Sensors and Materials, Vol. 38, No. 2 (2026) 1087–1101
MYU Tokyo

S & M 4365

Sensor-oriented Data-driven Fault Diagnosis for Parallel Robots: Sensing Mechanisms, Signal Characteristics, and Feature Representation

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(Received January 26, 2026; accepted February 17, 2026)

Keywords: parallel robots, sensor integration, feature representation, data-driven fault diagnosis

Parallel robots are governed by closed-loop kinematic constraints and strongly coupled nonlinear dynamics, which limit the transferability of purely analytical model-based fault diagnosis methods under varying operating conditions. To address this issue, in this paper, we present a sensor-oriented synthesis of data-driven fault diagnosis for parallel robots. In the proposed study, we span sensor integration, signal characteristics and selection, and feature representation derived from sensor signals, providing a structured, sensor-centered perspective on data-driven diagnostic approaches. By organizing existing methods from the viewpoint of sensing and signal interpretation, we clarify the role of sensor information in fault detection and diagnosis performance. In addition, key challenges, emerging trends, and potential solution directions for future research are discussed, aiming to support the development of more effective sensor-oriented fault diagnosis frameworks for parallel robotic systems.

1. Introduction

Parallel robots are primarily employed in pick-and-place operations and have been widely adopted across various industrial sectors, including manufacturing,(1) food processing,(2) and medical applications.(3) A typical parallel robot consists of a fixed base, an end effector (also referred to as the work platform), multiple independent kinematic chains, joints, and actuators. The end effector is connected to the base through these parallel kinematic chains, forming a closed-loop mechanical structure. According to their degrees of freedom (DOF), parallel robots can be classified into two-DOF, three-DOF, and six-DOF mechanisms. As the number of DOFs increases, the complexity of robot motion, coordination, and control correspondingly intensifies.(4) Compared with other robotic architectures, parallel robots exhibit several distinctive advantages. Their closed-loop configuration allows forces and motions to be distributed toward the base, thereby reducing structural deflection and enabling effective load

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https://doi.org/10.18494/SAM6226

management.[5] In addition, the inherently stable construction of parallel mechanisms contributes to vibration suppression, making such robots particularly suitable for high-precision operations. For example, millimeter-scale Delta robots have been successfully employed in microsurgical and microassembly tasks, where vibration elimination is critical for achieving high positioning accuracy and operational stability. Despite these advantages, the closed-loop kinematic chains of parallel robots also render them highly nonlinear and dynamically complex systems.[5]

External disturbances, internal uncertainties, and potential actuator failures can significantly degrade system performance, leading to positioning errors and reduced reliability.[6] Under high-speed operating conditions, the lightweight components commonly used in parallel robot designs inevitably introduce vibration, which directly affects the accuracy of position and posture, key factors affecting operation quality and long-term stability.[7] Consequently, the continuous health monitoring of parallel robots is essential, with fault diagnosis playing a pivotal role in ensuring safe and reliable operation. Existing fault diagnosis strategies for parallel robots can be broadly categorized into model-based[8] and data-driven approaches.[9] Model-based fault diagnosis relies on analytical or mathematical models to detect and diagnose faults and can theoretically achieve high diagnostic precision. For instance, a model-based method has been proposed to predict orientation errors in a three-DOF parallel manipulator by analyzing uncertainties associated with design parameters, joint clearances, nominal posture, and external loads.[10]

However, constructing accurate mathematical models remains a major challenge owing to the inherent structural complexity and strong coupling effects of parallel robots, particularly in six-DOF configurations. In contrast, sensor-based data-driven fault diagnosis methods have gained increasing attention, as they are capable of learning fault-related features directly from measured physical signals.[11] By deploying sensing devices such as vibration, current, or attitude sensors, subtle signal variations associated with mechanical degradation can be captured in real time. This enables intelligent health assessment and fault identification without requiring an explicit or highly accurate physical model of the robotic system, making such approaches especially attractive for complex parallel mechanisms. Fault diagnosis in parallel robots is further complicated by the distinctive characteristics of parallel mechanisms, notably closed-loop coupling and the need for multidimensional sensing. Unlike serial robots, which are composed of open-chain links with relatively decoupled joint motions and therefore allow more straightforward fault source localization, parallel robots present unique diagnostic challenges arising from their structural differences.[12]

The closed-loop architecture causes chain-level faults to be strongly coupled through the end effector, resulting in feature mixing across sensing channels. Moreover, the nonlinear dynamics of parallel robots lead to nonstationary signals that are susceptible to noise masking, rendering single-sensor observations insufficient for capturing spatially distributed fault patterns.[12] As a result, multisensor fusion strategies or sensing modalities that encode spatial correlations, such as end-effector attitude measurements, are often required to achieve robust and reliable diagnostic performance.[13] Keeping these considerations in mind, in this study, we adopt a sensor-oriented, data-driven perspective to systematically examine fault diagnosis in parallel robots, with particular emphasis on sensing mechanisms, signal characteristics and selection, and feature representation derived from sensor data. By integrating insights from sensing, signal analysis, and data-driven feature extraction, we aim to clarify the interdependence between sensor information and diagnostic performance while identifying key challenges and emerging directions to support the development of effective fault diagnosis frameworks for parallel robotic systems.

