different types of sensors that are not be compatible at the data- and feature-level. In the decision-level fusion strategy, each sensor provides a separate decision or classification. In such cases, all the sensors, including proprioceptive sensors and additional sensors, can be integrated together to achieve THE isolation of multiple faults of IRs.

The fault identification of IRs using data-driven methods remains an open challenge. To address this issue, it is essential to collect extensive sensor data from a wide range of IRs with various levels of faults. Additionally, a comprehensive understanding of the dynamic behaviors of both normal and faulty IRs is also crucial to identifying the relationships between sensor data and specific faults.

4 Challenges and prospects

4.1 Challenges

Based on the survey of existing methods and practical examples presented in the last section, this section examines the challenges related to condition monitoring and fault diagnosis of IRs from five key aspects: complex structures and numerous components, complex dynamics, complex operating conditions, various failure modes, and weak sensing ability.

(1) Complex structures and numerous components

Various types of IRs have emerged in the industry to adapt to different task requirements. Depending on the kinematic structure, IRs can be classified into serial, parallel, and hybrid types. The condition monitoring and fault diagnosis methods of IRs generally need to be customized to the robot structure. For example, the system performance evaluation and fault isolation methods need to be tailored to the robot structure since the source of positioning errors of a robot is related to the robot structure.

Further, even IRs with the same structure can have different components due to differences in workspace and load capacity. For example, light-weight IRs typically use harmonic reducers, while heavy-load IRs mostly use RV reducers. Different components typically have unique dynamic characteristics, requiring individualized condition monitoring and fault diagnosis methods. The diversity in structures and components makes the data acquisition, system modelling, and customization of condition monitoring and fault diagnosis methods costly and labour-intensive. This is evidenced by the scarcity of experimental data on faults of serial IRs, despite the fact that serial IRs have been a primary focus of robot condition monitoring and fault diagnosis for the past 30 years.

(2) Complex dynamics

Speed reducers provide IRs with powerful load capacity and reliable positioning accuracy but also introduce nonlinear characteristics to the robot system, such as contact, collision, flexibility, backlash, and friction. The time-varying excitation caused by the inherent nonlinearity of speed reducers is often coupled with fault excitation, posing significant challenges to the condition monitoring and fault diagnosis of speed reducers. Additionally, the joint structure of IRs is typically compact. Such compact structure makes the nonlinear behaviors of speed reducers affect not only the performance of electric motors but also the system performance of IRs. Since the nonlinear behaviors of speed reducers and the flexibility of robot links are difficult to model accurately, the system performance evaluation of IRs in real-time is therefore challenging. Consequently, a precise pose measurement sensor is essential for accurately estimating the positioning errors of IRs.

(3) Complex operating conditions

The complexity of operating conditions of IRs is mainly reflected in two aspects: the time-varying motion states and complex surroundings. The motion process of IRs involves continuous changes in the spatial configuration of the overall system. Correspondingly, motion states such as joint angular displacement, speed, acceleration, and torque are constantly changing. The time-varying characteristics of these motion states make the robot's dynamic responses complex, presenting obstacles to the extraction of fault features.

Further, the condition monitoring and fault diagnosis of IRs are also affected by their complex surroundings. For example, time-varying temperature and humidity of the environment affect the lubricant properties of speed reducers, electromagnetic radiation affects the performance of electronic components, etc. For IRs that interact with the external environment, they have to comply with the motion constraints and loads imposed by the environment. For example, in robotic grinding applications, motion constraints of the robot end-effector change with the surface morphology of the workpiece, and the reaction force from the workpiece can cause abnormal behaviors of the robot, such as the oscillation of robot links. The variety of internal and external time-varying excitations mentioned above poses significant challenges to the condition monitoring and fault diagnosis of IRs, particularly fault isolation and identification.

(4) Various failure modes

The complexity of failure modes in IRs is mainly influenced by two factors: the compact structure and the diversity of components. Clearly, the more components, the more failure modes of IRs. Table 1 lists about thirty common component faults of IRs documented in existing studies, each of them can be further subdivided into various specific fault types. For example, the sun gear fault of RV reducers includes tooth cracking, tooth pitting, tooth spalling, tooth wear, tooth chipping, tooth profile error, misalignment, etc. [317].

The compact structure of IRs means that each component affects the others during operation. For example, wear and tear of speed reducers due to poor lubrication tend to increase the friction forces and temperature of speed reducers, which subsequently elevates the current and temperature of electric motors. This, in turn, causes the current of electronic drives to rise, ultimately leading to the degradation of multiple components within the robot system. These characteristics of IRs—compact structure and numerous components—result in complex failure modes, making the identification of the root cause of failures and the degradation patterns of the entire system a challenging task.

(5) Weak sensing ability

The cost of IRs is a critical factor in determining the feasibility of implementing robotic automation in manufacturing processes. To maintain cost-effectiveness, IRs often have limited proprioceptive sensors and relatively low data sampling frequencies. This setup results in weak sensing abilities of IRs, leading to the following issues for condition monitoring and fault diagnosis: (i) The number of sensors is much fewer than the components of the robot, making fault localization and quantitative fault evaluation difficult; (ii) Proprioceptive sensors are typically located at the motor end, which means they may not effectively detect faults in other components of the robot; (iii) Data collected at low frequencies may miss high-frequency information crucial for diagnosing certain types of faults; (iv) Performance evaluation of the overall system of IRs, such as the positioning accuracy of the robot end-effector, necessitates an accurate robot model.

Additional sensors can be integrated into IRs to improve their sensing ability, but this introduces further considerations: (i) Careful cost-benefit analyses of adding sensors to IRs for condition monitoring and fault diagnosis are required to justify the potential benefits against added expense; (ii) More sensors make the robot system more complex, where additional sensors introduce additional faults to the entire system; (iii) Using additional sensors to collect intensive data of numerous faults of IRs is essential to understand the intrinsic relationship between faults of IRs and responses of additional sensors; (iv) The scarcity of cost-effective pose measurement sensors that is able to simultaneously offer large measurement ranges, high accuracy, and real-time tracking capability without altering operating conditions of IRs.

4.2 Prospects

Addressing the reliability issues of IRs necessitates advancements across multiple facets of robotics: modelling, sensing, planning, control, prognostics, and health management. This section explores the potential avenues to deal with the current challenges from five aspects: sensing ability, robotic-specific dataset, fault mechanism, multimodal model, and digital twin.

(1) Sensing ability

Enhancing the sensing ability of IRs is an intuitive way to address the challenges related to condition monitoring and fault diagnosis. For existing IRs, adding sensors is the primary approach to improve their sensing ability. The optimal selection of additional sensors is crucial to find a low-cost and reliable solution. Meanwhile, it is important to develop pose measurement sensors with a large measuring range, high accuracy, and high reliability to enable real-time measurement of the pose of IRs. For future IRs, it would be interesting to develop robot components with self-sensing abilities. Such self-sensing components not only simplify the health monitoring of themselves but also facilitate the performance evaluation of the overall system.

(2) Robotic-specific dataset

Data scarcity is a significant challenge in the condition monitoring and fault diagnosis of IRs, high-lighting the need to establish robotic-specific datasets of normal and faulty IRs. Clearly, data collection of real-world IRs that encompass various structures, faults, and operating conditions is a reliable way to establish robotics datasets. Meanwhile, simulations of normal and faulty IRs are also worth investigating to efficiently expand the quantity of robotics datasets, with careful attention to narrow the gap between simulation and reality. Further, a thorough investigation into data cleaning and data labelling is also essential to ensure the quality of the robotics datasets.

(3) Fault mechanism

Fault mechanism analysis of IRs, which aims to explain the causes and manifestation of faults, is essential for addressing issues related to fault diagnosis, fault simulation, and optimal selection of sensors. There is no doubt that extensive experimental data on IRs and their components are required to understand the nonlinear behaviors of IRs. Combining models based on physical laws, statistics, and neural networks remains by far an effective approach to understanding and learning the nonlinear behaviors of IRs, with particular attention to the complex behaviors involving contacts and friction.

(4) Multimodal model

Multimodal models are increasingly popular for processing data from multiple sources. They have the potential to provide a comprehensive understanding of the health status of IRs by integrating diverse types of data, including data from various proprioceptive and additional sensors, as well as logs and manual maintenance records. Further, the development of large multimodal models is particularly promising for diagnosing numerous faults simultaneously in IRs, especially when multiple faults emerge concurrently.

(5) Digital twin

The digital twin of IRs, functioning as a virtual representation of the physical robotic systems, facilitates real-time monitoring and predictive maintenance. Given the diverse degradation patterns and health assessment criteria of IRs across various applications, the development of task-specific digital twin systems shows great potential. By tailoring the digital twin systems to specific tasks, they can deliver reliable and computationally efficient health management services for IRs in actual industry.