In this work, we present a sensor-oriented perspective specifically designed for parallel robotics, distinguishing itself from evaluations that mostly emphasize computational approaches. The primary contributions encompass (i) mechanism-signal correlation, where a clear connection is established between closed-loop kinematic restrictions and nonstationary signal properties, highlighting the importance of spatial awareness; (ii) engineering insight where end-effector position sensing is highlighted as a concise and efficient method for detecting globally coupled problems; and (iii) systematic review whereby a cohesive framework is developed that amalgamates physical sensor implementation, feature representation, and multisource decision into a comprehensive roadmap.

2. Mechanisms of Parallel Robots

2.1 Kinematics and dynamics

Traditional approaches to robotic modeling primarily rely on kinematic and dynamic formulations to describe motion, tracking, and positioning behaviors. In parallel robots, kinematic analysis generally involves both forward and inverse kinematics. Forward kinematics aims to determine the position and orientation of the end effector from given joint parameters; however, owing to the nonlinear and strongly coupled nature of the governing equations, this problem is often mathematically complex and computationally demanding.[14] Inverse kinematics, on the other hand, focuses on determining the joint parameters required to achieve a desired end-effector position and orientation. Although typically more tractable than forward kinematics, inverse kinematics in parallel robots still requires careful consideration of mechanical constraints and coupling effects. Errors in inverse kinematic solutions can propagate through the control process and result in significant deviations between the actual and desired end-effector positions.[15] Dynamic analysis complements kinematic modeling by characterizing the forces and torques acting on the robot during motion. However, the development of accurate dynamic models for parallel robots is complicated by factors such as joint friction, inertial effects, and strong coupling between kinematic chains. These factors introduce modeling uncertainties that can lead to inaccuracies in dynamic representations.[16] The kinematic and dynamic models serve as simplified representations of complex parallel robotic systems and are widely used in simulation and performance prediction. Nevertheless, modeling uncertainties may lead to inaccurate state estimation, highlighting the need for measured physical signals to reflect actual system behavior. In this context, data-driven modeling leverages sensor signals for effective data collection and interpretation, providing an important complement to analytical approaches in fault diagnosis.

3. Sensor Integration for Fault Diagnosis

Figure 1 illustrates the structural configuration of a Delta robot, which represents a typical parallel robot architecture. In parallel robotic systems, data-driven fault diagnosis is commonly conducted within a structured framework that integrates sensor data acquisition, signal processing, feature selection, and fault recognition. As illustrated in Fig. 2, this framework covers the complete diagnostic workflow, spanning from raw sensor data collection to fault classification and prediction. Within this framework, each stage contributes critically to the overall accuracy and reliability of fault detection, highlighting the importance of appropriate sensor integration and data acquisition strategies. In particular, the selection and deployment of

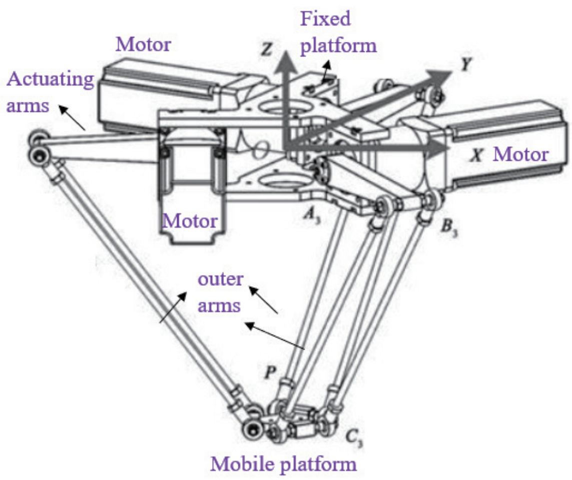


Fig. 1. (Color online) Structural diagram of Delta robot.

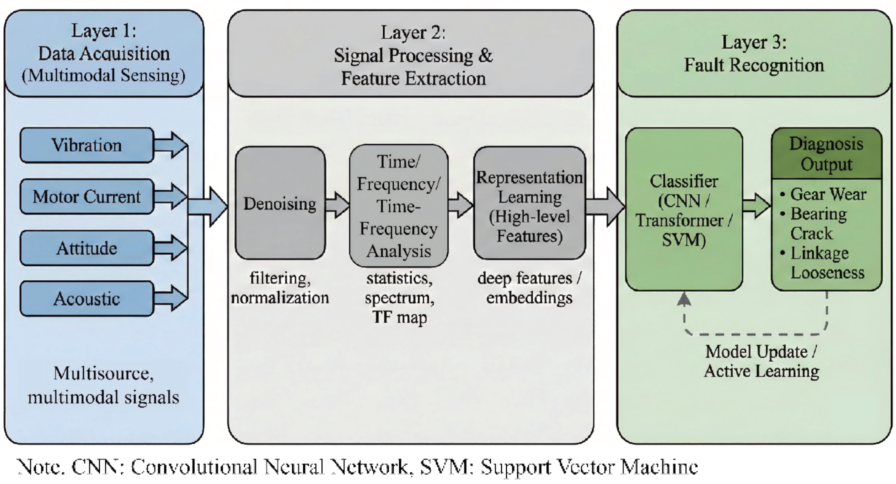


Fig. 2. (Color online) General framework of sensor-oriented data-driven fault diagnosis.

sensors directly affect the quality of diagnostic signals and the effectiveness of subsequent data-driven analysis. The following discussion therefore focuses on sensor integration for fault diagnosis in parallel robots, emphasizing its role as the foundation of sensor-oriented, data-driven diagnostic frameworks.

Data-driven fault diagnosis methods fundamentally depend on the quality and reliability of data acquired by sensors. During robot operation, the condition of the system can be inferred from measured signal data, and feedback information enables the identification of normal and abnormal operating states. Consequently, effective sensing plays a critical role in ensuring the accuracy of data-driven diagnostic processes. Modern parallel robots are typically equipped with a diverse range of sensing devices to capture different aspects of system behavior. Commonly used sensors include force/torque sensors,[8] position sensors,[17] acceleration sensors,[18] velocity sensors,[17] attitude sensors,[19] current sensors,[17] magnetic field sensors,[9] and acoustic emission (AE) sensors.[20] The integration of these heterogeneous sensors provides complementary information that supports comprehensive condition monitoring and fault diagnosis in parallel robotic systems.

3.1 Kinematic and dynamic state sensing—position, attitude, and force

For parallel robots such as Delta and Stewart platforms, the pose of the end effector provides an integrated representation of the kinematic states of all supporting chains. Although conventional joint encoders are capable of measuring the angular displacement of actuated joints, they cannot directly capture end-effector pose errors induced by link deformation or joint clearance. To address this limitation, MEMS-based attitude sensors, commonly implemented as inertial measurement units (IMUs), have, in recent years, been widely mounted on the moving platform. These sensors typically integrate an accelerometer, a gyroscope, and a magnetometer, enabling the real-time monitoring of three-dimensional attitude angles, including pitch, roll, and yaw. Previous studies have demonstrated a clear relationship between fluctuations in moving-platform attitude and chain-level degradations, such as bearing wear and linkage loosening.[21] In addition to pose-related sensing, force- and torque-related measurements provide critical information on interaction and load conditions in parallel robotic systems. Force sensors are commonly installed at actuated joints or between the end effector and the payload to capture operational force variations. In cable-driven parallel robots, tension sensors are employed to monitor cable forces in order to prevent failures associated with cable slackening or breakage. Furthermore, joint torque monitoring and end-effector contact force measurement can effectively detect abrupt force changes caused by the abnormal increase in friction or unexpected external collisions, thereby supporting timely fault detection and diagnosis.[21]

3.2 Electromechanical and vibro-acoustic sensing vibration, current, and AE

Electromechanical signals, together with vibration and acoustic signals, provide valuable information for revealing subtle internal physical degradation in machinery. Among these, vibration-based measurements are among the most widely used fault indicators. Piezoelectric or

MEMS accelerometers are commonly installed on bearing housings at joints or on gearbox casings. Through time-domain and frequency-domain analyses, vibration measurements can capture high-frequency impulsive components, thereby supporting the diagnosis of gear pitting and tooth breakage, as well as bearing inner-race and outer-race spalling. In parallel robotic systems, vibration responses originating from multiple kinematic chains are strongly coupled; consequently, multi-axis accelerometers are typically required to enable effective joint-level analysis.