5 Concluding remarks

This paper presents a comprehensive review of condition monitoring and fault diagnosis of IRs, highlighting both challenges and achievements in model-based and data-driven methods. Through examination of the existing literature, the paper analyses various failure modes of IRs and the root causes of robot failures. Meanwhile, the data accessible to IRs and the commonly used additional sensors have been explored, with accelerometers being the most popular, followed by current sensors and IMUs. Based on the knowledge of faults of IRs and available data, the paper delves into the current state of model-based and data-driven methods for condition monitoring and fault diagnosis. Further, some open issues are outlined, such as model uncertainties, data scarcity, and dependence on operating conditions. Finally, the paper summarizes the challenges in addressing these open issues and discusses promising pathways for future progress. We hope these insights will inspire readers who are interested in this research field to develop new targeted solutions.

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References

1 Kampa A. The review of reliability factors related to industrial robots. Robot Autom Eng J, 2018, 3: 555624
2 Siciliano B, Khatib O. Springer Handbook of Robotics. Berlin Heidelberg: Springer-Verlag, 2016
3 Zhou Q, Wang Y, Xu J. A summary of health prognostics methods for industrial robots. In: Proceedings of 2019 Prognostics and System Health Management Conference (PHM-Qingdao). IEEE, 2019. 1–6
4 Shi H, Li R, Bai X, et al. A review for control theory and condition monitoring on construction robots. J Field Robotics, 2023, 40: 934–954
5 Park K M, Park F C. Collision Detection for Robot Manipulators: Methods and Algorithms. Cham: Springer, 2023
6 Ding S X. Advanced Methods for Fault Diagnosis and Fault-Tolerant Control. Berlin Heidelberg: Springer-Verlag, 2021
7 Huang S, Tan K K, Er P V, et al. Intelligent Fault Diagnosis and Accommodation Control. Boca Raton: CRC Press, 2020
8 Caccavale F, Villani L. Fault Diagnosis and Fault Tolerance for Mechatronic Systems: Recent Advances. Berlin Heidelberg: Springer-Verlag, 2003
9 Haddadin S, De Luca A, Albu-Schaffer A. Robot collisions: A survey on detection, isolation, and identification. IEEE Trans Robot, 2017, 33: 1292–1312
10 Collins J, Chand S, Vanderkop A, et al. A review of physics simulators for robotic applications. IEEE Access, 2021, 9: 51416–51431
11 Hofer S, Bekris K, Handa A, et al. Sim2Real in robotics and automation: Applications and challenges. IEEE Trans Automat Sci Eng, 2021, 18: 398–400
12 Billard A, Kragic D. Trends and challenges in robot manipulation. Science, 2019, 364: eaat8414
13 Lai R, Dou L. Research progress of industrial robot fault diagnosis based on deep learning. In: Proceedings of 2023 IEEE 9th International Conference on Cloud Computing and Intelligent Systems (CCIS). IEEE, 2023. 126–131
14 Kumar P, Khalid S, Kim H. Prognostics and health management of rotating machinery of industrial robot with deep learning applications—A review. Mathematics, 2023, 11: 3008
15 Quamar M M, Nasir A. Review on fault diagnosis and fault-tolerant control scheme for robotic manipulators: Recent advances in AI, machine learning, and digital twin. arXiv: 2402.02980, 2024

16 Nentwich C E. Automated condition monitoring for industrial robot gears. Dissertation for the Doctoral Degree. Munich: Technical University Munich, 2023
17 Lei Y, Li N, Li X. Big Data-Driven Intelligent Fault Diagnosis and Prognosis for Mechanical Systems. Singapore: Springer, 2023
18 He Y, Zhao C, Zhou X, et al. MJAR: A novel joint generalization-based diagnosis method for industrial robots with compound faults. Robotics Comput-Integrated Manuf, 2024, 86: 102668
19 Qiao Y, Wang H, Cao J, et al. Sound-vibration spectrogram fusion method for diagnosis of RV reducers in industrial robots. Mech Syst Signal Processing, 2024, 214: 111411
20 Oh Y, Kim Y, Na K, et al. A deep transferable motion-adaptive fault detection method for industrial robots using a residual–convolutional neural network. ISA Trans, 2022, 128: 521–534
21 Xia B, Wang K, Xu A, et al. Intelligent fault diagnosis for bearings of industrial robot joints under varying working conditions based on deep adversarial domain adaptation. IEEE Trans Instrum Meas, 2022, 71: 3508313
22 Yang G, Tao H, Du R, et al. Compound fault diagnosis of harmonic drives using deep capsule graph convolutional network. IEEE Trans Ind Electron, 2023, 70: 4186–4195
23 Visinsky M L, Cavallaro J R, Walker I D. Robotic fault detection and fault tolerance: A survey. Reliability Eng Syst Saf, 1994, 46: 139–158
24 Dhillon B S, Fashandi A R M, Liu K L. Robot systems reliability and safety: A review. J Qual Maintenance Eng, 2002, 8: 170–212
25 Pettersson O. Execution monitoring in robotics: A survey. Robotics Autonomous Syst, 2005, 53: 73–88
26 Dhillon B S. Robot System Reliability and Safety: A Modern Approach. Boca Raton: CRC Press, 2015
27 Wang S J. A reprogrammable industrial robot control system. IEEE Trans Syst Man Cybern, 1976, SMC-6: 570–580
28 Brogårdh T. Present and future robot control development—An industrial perspective. Annu Rev Control, 2007, 31: 69–79
29 Tao B, Zhao X W, Ding H. Mobile-robotic machining for large complex components: A review study. Sci China Tech Sci, 2019, 62: 1388–1400
30 Ji W, Wang L. Industrial robotic machining: A review. Int J Adv Manuf Technol, 2019, 103: 1239–1255
31 Wang W, Guo Q, Yang Z, et al. A state-of-the-art review on robotic milling of complex parts with high efficiency and precision. Robotics Comput-Integrated Manuf, 2023, 79: 102436
32 Lemasurier G, Gautam A, Han Z, et al. Reactive or proactive? how robots should explain failures. In: Proceedings of the 2024 ACM/IEEE International Conference on Human-Robot Interaction. ACM, 2024
33 Cao X, Gautam A, Whiting T, et al. Robot proficiency self-assessment using assumption-alignment tracking. IEEE Trans Robot, 2023, 39: 3279–3298
34 Qiao G, Schlenoff C, Weiss B A. Quick positional health assessment for industrial robot prognostics and health management (PHM). In: Proceedings of 2017 IEEE International Conference on Robotics and Automation (ICRA). IEEE, 2017. 1815–1820
35 Dhillon B S, Aleem M A. A report on robot reliability and safety in Canada: A survey of robot users. J Qual Maintenance Eng, 2000, 6: 61–74
36 Lee Y, Tsagarakis N, Ott C, et al. A generalized index for fault-tolerant control in operational space under free-swinging actuation failure. IEEE Robot Autom Lett, 2022, 7: 1486–1493
37 Xie B, Maciejewski A A. Maximizing the probability of task completion for redundant robots experiencing locked joint failures. IEEE Trans Robot, 2022, 38: 616–625
38 Xiao B, Cao L, Xu S, et al. Robust tracking control of robot manipulators with actuator faults and joint velocity measurement uncertainty. IEEE ASME Trans Mechatron, 2020, 25: 1354–1365
39 Caccavale F, Marino A, Muscio G, et al. Discrete-time framework for fault diagnosis in robotic manipulators. IEEE Trans Contr Syst Technol, 2013, 21: 1858–1873
40 Algburi R N A, Gao H, Al-Huda Z. Improvement of an industrial robotic flaw detection system. IEEE Trans Automat Sci Eng, 2022, 19: 3953–3967
41 Algburi R N A, Gao H, Al-Huda Z. A new synergy of singular spectrum analysis with a conscious algorithm to detect faults in industrial robotics. Neural Comput Applic, 2022, 34: 7565–7580
42 Miao Z, Xia Y, Zhou F, et al. Fault diagnosis of wheeled robot based on prior knowledge and spatial-temporal difference graph convolutional network. IEEE Trans Ind Inf, 2023, 19: 7055–7065
43 Guo D, Zhang Y, Chen X. Robot predictive maintenance method based on program-position cycle. In: Liu X, Nie Z, Yu J, et al., eds. Lecture Notes in Artificial Intelligence. Berlin: Springer-Verlag, 2021. 78–88
44 Kim H, Lee H, Kim S W. Current only-based fault diagnosis method for industrial robot control cables. Sensors, 2022, 22: 1917
45 Orlowska-Kowalska T, Wolkiewicz M, Pietrzak P, et al. Fault diagnosis and fault-tolerant control of PMSM drives–State of the art and future challenges. IEEE Access, 2022, 10: 59979–60024
46 Choi S, Haque M S, Tarek M T B, et al. Fault diagnosis techniques for permanent magnet AC machine and drives—A review of vurrent state of the art. IEEE Trans Transp Electrific, 2018, 4: 444–463
47 Oh H, Han B, McCluskey P, et al. Physics-of-failure, condition monitoring, and prognostics of insulated gate bipolar transistor modules: A review. IEEE Trans Power Electron, 2015, 30: 2413–2426
48 Henao H, Capolino G A, Fernandez-Cabanas M, et al. Trends in fault diagnosis for electrical machines: A review of diagnostic techniques. EEE Ind Electron Mag, 2014, 8: 31–42
49 Liu L, Zhi Z, Yang Y, et al. Harmonic reducer fault detection with acoustic emission. IEEE Trans Instrum Meas, 2023, 72: 3522812
50 Metwly M Y, Clark L, Xie B, et al. Robust online diagnosis of inverter open-circuit switching faults for robotic joints with BLDC motors. In: Proceedings of 2024 IEEE Applied Power Electronics Conference and Exposition (APEC). IEEE, 2024. 2308–2313
51 Nguyen V, Marvel J. External load-based sensing of electrical current degradation in industrial robots. In: Proceedings of 2021 IEEE Sensors. IEEE, 2021. 1–4
52 Chen L, Fan D, Zheng J, et al. Functional safety analysis and design of sensors in robot joint drive system. Machines, 2022, 10: 360
53 Wang H, Zhang Z, Long J, et al. Reliability evaluation method for robot servo system based on accelerated degradation test. In: Proceedings of 2019 22nd International Conference on Electrical Machines and Systems (ICEMS). IEEE, 2019. 1–6
54 Li P, Xu X, Yang S, et al. Open circuit fault diagnosis strategy of PMSM drive system based on grey prediction theory for industrial robot. Energy Rep, 2023, 9: 313–320
55 Izagirre U, Andonegui I, Egea A, et al. A methodology and experimental implementation for industrial robot health assessment via torque signature analysis. Appl Sci, 2020, 10: 7883
56 Song J, Chen C, Wang T, et al. Fault diagnosis for industrial robots based on informer. In: Proceedings of 2023 28th International Conference on Automation and Computing (ICAC). IEEE, 2023. 1–6
57 Zhou X, Zeng H, Chen C, et al. An attention-enhanced multi-modal deep learning algorithm for robotic compound fault diagnosis. Meas Sci Technol, 2022, 34: 014007
58 Wu H, Feng J. A review of fault diagnosis methods of robot joint servo system. In: Proceedings of 2020 IEEE International Conference on Mechatronics and Automation (ICMA). IEEE, 2020. 61–66
59 Sathish V, Ramaswamy S, Butail S. Training data selection criteria for detecting failures in industrial robots. IFAC-PapersOnLine, 2016, 49: 385–390
60 Wang X, Liu M, Liu C, et al. Data-driven and Knowledge-based predictive maintenance method for industrial robots for the production stability of intelligent manufacturing. Expert Syst Appl, 2023, 234: 121136