In addition to vibration sensing, electrical and magnetic signals provide complementary diagnostic information related to the drive system. Current sensors are widely used to monitor motor stator currents through motor current signature analysis, which reflects variations in load conditions. Mechanical faults in the transmission chain, such as gear eccentricity or backlash, can induce load torque fluctuations that modulate the motor current signal. As a result, current-based analysis enables the nonintrusive diagnosis of drivetrain conditions. Furthermore, magnetometers not only assist in attitude estimation but also indicate rotor eccentricity and abnormal variations in the surrounding magnetic field environment, thereby contributing additional insight into electromechanical health states.(22) Acoustic emission sensing offers further diagnostic modality that complements vibration-based approaches. Unlike low-frequency vibration measurements, acoustic emission sensors are capable of capturing high-frequency elastic waves, typically in the range of 100 kHz to 1 MHz, which are generated during material deformation or crack propagation. This characteristic provides a distinct advantage for early fault detection as abnormal burst-type events may appear in acoustic emission signals during microcrack initiation well before macroscopic damage develops in gears or bearings.(23)

3.3 Sensor taxonomy and fault mapping

To present the correspondence between sensor modalities and fault types in a systematic manner, the sensor taxonomy and its statistical distribution in fault diagnosis studies on parallel robots are summarized in Table 1 and Fig. 3. Statistical analyses of sensor usage indicate that posture-related sensors are the most frequently adopted in fault diagnosis studies, accounting for approximately 48% of the total sensor deployments, followed by torque sensors, velocity sensors, position sensors, and accelerometers, as illustrated in Fig. 3. This distribution highlights the central role of pose-related measurements in capturing the coupled kinematic behavior of parallel robotic systems. Recent studies have further revealed the increasing sophistication of sensor utilization in data-driven fault diagnosis. For example, advanced learning techniques such as the Deep Support Vector Data Description method have been applied to fault diagnosis in Delta-type three-dimensional printers using magnetic field data, reflecting a growing emphasis on exploiting nontraditional sensing modalities.(6) In addition, strong noise was deliberately introduced during data acquisition in Zhang *et al.*'s study(9) to evaluate its effect on attitude sensor signals, providing insight into sensor robustness under adverse conditions.(6) As a result, posture-related sensing systems are increasingly employed to acquire comprehensive multidimensional information, including three-axis attitude angles, angular velocity, vibration acceleration, and magnetic field intensity.(6,19,24–26) The integration of these heterogeneous

Table 1
Mapping of sensors to diagnosable fault types in parallel robots.

Sensor category	Specific sensor	Key monitoring location	Diagnosable fault types
Vibration	MEMS/piezo accelerometer	Joints, gearbox, end-effector	Bearing defects (race/ball), gear defects (pitting/crack), structural resonance, looseness
Attitude/motion	IMU (Gyro, Acc, Mag), encode	Moving platform, active joints	Kinematic chain errors, joint clearance/backlash, geometric deformation, calibration errors
Force/torque	Load cell, torque sensor	Actuator output, cables	Cable slack/breakage, friction changes, external collision, overload
Electrical	Current probe, voltage sensor	Motor drive unit	Motor faults (short circuit), load anomalies induced by transmission jamming
Acoustic	AE sensor	Gearbox, structural frame	Incipient crack propagation, lubrication failure, rubbing/friction

Note: IMU: inertial measurement unit, Gyro: gyroscope, Acc: accelerometer, Mag: magnetometer, AE: acoustic emission

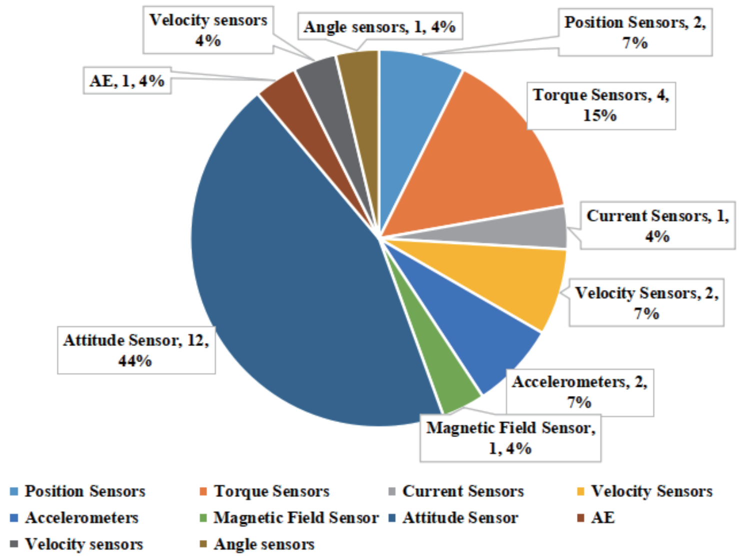


Fig. 3. (Color online) Sensor statistics of fault diagnosis for parallel robots.

measurements enables richer feature representations and supports more robust data-driven fault diagnosis in parallel robotic systems.

4. Signal Characteristics and Selection

Within data-driven fault diagnosis frameworks, the selection of diagnostic signals and the configuration of sensing devices play a decisive role in feature extraction quality and, consequently, in the upper bound of achievable diagnostic performance. Given the strong electromechanical coupling and structural complexity inherent in parallel robots, in this section, we examine the representational capabilities of different physical signals, discuss the necessity of multisensor fusion, and analyze the engineering implications associated with sensor placement strategies.