61 Gong T, Wang Z, Ma Q, et al. Motor bearing fault diagnosis in an industrial robot under complex variable speed conditions. J Comput Nonlinear Dyn, 2024, 19: 021007
62 Kumar P, Raouf I, Kim H S. Transfer learning for servomotor bearing fault detection in the industrial robot. Adv Eng Software, 2024, 194: 103672
63 Liu Y, Chen C, Wang T, et al. Model-agnostic meta-learning for fault diagnosis of industrial robots. In: Proceedings of 2023 28th International Conference on Automation and Computing (ICAC). IEEE, 2023. 1–6
64 Chen C, Liu C, Wang T, et al. Compound fault diagnosis for industrial robots based on dual-transformer networks. J Manufacturing Syst, 2023, 66: 163–178
65 Chen C, Wang T, Liu C, et al. Lightweight convolutional transformers enhanced meta-learning for compound fault diagnosis of industrial robot. IEEE Trans Instrum Meas, 2023, 72: 1–12
66 Nentwich C, Reinhart G. Towards data acquisition for predictive maintenance of industrial robots. Procedia CIRP, 2021, 104: 62–67
67 Zhou X, Zhou H C, He Y M, et al. Harmonic reducer in-situ fault diagnosis for industrial robots based on deep learning. Sci China Tech Sci, 2022, 65: 2116–2126
68 Wang Y, He Y, Kang B, et al. ProbSparse attention-based fault diagnosis for industrial robots under different working conditions. IEEE Trans Instrum Meas, 2024, 73: 3514512
69 He Y, Chen J, Zhou X, et al. In-situ fault diagnosis for the harmonic reducer of industrial robots via multi-scale mixed convolutional neural networks. J Manufacturing Syst, 2023, 66: 233–247
70 Rohan A. Deep scattering spectrum germaneness for fault detection and diagnosis for component-level prognostics and health management (PHM). Sensors, 2022, 22: 9064
71 Raviola A, De Martin A, Guida R, et al. Harmonic drive gear failures in industrial robots applications: An overview. PHME_CONF, 2021, 6: 11
72 Yang G, Tao H, Yu T, et al. Online fault diagnosis of harmonic drives using semisupervised contrastive graph generative network via multimodal data. IEEE Trans Ind Electron, 2024, 71: 3055–3063
73 Yang G, Zhong Y, Yang L, et al. Fault detection of harmonic drive using multiscale convolutional neural network. IEEE Trans Instrum Meas, 2021, 70: 3502411
74 Yang G, Zhong Y, Yang L, et al. Fault diagnosis of harmonic drive with imbalanced data Using generative adversarial network. IEEE Trans Instrum Meas, 2021, 70: 3519911
75 Lee I, Park H J, Jang J W, et al. System-level fault diagnosis for an industrial wafer transfer robot with multi-component failure modes. Appl Sci, 2023, 13: 10243
76 Pu Z, Li C, de Oliveira J V. On the effect of loss function in GAN based data augmentation for fault diagnosis of an industrial robot. In: Lyu Z, eds. Applications of Generative AI. Cham: Springer International Publishing, 2024. 309–349
77 Liu H, Emami M R, Lei Y. Model-based health monitoring of rotate-vector reducers in robot manipulators. Mechatronics, 2024, 99: 103162
78 Qiao Y, Wang H, Cao J, et al. Nonlinear spectrum feature fusion diagnosis method for RV reducer of industrial robots. Mech Syst Signal Processing, 2023, 204: 110750
79 Long J, Qin Y, Yang Z, et al. Discriminative feature learning using a multiscale convolutional capsule network from attitude data for fault diagnosis of industrial robots. Mech Syst Signal Processing, 2023, 182: 109569
80 Pu Z, Cabrera D, Bai Y, et al. Generative adversarial one-shot diagnosis of transmission faults for industrial robots. Robotics Comput-Integrated Manuf, 2023, 83: 102577
81 Pu Z, Cabrera D, Li C, et al. Sliced Wasserstein cycle consistency generative adversarial networks for fault data augmentation of an industrial robot. Expert Syst Appl, 2023, 222: 119754
82 Song Z, Shi H, Bai X, et al. Digital twin-assisted fault diagnosis system for robot joints with insufficient data. J Field Robotics, 2023, 40: 258–271
83 Yin T, Lu N, Guo G, et al. Knowledge and data dual-driven transfer network for industrial robot fault diagnosis. Mech Syst Signal Processing, 2023, 182: 109597
84 Pu Z, Cabrera D, Bai Y, et al. A one-class generative adversarial detection framework for multifunctional fault diagnoses. IEEE Trans Ind Electron, 2022, 69: 8411–8419
85 Pu Z. Exploiting GAN as an oversampling method for imbalanced data augmentation with application to the fault diagnosis of an industrial robot. Dissertation for the Doctoral Degree. Faro: University of Algarve, 2022
86 Pu Z, Cabrera D, Li C, et al. VGAN: Generalizing MSE GAN and WGAN-GP for robot fault diagnosis. IEEE Intell Syst, 2022, 37: 65–75
87 Nentwich C, Daub R. Comparison of data sources for robot gear condition monitoring. Procedia CIRP, 2022, 107: 314–319
88 Nentwich C, Reinhart G. A combined anomaly and trend detection system for industrial robot gear condition monitoring. Appl Sci, 2021, 11: 10403
89 Long J, Mou J, Zhang L, et al. Attitude data-based deep hybrid learning architecture for intelligent fault diagnosis of multi-joint industrial robots. J Manufacturing Syst, 2021, 61: 736–745
90 Kong L J, Huang Y W, Yu Q B, et al. Joint feature enhancement mapping and reservoir computing for improving fault diagnosis performance. IOP Conf Ser-Mater Sci Eng, 2021, 1207: 012020
91 Danielson H, von Schmuck B. Robot condition monitoring: A first step in condition monitoring for robotic applications. Dissertation for the Master's Degree. Luleå: University of Technology, 2017
92 Hong Y, Sun Z, Zou X, et al. Multi-joint industrial robot fault identification using deep sparse auto-encoder network with attitude data. In: Proceedings of 2020 Prognostics and Health Management Conference (PHM-Besançon). IEEE, 2020. 176–179
93 Bittencourt A C, Saarinen K, Sander-Tavallaey S. A data-driven method for monitoring systems that operate repetitively-applications to wear monitoring in an industrial robot joint1. IFAC Proc Volumes, 2012, 45: 198–203
94 Bittencourt A C, Axelsson P, Jung Y, et al. Modeling and identification of wear in a robot joint under temperature uncertainties. IFAC Proc Volumes, 2011, 44: 10293–10299
95 Wu Y, Bai Y, Yang S, et al. Extracting random forest features with improved adaptive particle swarm optimization for industrial robot fault diagnosis. Measurement, 2024, 229: 114451
96 Raouf I, Lee H, Kim H S. Mechanical fault detection based on machine learning for robotic RV reducer using electrical current signature analysis: A data-driven approach. J Comput Des Eng, 2022, 9: 417–433
97 Yang J, Liu C, Xu Q, et al. Acoustic emission signal fault diagnosis based on compressed sensing for RV reducer. Sensors, 2022, 22: 2641
98 Kim Y, Park J, Na K, et al. Phase-based time domain averaging (PTDA) for fault detection of a gearbox in an industrial robot using vibration signals. Mech Syst Signal Processing, 2020, 138: 106544
99 Wang S J, Tao J F, Jiang Q C, et al. Manipulator joint fault localization for intelligent flexible manufacturing based on reinforcement learning and robot dynamics. Robotics Comput-Integrated Manuf, 2024, 86: 102684
100 Hsu H K, Ting H Y, Huang M B, et al. Intelligent fault detection, diagnosis and health evaluation for industrial robots. Mechanics, 2021, 27: 70–79
101 Bonci A, Longhi S, Nabissi G, et al. Predictive maintenance system using motor current signal analysis for industrial robot. In: Proceedings of 2019 24th IEEE International Conference on Emerging Technologies and Factory Automation (ETFA). IEEE, 2019. 1453–1456
102 Sun Y, Xu A, Wang K, et al. Intelligent fault diagnosis of industrial robot based on multiclass Mahalanobis-Taguchi system for imbalanced data. Entropy, 2022, 24: 871

103 Jaber A A, Bicker R. Fault diagnosis of industrial robot gears based on discrete wavelet transform and artificial neural network. Insight, 2016, 58: 179–186
104 Wang X, Sun L, Yu K, et al. Research on SCARA robot fault diagnosis based on Hilbert-Huang transform and decision tree. In: Proceedings of 2021 IEEE 9th International Conference on Computer Science and Network Technology (ICCSNT). IEEE, 2021. 115–118
105 Xu K, Wu X, Wang D, et al. Electromechanical coupling modeling and motor current signature analysis of bolt loosening of industrial robot joint. Mech Syst Signal Processing, 2023, 184: 109681
106 Deibert R, Höfling T. Model-based fault diagnosis of industrial robots: A comparison of different methods. IFAC Proceedings Volumes, 1992, 25: 251–255
107 Wünnenberg J, Frank P M. Dynamic model based incipient fault detection concept for robots. IFAC Proceedings Volumes, 1990, 23: 61–66
108 Visinsky M L, Walker I D, Cavallaro J R. New dynamic model-based fault detection thresholds for robot manipulators. In: Proceedings of the 1994 IEEE International Conference on Robotics and Automation. IEEE, 1994. 1388–1395
109 Visinsky M L, Cavallaro J R, Walker I D. A dynamic fault tolerance framework for remote robots. IEEE Trans Robot Automat, 1995, 11: 477–490
110 Ebrahimi S M, Norouzi F, Dastres H, et al. Sensor fault detection and compensation with performance prescription for robotic manipulators. J Franklin Institute, 2024, 361: 106742
111 Yuan J, Liu G, Wu B. Power efficiency estimation-based health monitoring and fault detection of modular and reconfigurable robot. IEEE Trans Ind Electron, 2011, 58: 4880–4887
112 Caccavale F, Cilibrizzi P, Pierri F, et al. Actuators fault diagnosis for robot manipulators with uncertain model. Control Eng Pract, 2009, 17: 146–157
113 Halder B, Sarkar N. Analysis of order of redundancy relation for robust actuator fault detection. Control Eng Pract, 2009, 17: 966–973
114 McIntyre M L, Dixon W E, Dawson D M, et al. Fault identification for robot manipulators. IEEE Trans Robot, 2005, 21: 1028–1034
115 Capisani L M, Ferrara A, Ferreira de Loza A, et al. Manipulator fault diagnosis via higher order sliding-mode observers. IEEE Trans Ind Electron, 2012, 59: 3979–3986
116 Brambilla D, Capisani L M, Ferrara A, et al. Actuators and sensors fault detection for robot manipulators via second order sliding mode observers. In: Proceedings of 2008 International Workshop on Variable Structure Systems. IEEE, 2008. 61–66
117 Halder B, Sarkar N. Robust fault detection of a robotic manipulator. Int J Robotics Res, 2007, 26: 273–285
118 Qiao G, Weiss B A. Industrial robot accuracy degradation monitoring and quick health assessment. J Manuf Sci Eng, 2019, 141: 071006
119 Liu S, Zhou S, Li B, et al. Servo torque fault diagnosis implementation for heavy-legged robots using insufficient information. ISA Trans, 2024, 147: 439–452
120 Ahmad S, Zhang H, Liu G. Distributed fault detection for modular and reconfigurable robots with joint torque sensing: A prediction error based approach. Mechatronics, 2013, 23: 607–616
121 Kim H, Cheong J, Lee S, et al. Task-oriented synchronous error monitoring framework in robotic manufacturing process. In: Proceedings of 2012 IEEE International Conference on Automation Science and Engineering (CASE). IEEE, 2012. 485–490
122 Haddadin S, Albu-Schäffer A, Hirzinger G. Requirements for safe robots: Measurements, analysis and new insights. Int J Robotics Res, 2009, 28: 1507–1527
123 Sneider H, Frank P M. Observer-based supervision and fault detection in robots using nonlinear and fuzzy logic residual evaluation. IEEE Trans Contr Syst Technol, 1996, 4: 274–282
124 Yang X, Li X, Lei Y, et al. Dynamic modeling of gear compound faults and stiffness sensitivity analysis against arbitrary spatial configuration of defect. Mech Syst Signal Processing, 2024, 218: 111564
125 Song W, Yang X, Liu H, et al. A new method for calculating time-varying torsional stiffness of RV reducers with variable loads and tooth modifications. J Field Robotics, 2023, 40: 1339–1345
126 Yang X, Qiang D, Chen Z, et al. Dynamic modeling and digital twin of a harmonic drive based collaborative robot joint. In: Proceedings of 2022 International Conference on Robotics and Automation (ICRA). IEEE, 2022. 4862–4868
127 Vallachira S, Orkisz M, Norrlof M, et al. Data-driven gearbox failure detection in industrial robots. IEEE Trans Ind Inf, 2020, 16: 193–201
128 Bittencourt A C, Axelsson P. Modeling and experiment design for identification of wear in a robot joint under load and temperature uncertainties based on friction data. IEEE ASME Trans Mechatron, 2014, 19: 1694–1706
129 Jiang L L, Tao Y R, Wang J. Remaining useful life prediction for reducer of industrial robots based on MCSA. In: Proceedings of 2021 Global Reliability and Prognostics and Health Management (PHM-Nanjing). IEEE, 2021. 1–7
130 Wu J, Jiang L, Li J, et al. Discovering new prognostic features for the harmonic reducer in remaining useful life prediction. Shock Vib, 2023, 2023: 2381638
131 Lee J H, Cho Y H, Kim D S, et al. Lifetime estimation of harmonic reducer for manufacturing robot using accelerated life test. J Mech Sci Technol, 2022, 36: 2879–2887
132 Nentwich C, Daub R. Cost-benefit analysis of industrial robot gear condition monitoring. Procedia CIRP, 2022, 107: 143–148
133 Korayem M H, Iravani A. Improvement of 3P and 6R mechanical robots reliability and quality applying FMEA and QFD approaches. Robotics Comput-Integrated Manuf, 2008, 24: 472–487
134 Gao Z, Cecati C, Ding S X. A survey of fault diagnosis and fault-tolerant techniques—Part I: Fault diagnosis with model-based and signal-based approaches. IEEE Trans Ind Electron, 2015, 62: 3757–3767
135 Patton R J, Chen J, Nielsen S B. Model-based methods for fault diagnosis: Some guide-lines. Trans Institute Measurement Control, 1995, 17: 73–83
136 Birjandi S A B, Kuhn J, Haddadin S. Joint velocity and acceleration estimation in serial chain rigid body and flexible joint manipulators. In: Proceedings of 2019 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS). IEEE, 2019. 7503–7509
137 Xu X, Sun Y, Tian X, et al. A novel joint angle estimation method for serial manipulator using micro-electromechanical systems sensors. IEEE Trans Ind Electron, 2020, 67: 10610–10620
138 Filaretov V, Zuev A, Procenko A, et al. Fault detection of actuators of robot manipulator by vision system. Appl Mech Mater, 2017, 865: 457–462
139 Featherstone R. Rigid body dynamics algorithms. New York: Springer-Verlag, 2008
140 Park F C, Kim B, Jang C, et al. Geometric algorithms for robot dynamics: A tutorial review. Appl Mech Rev, 2018, 70: 010803
141 Gaz C, Cristofaro A, De Luca A. Detection and isolation of actuator faults and collisions for a flexible robot arm. In: Proceedings of 2020 59th IEEE Conference on Decision and Control (CDC). IEEE, 2020. 2684–2689
142 Liu H, Lei Y, Yang X, et al. Deflection estimation of industrial robots with flexible joints. Fundamental Res, 2022, 2: 447–455
143 Li B, Li X, Gao H, et al. Advances in flexible robotic manipulator systems—Part I: Overview and dynamics modeling methods. IEEE ASME Trans Mechatron, 2024, 29: 1100–1110
144 Wu K, Li J, Zhao H, et al. Review of industrial robot stiffness identification and modelling. Appl Sci, 2022, 12: 8719
145 Erez T, Tassa Y, Todorov E. Simulation tools for model-based robotics: Comparison of Bullet, Havok, MuJoCo, ODE and PhysX. In: Proceedings of 2015 IEEE International Conference on Robotics and Automation (ICRA). IEEE, 2015. 4397–4404
146 Horne B, Jamshidi M, Vadiee N. Neural networks in robotics: A survey. J Intelligent Robotic Syst, 1990, 3: 51–66
147 Lutter M, Ritter C, Peters J. Deep Lagrangian networks: Using physics as model prior for deep learning. In: Proceedings of 7th