4.1 Memory retention effect analysis

For complex electromechanical parallel robots, commonly monitored signals include vibration, attitude, and magnetic field measurements, which characterize system health from three complementary perspectives: high-frequency impact responses, spatial motion behavior, and electromagnetic coupling effects. Among these modalities, acceleration-based vibration measurements are the most widely adopted health indicators owing to their high sensitivity to impacts and cyclic stresses. Vibration signals are particularly effective for detecting high-frequency faults such as bearing pitting, gear tooth breakage, and Reduction Gearbox (RV) reducer wear.(27) However, in parallel robots, the closed-loop coupling of multiple kinematic chains causes vibration responses to be mixed at the moving platform, which reduces the signal-to-noise ratio for localized faults. Moreover, early fault detection based on vibration analysis often requires sampling rates exceeding 10 kHz, imposing stringent constraints on sensing bandwidth and edge computing capabilities.(21) With advances in MEMS technology, attitude sensing based on attitude and heading reference systems or IMUs, which integrate gyroscopes, accelerometers, and magnetometers, has emerged as an alternative monitoring approach for parallel robots. Unlike vibration measurements that emphasize localized high-frequency impacts, attitude-related signals such as Euler angles and angular rates directly reflect spatial kinematic errors of the end effector.

Long *et al.* reported that, in Delta-type parallel robots, joint clearance or link deformation in any kinematic chain can propagate through the closed-loop structure and manifest as attitude fluctuations of the moving platform.(6) As a result, attitude signals are capable of capturing spatial signatures induced by transmission chain errors and are often more sensitive to low-frequency trajectory deviations than vibration-based measurements. Magnetic field measurements provide an additional nonintrusive sensing modality that complements mechanical and kinematic observations. In motor-driven systems, faults such as stator or rotor defects and air-gap eccentricity can induce abnormal disturbances in the surrounding magnetic field. Zhang *et al.* demonstrated that subtle deformations caused by certain mechanical faults can alter the magnetic field distribution, with the resulting variations exhibiting axis-dependent characteristics.(28) Consequently, multi-axis magnetic field data can supplement vibration-based monitoring under low-speed and heavy-load conditions, and this sensing approach is particularly suitable for early fault warning in lightweight parallel robotic devices, such as three-dimensional printers.

4.2 Single-sensor vs multisensor approaches

In sensor-oriented fault diagnosis frameworks, single-sensor deployment is often favored for its simplicity and cost effectiveness. However, such configurations are highly sensitive to sensor placement and environmental interference and may suffer from inherent monitoring blind zones.

For instance, a vibration sensor mounted on a single kinematic chain may exhibit limited sensitivity to faults occurring on a distal or symmetric chain. In addition, reliance on a single sensing modality increases susceptibility to false alarms induced by ambient disturbances, such as external impacts or electromagnetic interference. To address these limitations, multisensor fusion has emerged as a key strategy for enhancing diagnostic robustness and reliability. Existing studies indicate that fusion strategies can be broadly organized into three levels: data-level, feature-level, and decision-level fusion, as schematically illustrated in Fig. 4.[29] Data-level fusion typically involves the direct combination of multichannel signals, such as current or vibration measurements, through concatenation or weighted averaging. This approach preserves the most direct physical information and is particularly suitable for homogeneous sensor types with consistent sampling characteristics.

Feature-level fusion, in contrast, operates on extracted representations rather than raw signals. In this scheme, time-domain and frequency-domain features derived from different sensors, such as wavelet packet energy or spectral entropy, are concatenated to form a unified feature vector. For example, Zhang *et al.* proposed the 2MNet model, which integrates features from multidirectional vibration measurements and demonstrates improved rolling bearing fault recognition performance under complex operating conditions.[11] At the decision level, separate diagnostic models are trained independently for each sensor modality, and their outputs are subsequently combined in the decision space rather than being aligned at the signal or feature level. Common decision-level fusion operators include majority voting, confidence-weighted probability aggregation, and Dempster–Shafer evidence combination. This late-fusion strategy is generally more tolerant of sampling mismatches, temporal misalignment, and missing sensor modalities. However, it also requires careful calibration of model confidences and condition-dependent weighting mechanisms to effectively resolve conflicting diagnostic evidence.