International Conference on Learning Representations (ICLR). ICLR, 2019
148 Lutter M, Peters J. Combining physics and deep learning to learn continuous-time dynamics models. Int J Robotics Res, 2023, 42: 83–107
149 Yang X, Du Y, Li L, et al. Physics-informed neural network for model prediction and dynamics parameter identification of collaborative robot joints. IEEE Robot Autom Lett, 2023, 8: 8462–8469
150 Deng W, Ardiani F, Nguyen K T P, et al. Physics informed machine learning model for inverse dynamics in robotic manipulators. Appl Soft Comput, 2024, 163: 111877
151 Lee T, Kwon J, Wensing P M, et al. Robot model identification and learning: A modern perspective. Annu Rev Control Robotics Autonomous Syst, 2024, 7: 311–334
152 Pillonetto G, Aravkin A, Gedon D, et al. Deep networks for system identification: A survey. Automatica, 2025, 171: 111907
153 Frank P M. Fault diagnosis in dynamic systems using analytical and knowledge-based redundancy. Automatica, 1990, 26: 459–474
154 Gautier M, Khalil W. Direct calculation of minimum set of inertial parameters of serial robots. IEEE Trans Robot Automat, 1990, 6: 368–373
155 Poignet P, Gautier M. Comparison of weighted least squares and extended Kalman filtering methods for dynamic identification of robots. In: Proceedings 2000 ICRA. Millennium Conference. IEEE International Conference on Robotics and Automation. Symposia Proceedings (Cat. No. 00CH37065). IEEE, 2000. 4: 3622–3627
156 Gautier M, Poignet P. Extended Kalman filtering and weighted least squares dynamic identification of robot. Control Eng Pract, 2001, 9: 1361–1372
157 Swevers J, Ganseman C, Tukel D B, et al. Optimal robot excitation and identification. IEEE Trans Robot Automat, 1997, 13: 730–740
158 Olsen M M, Swevers J, Verdonck W. Maximum likelihood identification of a dynamic robot model: Implementation issues. Int J Robotics Res, 2002, 21: 89–96
159 Ramdani N, Poignet P. Robust dynamic experimental identification of robots with set membership uncertainty. IEEE ASME Trans Mechatron, 2005, 10: 253–256
160 Reppa V, Tzes A. Fault detection based on orthotopic set membership identification for robot manipulators. IFAC Proc Volumes, 2008, 41: 7344–7349
161 Janot A, Vandanjon P O, Gautier M. A generic instrumental variable approach for industrial robot identification. IEEE Trans Contr Syst Technol, 2014, 22: 132–145
162 Brunot M, Janot A, Young P C, et al. An improved instrumental variable method for industrial robot model identification. Control Eng Pract, 2018, 74: 107–117
163 Mata V, Benimeli F, Farhat N, et al. Dynamic parameter identification in industrial robots considering physical feasibility. Adv Robotics, 2005, 19: 101–119
164 Sousa C D, Cortesão R. Physical feasibility of robot base inertial parameter identification: A linear matrix inequality approach. Int J Robotics Res, 2014, 33: 931–944
165 Wensing P M, Kim S, Slotine J J E. Linear matrix inequalities for physically consistent inertial parameter identification: A statistical perspective on the mass distribution. IEEE Robot Autom Lett, 2018, 3: 60–67
166 Sousa C D, Cortesao R. Inertia tensor properties in robot dynamics identification: A linear matrix inequality approach. IEEE ASME Trans Mechatron, 2019, 24: 406–411
167 Leboutet Q, Roux J, Janot A, et al. Inertial parameteridentification in robotics: A survey. Appl Sci, 2021, 11: 4303
168 Ma H J, Yang G H. Simultaneous fault diagnosis for robot manipulators with actuator and sensor faults. Inf Sci, 2016, 366: 12–30
169 Xia H, Zhao B, Zhou F, et al. Fault tolerant control for reconfigurable manipulators based on adaptive dynamic programming with an improved performance index function. In: Proceedings of 2016 12th World Congress on Intelligent Control and Automation (WCICA). IEEE, 2016. 2273–2278
170 De Luca A, Mattone R. An adapt-and-detect actuator FDI scheme for robot manipulators. In: Proceedings of IEEE International Conference on Robotics and Automation. IEEE, 2004. 4975–4980
171 Caccavale F, Pierri F, Villani L. Adaptive observer for fault diagnosis in nonlinear discrete-time systems. J Dynamic Syst Measurement Control, 2008, 130: 021005
172 Chow E, Willsky A. Analytical redundancy and the design of robust failure detection systems. IEEE Trans Automat Contr, 1984, 29: 603–614
173 Leuschen M L. Derivation and application of nonlinear analytical redundancy techniques with applications to robotics. Dissertation for the Doctoral Degree. Houston: Rice University, 2002
174 Leuschen M L, Cavallaro J R, Walker I D. Robotic fault detection using nonlinear analytical redundancy. In: Proceedings of 2002 IEEE International Conference on Robotics and Automation (Cat. No. 02CH37292). IEEE, 2002. 456–463
175 Halder B, Sarkar N. Robust fault detection of robotic systems: New results and experiments. In: Proceedings of 2006 IEEE International Conference on Robotics and Automation (ICRA). IEEE, 2006. 3795–3800
176 Ding X, Guo L, Jeinsch T. A characterization of parity space and its application to robust fault detection. IEEE Trans Automat Contr, 1999, 44: 337–343
177 Halder B, Sarkar N. Impact of the order of redundancy relation in robust fault detection of robotic systems. In: Proceedings of the 45th IEEE Conference on Decision and Control. IEEE, 2006. 6500–6505
178 Lomakin A, Deutscher J. Algebraic fault detection and identification for rigid robots. In: Proceedings of 2020 IEEE International Conference on Robotics and Automation (ICRA). IEEE, 2020. 9352–9358
179 Yan B, Su H, Ma W. Fault detection and identification for a class of nonlinear systems with model uncertainty. Appl Math Model, 2016, 40: 7368–7381
180 Filaretov V, Zhirabok A, Zuev A, et al. Synthesis method of fault tolerant control system for manipulators. Adv Mater Res, 2013, 717: 551–556
181 Caccavale F, Chiacchio P, Walker I D. A time-delayed observer for fault detection and isolation in industrial robots. Robotica, 2006, 24: 557–565
182 Caccavale F, Marino A, Pierri F. Sensor fault diagnosis for manipulators performing interaction tasks. In: Proceedings of 2010 IEEE International Symposium on Industrial Electronics. IEEE, 2010. 2121–2126
183 Caccavale F. Experiments of observer-based fault detection for an industrial robot. In: Proceedings of the 1998 IEEE International Conference on Control Applications. IEEE, 1998. 480–484
184 Caccavale F, Walker I D. Observer-based fault detection for robot manipulators. In: Proceedings of International Conference on Robotics and Automation. IEEE, 1997. 2881–2887
185 Birjandi S A B, Haddadin S. Model-adaptive high-speed collision detection for serial-chain robot manipulators. IEEE Robot Autom Lett, 2020, 5: 6544–6551
186 Ahmad S, Liu G. Model-based fault detection of modular and reconfigurable robots with joint torque sensing. In: Proceedings of 2013 IEEE/ASME International Conference on Advanced Intelligent Mechatronics. IEEE, 2013. 134–139
187 Muradore R, Fiorini P. A PLS-based statistical approach for fault detection and isolation of robotic manipulators. IEEE Trans Ind Electron, 2012, 59: 3167–3175
188 Muscio G, Pierri F. A fault tolerant adaptive control for robot manipulators. In: Proceedings of 2012 IEEE International Conference on Robotics and Biomimetics (ROBIO). IEEE, 2012. 1697–1702
189 Mohseni S, Namvar M. Fault diagnosis in robot manipulators in presence of modeling uncertainty and sensor noise. In: Proceedings of 2009 IEEE Control Applications, (CCA) & Intelligent Control, (ISIC). IEEE, 2009. 1750–1755