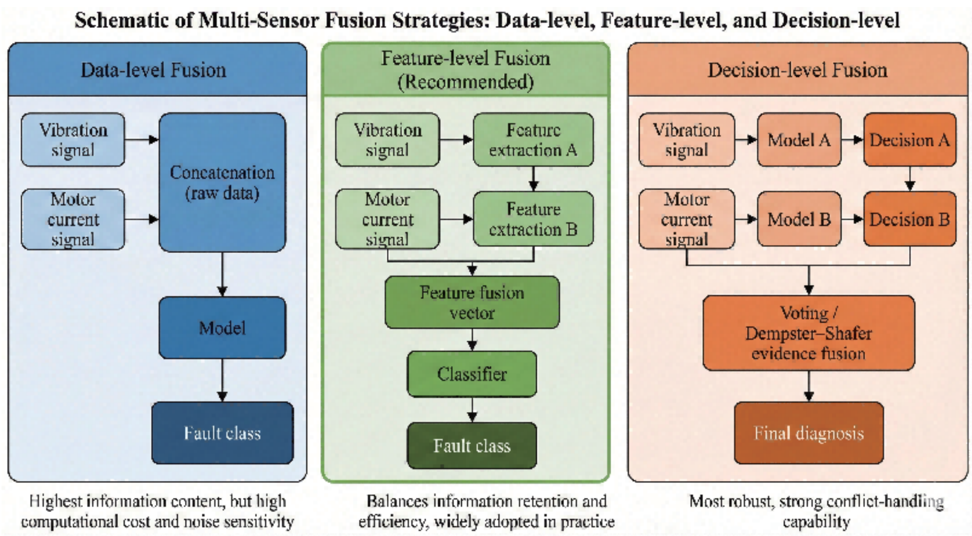


Fig. 4. (Color online) Schematic of multisensor fusion strategies: data level, feature level, and decision level.

4.3 Engineering significance of sensor placement

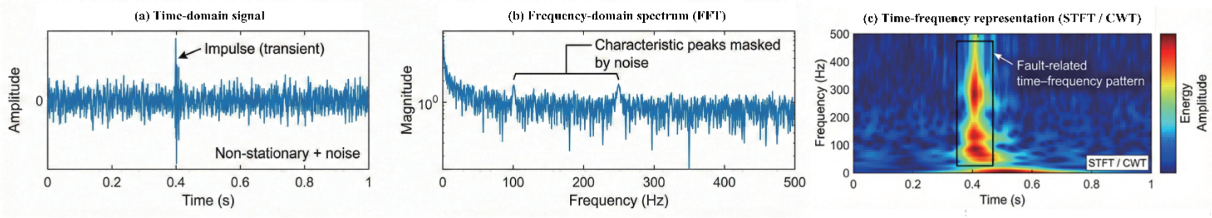
In practical implementations, sensor placement constitutes a critical design variable that balances diagnostic capability against system cost and integration complexity. Although vibration theory suggests locating sensors in close proximity to excitation sources, instrumenting every joint and kinematic chain in a parallel robot inevitably results in excessive wiring, increased hardware cost, and additional mass, which may in turn degrade the robot's dynamic performance. As a widely adopted alternative, end-effector-based sensing strategies place sensors directly on the moving platform, allowing chain-level degradations to be indirectly reflected through platform motion via closed-loop coupling effects. This approach significantly reduces sensing redundancy while preserving diagnostic relevance. For instance, a single high-precision attitude sensor mounted on the moving platform of a Delta robot can provide compact yet informative measurements for inferring transmission health while simultaneously simplifying system integration and improving cost effectiveness.[6]

5. Feature Representation from Sensor Signals

Sensor signals acquired from parallel robots commonly exhibit nonstationarity, nonlinearity, and significant background noise. As a result, performing direct classification on raw sensor signals often leads to high computational burden and degraded performance owing to the curse of dimensionality. Consequently, constructing effective feature representations becomes a critical step in data-driven fault diagnosis, enabling the transformation of high-dimensional time-series data into compact, informative, and discriminative health indicators.

5.1 Feature extraction in time, frequency, and time–frequency domains

Time-domain features provide compact health indicators with low computational cost and are therefore widely adopted in data-driven fault diagnosis. Basic statistical measures, such as the mean, root mean square, and peak value, describe signal amplitude and energy characteristics, while higher-order moments, including kurtosis and skewness, emphasize impulsive transients and have proven effective for early-stage bearing damage detection.[30] Frequency-domain analysis based on the fast Fourier transform (FFT) and demodulation techniques can further expose component-related characteristic frequencies associated with specific fault mechanisms. However, the assumption of signal stationarity inherent in these methods may lead to spectral smearing under time-varying motion conditions.[31] For this reason, time–frequency analysis is generally preferred for nonstationary sensor signals. The short-time Fourier transform provides localized spectral representations with a fixed time–frequency resolution trade-off, while wavelet-based multiresolution analysis enables adaptive resolution across scales and is widely used for denoising, transient extraction, and feature construction in condition monitoring applications.[32] As illustrated in the transformation from one-dimensional sensor signals to two-dimensional time–frequency representations shown in Fig. 5, continuous wavelet transform scalograms further extend this concept by mapping one-dimensional time-series signals into



Note. FFT: Fast Fourier Transform, STFT: Short-Time Fourier Transform, CWT: Continuous Wavelet Transform

Fig. 5. (Color online) Transformation from 1D sensor signals to 2D time–frequency representations.

two-dimensional representations. These scalograms can serve as standardized inputs for convolutional neural networks when image-based learning frameworks are adopted, thereby facilitating automated feature learning from complex, nonstationary sensor data.[33]

5.2 Advanced feature extraction techniques: principal component analysis (PCA), FFT, and AE

To further reduce dimensionality and learn more informative representations, dimensionality reduction techniques and unsupervised learning models are widely employed in data-driven fault diagnosis. PCA is frequently combined with FFT-based features to compress high-dimensional spectra or multifeature sets by projecting correlated variables onto a reduced number of orthogonal principal components. This process effectively removes redundancy while preserving most of the variance for subsequent analysis and visualization. Nevertheless, PCA primarily captures global linear structures and may be inadequate for representing nonlinear manifolds commonly observed in complex sensor signals.[34] In contrast, autoencoders and their variants, including sparse autoencoders and denoising autoencoders, are capable of learning nonlinear latent representations directly from raw signals or spectral inputs by minimizing reconstruction error. In particular, denoising autoencoder architectures enhance robustness by enforcing invariance to input corruption under strong noise conditions, making them well suited for feature learning in noisy and nonstationary sensing environments.[35]

5.3 Why feature engineering is critical to diagnostic success

The quality of feature engineering directly determines the attainable performance ceiling of a fault diagnosis model in several key aspects, as Fig. 6 shows. First, effective feature extraction improves the signal-to-noise ratio (*SNR*) and facilitates information decoupling. Techniques such as envelope analysis and wavelet threshold denoising can suppress background noise while amplifying weak impulsive fault signatures, thereby providing a necessary foundation for reliable classification and decision-making.[36] Second, feature engineering reduces data dimensionality and mitigates the risk of overfitting. High-sampling-rate raw sensor signals are inherently high dimensional, and directly feeding such data into diagnostic models significantly increases computational burden and exacerbates the curse of dimensionality. Dimensionality reduction methods, including PCA and autoencoder-based representations, enable the extraction of low-dimensional core features that reduce model complexity and support improved generalization, particularly in few-shot or data-limited scenarios.(34) Third, appropriate feature representations enhance robustness against operating condition variations. Parallel robots frequently operate under changing speeds and loads, which can cause significant distribution shifts in raw sensor signals. Feature representations such as time–frequency maps and dimensionless indicators provide partial invariance to operating conditions, thereby simplifying cross-domain diagnosis and improving diagnostic reliability under previously unseen conditions.