190 Antonelli G, Caccavale F, Villani L. Adaptive discrete-time fault diagnosis for a class of nonlinear systems: Application to a mechanical manipulator. In: Proceedings of the 2003 IEEE International Symposium on Intelligent Control. IEEE, 2003. 667–672
191 Dixon W E, Walker I D, Dawson D M, et al. Fault detection for robot manipulators with parametric uncertainty: A prediction-error-based approach. IEEE Trans Robot Automat, 2000, 16: 689–699
192 Zhang T, Shi P, Li W, et al. Adaptive EKF enhanced fault diagnosis and fault tolerant control for space manipulators with position measurements only. J Franklin Institute, 2024, 361: 106824
193 Liu S, Wang L, Wang X V. Sensorless force estimation for industrial robots using disturbance observer and neural learning of friction approximation. Robotics Comput-Integrated Manuf, 2021, 71: 102168
194 Hsiao T, Weng M C. A hierarchical multiple-model approach for detection and isolation of robotic actuator faults. Robotics Autonomous Syst, 2012, 60: 154–166
195 Beikzadeh H, Liu G, Marquez H J. Robust sensitive fault detection and estimation for single-rate and multirate nonlinear sampled-data systems. Syst Control Lett, 2018, 119: 71–80
196 Rezazadeh A S, Koofigar H R, Hosseinnia S. Adaptive fault detection and isolation for a class of robot manipulators with time-varying perturbation. J Mech Sci Technol, 2015, 29: 4901–4911
197 Wahrburg A, Matthias B, Ding H. Cartesian contact force estimation for robotic manipulators–A fault isolation perspective. IFAC-PapersOnLine, 2015, 48: 1232–1237
198 Hoang N B, Kang H J. Enhancing the robustness of fault isolation estimator for fault diagnosis in robotic systems. In: Park J J, Chen S, Gil J, et al., eds. Multimedia and Ubiquitous Engineering. Netherlands: Springer, 2013. 1099–1105
199 Al-Bayati A H, Wang H. A robust new nonlinear fault tolerant control for robot via an observer. In: Proceedings of 2011 9th World Congress on Intelligent Control and Automation. IEEE, 2011. 529–534
200 Yüksel T, Sezgin A. A model-based fault function approximation scheme for robot manipulators using M-ANFIS. In: Proceedings of Melecon 2010-2010 15th IEEE Mediterranean Electrotechnical Conference. IEEE, 2010. 47–51
201 Henrique Terra M, Aznar Mendes R. Fault detection and isolation applied in a manipulator robot via Luenberger observers. IFAC Proc Volumes, 2000, 33: 517–522
202 Terra M H, Mendes R A, Bergerman M. Fault detection and isolation for mechanical manipulators via Luenberger observers. IFAC Proc Volumes, 2000, 33: 25–30
203 Naughton J M, Chen Y C, Jiang J. A neural network application to fault diagnosis for robotic manipulator. In: Proceedings of the 1996 IEEE International Conference on Control Applications IEEE International Conference on Control Applications held together with IEEE International Symposium on Intelligent Contro. IEEE, 1996. 988–993
204 Omali K O, Kabbaj M N, Benbrahim M. Nonlinear observer-based fault detection and isolation for a manipulator robot. In: Derbel Na, Ghommam J, Zhu Q, eds. New Developments and Advances in Robot control. Singapore: Springer, 2019. 163–185
205 Capisani L M, Ferrara A, Pisu P. Sliding mode observers for vision-based fault detection, isolation and identification in robot manipulators. In: Proceedings of the 2010 American Control Conference. IEEE, 2010. 4540–4545
206 Sacchi N, Incremona G P, Ferrara A. Sliding mode based fault diagnosis with deep reinforcement learning add-ons for intrinsically redundant manipulators. Intl J Robust Nonlinear, 2023, 33: 9109–9127
207 Piltan F, Prosvirin A E, Sohaib M, et al. An SVM-based neural adaptive variable structure observer for fault diagnosis and fault-tolerant control of a robot manipulator. Appl Sci, 2020, 10: 1344
208 Protsenko A. The development of a fault detection and identification system for executive units of manipulators using technical vision. In: Proceedings of 2020 International Multi-Conference on Industrial Engineering and Modern Technologies (FarEastCon). IEEE, 2020. 1–5
209 Filaretov V F, Zuev A V, Zhirabok A N. Fault detection and identification system for actuators of robot manipulators. In: Proceedings of 2019 IEEE/ASME International Conference on Advanced Intelligent Mechatronics (AIM). IEEE, 2019. 666–671
210 Zuev A, Protsenko A, Zhirabok A. The development of fault detection and identification systems for underwater manipulators. In: Proceedings of 2019 International Multi-Conference on Industrial Engineering and Modern Technologies (FarEastCon). IEEE, 2019. 1–4
211 Xiao B, Yin S. An intelligent actuator fault reconstruction scheme for robotic manipulators. IEEE Trans Cybern, 2018, 48: 639–647
212 Van M, Kang H J, Suh Y S. A novel neural second-order sliding mode observer for robust fault diagnosis in robot manipulators. Int J Precis Eng Manuf, 2013, 14: 397–406
213 Van M, Kang H J, Suh Y S, et al. A robust fault diagnosis and accommodation scheme for robot manipulators. Int J Control Autom Syst, 2013, 11: 377–388
214 Van M, Kang H. Fault tolerant control for robot manipulators using neural network and second-order sliding mode observer. In: Huang D, Bevilacqua V, Figueroa J C, et al., eds. Intelligent Computing Theories. ICIC 2013. Lecture Notes in Computer Science. Berlin Heidelberg: Springer, 2013. 526–535
215 Van M, Kang H, Suh Y. Third order sliding mode observer based robust fault diagnosis for robot manipulators. J Inst Control Robot Syst, 2012, 12: 669–672
216 Capisani L M, Ferrara A, Ferreira A, et al. Higher order sliding mode observers for actuator faults diagnosis in robot manipulators. In: Proceedings of 2010 IEEE International Symposium on Industrial Electronics. IEEE, 2010. 2103–2108
217 Liu S, Xia X, Zhou S, et al. Robot manipulator disturbance observation and servo-fault diagnosis without speed sensor. In: Proceedings of 2022 International Conference on High Performance Big Data and Intelligent Systems (HDIS). IEEE, 2022. 48–53
218 Brambilla D, Capisani L M, Ferrara A, et al. Second order sliding mode observers for fault detection of robot manipulators. In: Proceedings of 2008 47th IEEE Conference on Decision and Control. IEEE, 2008. 2949–2954
219 Sacchi N, Incremona G P, Ferrara A. Actuator fault diagnosis with neural network-integral sliding mode based unknown input observers. IFAC-PapersOnLine, 2023, 56: 773–778
220 Freddi A, Longhi S, Monteriù A, et al. Fault tolerant control scheme for robotic manipulators affected by torque faults. IFAC-PapersOnLine, 2018, 51: 886–893
221 Paviglianiti G, Caccavale F, Mattei M, et al. Sensor fault detection and isolation for robot manipulators. In: Proceedings of the 13th Mediterranean Conference on Control and Automation. IEEE, 2005. 668–673
222 Paviglianiti G, Pierri F, Caccavale F, et al. Robust fault detection and isolation for proprioceptive sensors of robot manipulators. Mechatronics, 2010, 20: 162–170
223 De Luca A, Mattone R. An identification scheme for robot actuator faults. In: Proceedings of 2005 IEEE/RSJ International Conference on Intelligent Robots and Systems. IEEE, 2005. 1127–1131
224 Chen W. Fault detection and isolation in nonlinear systems: Observer and energy-balance based approaches. Dissertation for the Doctoral Degree. Duisburg: University of Duisburg-Essen, 2011
225 Namvar M, Aghili F. Failure detection and isolation in robotic manipulators using joint torque sensors. Robotica, 2010, 28: 549–561
226 Lu P, Zhao B, Li Y. Fault detection methods for reconfigurable manipulators via decentralized adaptive fuzzy nonlinear observer. In: Proceedings of 2010 IEEE International Conference on Industrial Engineering and Engineering Management. IEEE, 2010. 1937–1941
227 Abdul S, Liu G. Decentralised fault tolerance and fault detection of modular and reconfigurable robots with joint torque sensing. In:

Proceedings of 2008 IEEE International Conference on Robotics and Automation. IEEE, 2008. 3520–3526
228 Huang S N, Tan K K. Fault detection, isolation, and accommodation control in robotic systems. IEEE Trans Automat Sci Eng, 2008, 5: 480–489
229 Namvar M, Aghili F. Fault diagnosis in robotic manipulators using joint torque sensing. IFAC Proc Volumes, 2008, 41: 5330–5334
230 McIntyre M L, Dixon W E, Dawson D M, et al. Fault detection and identification for robot manipulators. In: Proceedings of IEEE International Conference on Robotics and Automation ICRA. IEEE, 2004. 4981–4986
231 Schneider H, Frank P M. Fuzzy logic based threshold adaption for fault detection in robots. In: Proceedings of 3rd IEEE Conference on Control Applications. IEEE, 1994. 1127–1132
232 Chen S, Luo M, He F. A universal algorithm for sensorless collision detection of robot actuator faults. Adv Mech Eng, 2018, 10: 1687814017740710
233 Guo S C, Yang M H, Xing Z R, et al. Actuator fault detection and isolation for robot manipulators with the adaptive observer. Adv Mater Res, 2012, 482: 529–532
234 De Luca A, Ferrajoli L. A modified Newton-Euler method for dynamic computations in robot fault detection and control. In: Proceedings of 2009 IEEE International Conference on Robotics and Automation. IEEE, 2009. 3359–3364
235 De Luca A, Mattone R. Sensorless robot collision detection and hybrid force/motion control. In: Proceedings of the 2005 IEEE International Conference on Robotics and Automation. IEEE, 2005. 999–1004
236 De Luca A, Mattone R. Actuator failure detection and isolation using generalized momenta. In: 20th IEEE International Conference on Robotics and Automation (ICRA). IEEE, 2003. 634–639
237 Zhang J, Swain A K, Nguang S K. Robust Observer-Based Fault Diagnosis for Nonlinear System Using MATLAB. Springer International Publishing, 2016
238 Li T, Xing H, Hashemi E, et al. A brief survey of observers for disturbance estimation and compensation. Robotica, 2023, 41: 3818–3845
239 Yüksel T, Sezgin A. Two fault detection and isolation schemes for robot manipulators using soft computing techniques. Appl Soft Comput, 2010, 10: 125–134
240 Dev Anand M. Fault detection and isolation in robotic manipulator via hybrid neural networks. Int J Simul Model, 2008, 7: 5–16
241 Anand M D, Selvaraj T, Kumanan S, et al. Fault diagnosis system for a robot manipulator through neuro fuzzy approach. Int J Model Identif Control, 2008, 3: 181–192
242 Anand M D, Selvaraj T, Kumanan S, et al. A hybrid fuzzy logic artificial neural network algorithm-based fault detection and isolation for industrial robot manipulators. Int J Manuf Res, 2007, 2: 279–302
243 Tinós R, Terra M H, Bergerman M. Fault tolerance in cooperative manipulators. In: 19th IEEE International Conference on Robotics and Automation (ICRA). IEEE, 2002. 470–475
244 Tinós R, Terra M H, Bergerman M. Fault detection and isolation in cooperative manipulators via artificial neural networks. In: Proceedings of the 2001 IEEE International Conference on Control Applications (CCA'01) (Cat. No. 01CH37204). IEEE, 2001. 492–497
245 Tinós R, Terra M H. Fault detection and isolation in robotic manipulators using a multilayer perceptron and a RBF network trained by the Kohonen's self-organizing map. SBA Control Autom, 2001, 12: 11–18
246 Terra M H, Tinós R. Fault detection and isolation in robotic manipulators via neural networks: A comparison among three architectures for residual analysis. J Robotic Syst, 2001, 18: 357–374
247 Tinós R, Terra M H, Bergerman M. A fault tolerance system for robotic manipulators with free-swinging joint failures. IFAC Proceedings Volumes, 2000, 33: 813–818
248 Jain A A, Demetriou M A. A neural network based actuator fault detection and diagnostic scheme for a SCARA manipulator. In: Proceedings of the 2000 IEEE International Symposium on Intelligent Control. Held jointly with the 8th IEEE Mediterranean Conference on Control and Automation. IEEE, 2000. 297–302
249 Henrique Terra M, Tinós R. Fault detection and isolation in robotic systems via artificial neural networks. IFAC Proc Volumes, 2000, 33: 183–188
250 Henrique Terra M, Tinós R. Fault detection and isolation in a Puma 560 manipulator via neural networks. IFAC Proc Volumes, 1999, 32: 7855–7860
251 Terra M H, Tinós R. Fault detection and isolation for robotic systems using a multilayer perceptron and a radial basis function network. In: IEEE International Conference on Systems, Man, and Cybernetics–Intelligent Systems for Humans in a Cyberworld (SMC 98). IEEE, 1998. 1880–1885
252 Mien V, Kang H, Ro Y. A robust detection and isolation scheme for incipient and abrupt faults in robot manipulator using neural network. In: Proceedings of 2011 6th International Forum on Strategic Technology. IEEE, 2011. 1: 313–316
253 Van M, Kang H, Ro Y. A robust fault detection and isolation scheme for robot manipulators based on neural networks. In: Huang D, Gan Y, Bevilacqua V, et al., eds. Advanced Intelligent Computing. ICIC 2011. Lecture Notes in Computer Science. Berlin Heidelberg: Springer, 2011. 25–32
254 Huang S, Tan K K. Fault detection and diagnosis based on modeling and estimation methods. IEEE Trans Neural Netw, 2009, 20: 872–881
255 Vemuri A T, Polycarpou M M. A methodology for fault diagnosis in robotic systems using neural networks. Robotica, 2004, 22: 419–438
256 Kmelnitsky V M. Automated on-line diagnosis and control configuration in robotic systems using model based analytical redundancy. Dissertation for the Master's Degree. Worcester: Worcester Polytechnic Institute, 2002
257 Song Q, Hu W J, Yin L, et al. Robust adaptive dead zone technology for fault-tolerant control of robot manipulators using neural networks. J Intelligent Robotic Syst, 2002, 33: 113–137
258 Vemuri A T, Polycarpou M M, Diakourtis S A. Neural network based fault detection in robotic manipulators. IEEE Trans Robot Automat, 1998, 14: 342–348
259 Vemuri A T, Polycarpou M M. Neural-network-based robust fault diagnosis in robotic systems. IEEE Trans Neural Netw, 1997, 8: 1410–1420
260 Noureddine F, Lazeregue M S, Noyes D. Fault detection-location in robots using a scheme of observers. IFAC Proc Volumes, 1994, 27: 323–328
261 Zhao J, Zhang K, Hou M, et al. Actuator fault detection for masonry robot manipulator arm with the interval observer. J Field Robot, 2023, 40: 147–160
262 Pucher F, Gattringer H, Müller A. Collision detection for flexible link robots using accelerometers. IFAC-PapersOnLine, 2019, 52: 514–519
263 Yuksel T, Sezgin A. Model-based FDI schemes for robot manipulators using soft computing techniques. In: Zhang W, ed. Fault Detection. Intech, 2010
264 Bi R. Immune-inspired fault diagnosis for a robotic system. Dissertation for the Doctoral Degree. York: The University of York, 2012
265 Park K M, Kim J, Park J, et al. Learning-based real-time detection of robot collisions without joint torque sensors. IEEE Robot Autom Lett, 2021, 6: 103–110
266 Park K M, Park Y, Yoon S, et al. Collision detection for robot manipulators using unsupervised anomaly detection algorithms. IEEE ASME Trans Mechatron, 2022, 27: 2841–2851
267 Kim D, Lim D, Park J. Transferable collision detection learning for collaborative manipulator using versatile modularized neural network. IEEE Trans Robot, 2022, 38: 2426–2445
268 Yang Y, Yang M, Jiang P. The design of an integrated monitoring

and maintenance framework for newly developed equipment: Using industrial robot as example. IFAC-PapersOnLine, 2022, 55: 42–47
269 Deng J, Wang T, Wang Z, et al. Research on event logic knowledge graph construction method of robot transmission system fault diagnosis. IEEE Access, 2022, 10: 17656–17673
270 Lin R, Cheng L, Wang T, et al. Trans-SBLGCN: A transfer learning model for event logic knowledge graph construction of fault diagnosis. In: Proceedings of 2022 International Joint Conference on Neural Networks (IJCNN). IEEE, 2022. 1–8
271 Zhou J, Wang T, Deng J. Corpus construction and entity recognition for the field of industrial robot fault diagnosis. In: Proceedings of the 2021 13th International Conference on Machine Learning and Computing. ACM, 2021
272 Li Y, Yang H. Fault localization of industrial robot system based on knowledge graph and Bayesian network. In: Proceedings of 2022 China Automation Congress (CAC). IEEE, 2022. 2902–2907
273 Li Y, Li Z. Fault diagnosis of industrial robot based on fuzzy multi-attribute decision-making of knowledge graph. In: Proceedings of 2021 China Automation Congress (CAC). IEEE, 2021. 2538–2542
274 Lynch K M, Park F C. Modern Robotics: Mechanics, Planning, and Control. Cambridge University Press, 2017
275 Nabissi G, Longhi S, Bonci A. ROS-based condition monitoring architecture enabling automatic faults detection in industrial collaborative robots. Appl Sci, 2023, 13: 143
276 Ma Z, Xiao H, Pan Y, et al. Multi-axis industrial robot fault diagnosis model based on improved one-dimensional convolutional neural network. In: Tan Y, Shi Y, Zomaya A, et al., eds. Data Mining and Big Data. DMBD 2021. Communications in Computer and Information Science. Singapore: Springer, 2021. 397–410
277 Li P, Xiao H, Jiang W, et al. Compound fault diagnosis of industrial robot based on improved multi-label one-dimensional convolutional neural network. In: Tan Y, Shi Y, Zomaya A, et al., eds. Data Mining and Big Data. DMBD 2021. Communications in Computer and Information Science. Singapore: Springer, 2021. 205–216
278 Lu K, Chen C, Wang T, et al. Fault diagnosis of industrial robot based on dual-module attention convolutional neural network. Auton Intell Syst, 2022, 2: 12
279 Heo Y J, Kim D, Lee W, et al. Collision detection for industrial collaborative robots: A deep learning approach. IEEE Robot Autom Lett, 2019, 4: 740–746
280 Shuai Y. Research on fault diagnosis technology of industrial robot operation based on deep belief network. Sci Program, 2022, 2022: 9260992
281 Nentwich C, Reinhart G. A method for health indicator evaluation for condition monitoring of industrial robot gears. Robotics, 2021, 10: 80
282 Yang G, Zhong Y, Yang L, et al. An intelligent compound fault diagnosis method using convolutional neural network for harmonic drive. In: Proceedings of 2021 China Automation Congress (CAC). IEEE, 2021. 619–623
283 Nentwich C, Junker S, Reinhart G. Data-driven models for fault classification and prediction of industrial robots. Procedia CIRP, 2020, 93: 1055–1060
284 Wu Y, Fu Z, Fei J. Fault diagnosis for industrial robots based on a combined approach of manifold learning, treelet transform and Naive Bayes. Rev Sci Instruments, 2020, 91: 015116
285 Min F, Wang G, Liu N. Collision detection and identification on robot manipulators based on vibration analysis. Sensors, 2019, 19: 1080
286 Bilal H, Obaidat M S, Aslam M S, et al. Online fault diagnosis of industrial robot using IoRT and hybrid deep learning techniques: An experimental approach. IEEE Internet Things J, 2024, 11: 31422–31437
287 Jaber A A, Bicker R. Industrial robot fault detection based on wavelet transform and LabVIEW. In: Proceedings of the 2014 First International Conference on Systems Informatics, Modelling and Simulation. IEEE, 2014
288 Jaber A A, Bicker R. The optimum selection of wavelet transform parameters for the purpose of fault detection in an industrial robot. In: Proceedings of 2014 IEEE International Conference on Control System, Computing and Engineering (ICCSCE 2014). IEEE, 2014. 304–309
289 Eski I, Erkaya S, Savas S, et al. Fault detection on robot manipulators using artificial neural networks. Robotics Comput-Integrated Manufacturing, 2011, 27: 115–123
290 Liu H W, Wei T, Wang X S, et al. Signal decomposition and fault diagnosis of a SCARA robot based only on tip acceleration measurement. In: Proceedings of 2009 International Conference on Mechatronics and Automation. IEEE, 2009. 4811–4816
291 Lee H, Raouf I, Song J, et al. Prognostics and health management of the robotic servo-motor under variable operating conditions. Mathematics, 2023, 11: 398
292 Fu R, Xiao L, Ma B. Unsupervised fault detection of industrial robot joints using current signal. In: Proceedings of 2022 Global Reliability and Prognostics and Health Management (PHM-Yantai). IEEE, 2022. 1–8
293 Cheng F, Raghavan A, Jung D, et al. High-accuracy unsupervised fault detection of industrial robots using current signal analysis. In: Proceedings of 2019 IEEE International Conference on Prognostics and Health Management (ICPHM). IEEE, 2019. 1–8
294 Birjandi S A B, Kuhn J, Haddadin S. Observer-extended direct method for collision monitoring in robot manipulators using proprioception and IMU sensing. IEEE Robot Autom Lett, 2020, 5: 954–961
295 Hedberg E, Norén J, Norrlöf M, et al. Industrial robot tool position estimation using inertial measurements in a complementary filter and an EKF. IFAC-PapersOnLine, 2017, 50: 12748–12752
296 Pan J, Qu L, Peng K. Research on robotic manipulator fault detection and diagnosis technology based on machine vision in complex environments. J Field Robotics, 2023, 40: 231–242
297 Izagirre U, Andonegui I, Eciolaza L, et al. Towards manufacturing robotics accuracy degradation assessment: A vision-based data-driven implementation. Robotics Comput-Integrated Manuf, 2021, 67: 102029
298 Peng Y, Chen D. Vision-based fault action detection for industrial robots. Open Access Lib J, 2021, 8: 1–10
299 Qiao G, Weiss B A. Monitoring, diagnostics, and prognostics for robot tool center accuracy degradation. In: Proceedings of the ASME 2018 13th International Manufacturing Science and Engineering Conference. ASME, 2018
300 Qiao G, Weiss B A. Quick health assessment for industrial robot health degradation and the supporting advanced sensing development. J Manuf Syst, 2018, 48: 51–59
301 Qiao G, Weiss B A. Accuracy degradation analysis for industrial robot systems. In: Proceedings of 2017 ASME International Manufacturing Science and Engineering Conference. ASME, 2017
302 Zhang Y, An H, Ding X, et al. Industrial robot rotate vector reducer fault detection based on hidden Markov models. In: Proceedings of 2019 IEEE International Conference on Robotics and Biomimetics (ROBIO). IEEE, 2019. 3013–3018
303 An H, Liang W, Zhang Y, et al. Retrogressive analysis of industrial robot rotate vector reducer using acoustic emission techniques. In: Proceedings of 2018 IEEE 8th Annual International Conference on CYBER Technology in Automation, Control, and Intelligent Systems (CYBER). IEEE, 2018. 366–372
304 Yun H, Kim H, Jeong Y H, et al. Autoencoder-based anomaly detection of industrial robot arm using stethoscope based internal sound sensor. J Intell Manuf, 2023, 34: 1427–1444
305 Zhou J, Zheng L, Fan W, et al. Adaptive hierarchical positioning error compensation for long-term service of industrial robots based on incremental learning with fixed-length memory window and incremental model reconstruction. Robotics Comput-Integrated Manuf, 2023, 84: 102590

306 Khojet El Khil S, Jlassi I, Marques Cardoso A J, et al. Diagnosis of open-switch and current sensor faults in PMSM drives through stator current analysis. IEEE Trans Ind Applicat, 2019, 55: 5925–5937
307 Jlassi I, Estima J O, El Khil S K, et al. A robust observer-based method for IGBTs and current sensors fault diagnosis in voltage-source inverters of PMSM drives. IEEE Trans Ind Applicat, 2017, 53: 2894–2905
308 Birjandi S A B, Fortunić E P, Haddadin S. Evaluation of robot manipulator link velocity and acceleration observer. IFAC-PapersOnLine, 2023, 56: 292–299
309 Olofsson B, Antonsson J, Kortier H G, et al. Sensor fusion for robotic workspace state estimation. IEEE ASME Trans Mechatron, 2016, 21: 2236–2248
310 Chen X, Soh G S, Foong S, et al. Pose estimation of robotic end-effectors under low speed motion using EKF with inertial and SE (3) measurements. In: Proceedings of 2015 IEEE International Conference on Advanced Intelligent Mechatronics (AIM). IEEE, 2015. 1585–1590
311 Cao X, Crandall J W, Pedersen E, et al. Proficiency self-assessment without breaking the robot: Anomaly detection using assumption-alignment tracking from safe experiments. In: Proceedings of 2023 IEEE International Conference on Robotics and Automation (ICRA). IEEE, 2023. 12714–12720
312 Robla-Gómez S, Becerra V M, Llata J R, et al. Working together: A review on safe human-robot collaboration in industrial environments. IEEE Access, 2017, 5: 26754–26773
313 Sabry A H, Nordin F H, Sabry A H, et al. Fault detection and diagnosis of industrial robot based on power consumption modeling. IEEE Trans Ind Electron, 2020, 67: 7929–7940
314 Klimchik A, Pashkevich A. Serial vs. quasi-serial manipulators: Comparison analysis of elastostatic behaviors. Mech Mach Theory, 2017, 107: 46–70
315 Ding S X. Model-Based Fault Diagnosis Techniques: Design Schemes, Algorithms, and Tools. London: Springer-Verlag, 2013
316 Izagirre U, Andonegui I, Landa-Torres I, et al. A practical and synchronized data acquisition network architecture for industrial robot predictive maintenance in manufacturing assembly lines. Robotics Comput-Integrated Manuf, 2022, 74: 102287
317 Liang X, Zuo M J, Feng Z. Dynamic modeling of gearbox faults: A review. Mech Syst Signal Processing, 2018, 98: 852–876