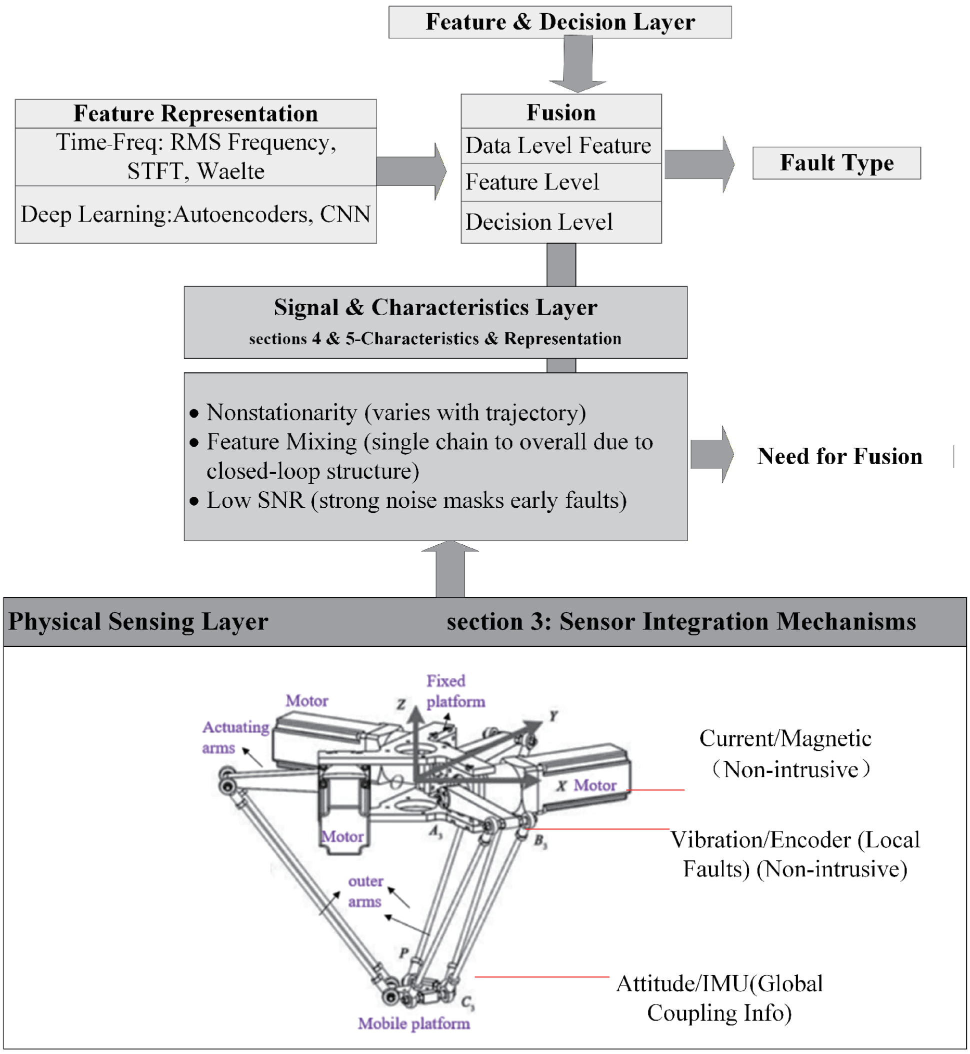


Fig. 6. (Color online) Schematic synthesis of sensor-oriented data-driven fault diagnosis for parallel robots. Note: IMUs: inertial measurement units, CNNs: convolutional neural networks, STFT: short-time Fourier transform, *RMS*: root mean square, and *SNR*: signal-to-noise ratio.

6. Challenges and Perspectives (Sensor-oriented)

Although sensor-based data-driven methods have achieved substantial progress in fault diagnosis for parallel robots, several challenges still hinder their practical deployment in industrial environments. Future research must address issues related to signal quality, fusion architecture complexity, and cost-effectiveness trade-offs in sensing system design. One major challenge arises from the inherently low *SNR* of early fault signatures. Incipient faults in parallel robots, such as weak bearing spalling or early-stage gear wear, typically exhibit low energy and are easily masked by ambient vibration, electromagnetic interference, and structural resonance. Under variable-speed or highly dynamic operating conditions, nonstationary noise further degrades the effectiveness of conventional time–frequency feature extraction methods, making reliable early fault detection particularly difficult.

Another challenge concerns information conflict and redundancy in multisource fusion. When multiple sensing modalities are integrated, especially at the decision level, different sensors may provide conflicting diagnostic evidence. For example, vibration-based diagnostics may indicate normal operating conditions, while acoustic emission signals suggest abnormal behavior. Enhancing diagnostic reliability under such circumstances requires principled uncertainty handling and conflict resolution mechanisms, such as Dempster–Shafer evidence combination and related probabilistic or evidential fusion frameworks. Finally, deployment cost and physical constraints impose practical limitations on sensing system design. Although increasing the number of sensors can enrich diagnostic information, it also leads to higher hardware costs, increased wiring complexity, and greater maintenance burden. Consequently, selecting appropriate sensor types and placement strategies under constrained budgets and limited installation space—while maximizing diagnostic information gain—remains an important optimization problem for real-world applications of sensor-oriented fault diagnosis in parallel robotic systems.

7. Conclusions

Parallel robots are characterized by closed-loop kinematic constraints and strongly coupled nonlinear dynamics, which limit the robustness and transferability of purely analytical, model-based fault diagnosis under varying operating conditions. To circumvent the complexities of purely analytical modeling, in this paper, we provided a structured synthesis of data-driven fault diagnosis specifically for parallel robots. Focusing on the physical link between sensing and mechanism health, we investigated three critical aspects: the engineering implications of sensor modality and placement, the extraction of effective features under dynamic coupling, and the implementation of multisensor fusion strategies. This sensor-centered approach offers a systematic roadmap for understanding how to bridge physical signal characteristics with intelligent diagnosis. Despite recent progress, several challenges still impede large-scale industrial deployment. Early fault signatures often exhibit low *SNR*s and are further degraded by nonstationary noise, complicating reliable feature extraction and confidence calibration. In addition, multisensor fusion introduces information conflict and redundancy, while sensing system design is constrained by cost, wiring complexity, added mass, and maintainability. Future research should emphasize data-efficient learning strategies under severe data scarcity, including zero-shot transfer supported by digital twins and virtual–physical data collaboration. Real-time deployment will require increasingly lightweight architectures and edge-oriented implementations, while improved trustworthiness depends on physics-informed constraints and interpretable representations aligned with the underlying mechanics of parallel robotic systems.

Acknowledgments

This work was supported by Guangdong University Research Project through grant no. 2022KTSCX219 and Yuejiao Gao Han through grant no. [2021]. This work was also supported by Summit-Tech Resource Corp. and by projects under grant nos. NSTC 113-2221-E-390-011 and NSTC 114-2622-E-390-001.

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