Distributed Operation Health Monitoring for Modular and Reconfigurable Robot With Consideration of Actuation Limitation

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ABSTRACT A distributed operation health monitoring (OHM) method of modular and reconfigurable robot (MRR) is presented in this paper. The proposed method is shown to be able to monitor the health of each MRR joint module based on the deviation of the actuator output from what is commanded. Driven by the desire of avoiding the need of joint acceleration measurement, a novel health indicator that reflects the operation health of an MRR module is developed by filtering the commanded joint torque generated by the joint controller and comparing it with a filtered torque estimate derived from the dynamic model of MRR. The proposed approach can work effectively for MRR modules in any working mode, including stationary state. The proposed scheme has been evaluated experimentally, and the results demonstrate its efficacy.

INDEX TERMS Modular and reconfigurable robot (MRR), operation health monitoring (OHM), model-based estimation, health indicator.

I. INTRODUCTION As modular and reconfigurable robots (MRRs) can fulfill numerous tasks by adjusting its configuration and task spaces, they have the advantages of versatility, flexibility, and adaptability, making them promising for various applications [1]. With the growing demand of low volume and customized products, MRR provides an advantage in flexible manufacturing with high flexibility and efficiency. Human robot collaboration has attracted extensive research and development interests recently, and reliability is among the most crucial issues in the design of such robot cells [2]–[4].

MRRs require safe actuator systems to perform intended tasks, where suitably selected actuators play a significant role [5]. The maximum continuous current (torque) of a motor is limited by the motor drive to safeguard both the drive circuit and motor. Therefore, the commanded torque cannot exceed the input limit of the motor [6]. On the other hand, fault tolerant control (FTC) methods have been developed over the years to boost system reliability and maintain system stability in unhealthy situations, which could lead to substantially high commanded torque [7]–[9]. As soon as the commanded torque exceeds the actuator input limit, the controller may suffer instability and cause damage. Typical MRR control methods assume that the actuator has unlimited input. However, the actuator input is always limited in practice, which can affect the control performance [10]. Addressing this issue forms the basis for the overall joint system OHM approach that is proposed in this paper.

Many FTC schemes have been proposed, and most of them are based on fault detection and identification (FDI) or fault detection and diagnosis (FDD) [11]–[13]. A prediction error-based approach has been designed to measure the common faults of joint actuator by detecting the faults of each joint module independently [14]. A discrete-time framework for faults diagnosis of joint sensors, wrist-mounted force/torque sensors, and actuators of robotic manipulators has also been proposed [15]. Using a model-based fault diagnosis technique, a diagnostic system for the faults in actuator and sensor of robot manipulators is presented [16]. Even though an FDI/FDD method can accurately obtain fault information, it cannot detect whether the commanded torque exceeds the input limit of the actuator. Operation health monitoring (OHM) determines the health of each joint module of MRR based on the input limits of the actuator.
Recent advances in system health monitoring have attracted considerable research attention [17]–[19]. However, few work has been reported for the joint module system OHM of MRR. A monitoring and fault detection technique, based on power efficiency estimation, is developed for MRR with joint torque sensing, which can effectively monitor the performance of a joint system [20]. However, due to the need to calculate the output power, it is not applicable to all working mode. By using the torque estimation-based approach, a monitoring and fault detection scheme has been proposed for MRR with abrupt faults and degradation faults [21].

In this work, the proposed method is devoted to monitoring the health of each MRR joint module during any state using the deviation between the commanded output and actually delivery of the actuator. Joint commanded torque generated by the joint controller is filtered and compared with a filtered torque estimate obtained through the dynamic model of MRR, based on which a novel health indicator that reflects the operation health of an MRR module is developed. When joint module systems are operated in healthy situations, the health indicator is close to zero. In an unhealthy situation, such as components degradation, the health indicator increases as the performance of joint gets worse. Any effective controller that has been published or verified by theory and experiment can be used to control the MRR system to verify the effectiveness of the proposed method [22], [23]. Different from FDD or FDI method, which may obtain accurate fault information, but cannot detect whether the commanded torque generated exceeds the input limit of the actuator, the proposed OHM method can detect the operation health of an MRR module by developing a novel health indicator, and stop working timely when the command torque exceeds input torque allowable range of the actuator, making the system more secure and reliable. Drawing on the results presented in [20], which is not applicable to manipulators working in no power output state, such as in stationary state, the proposed approach can be applied to MRR modules in any working mode. In addition, joint torque sensors are used in the method proposed in [20], which is expensive and will reduce the stiffness of the manipulator. The proposed method can avoid the use of joint torque sensors, increasing application potentials and making it more suitable for MRR.

The following of this paper includes: Section 2 outlines the development of the MRR dynamic model and analyzes the unhealthy situations of an MRR. Section 3 describes the distributed module system OHM method in an MRR module. Section 4 provides discussion on the experimental results. Last, the conclusions are provided in Section 5.

II. DYNAMIC MODEL AND ANALYSIS OF UNHEALTHY SITUATIONS

A. MODEL FORMULATION

The modular and reconfigurable robot under consideration consists of n modules as illustrated in Fig. 1.

Fig. 1. Schematic diagram of the joint module.

Specifically, a torque sensor, a speed reducer, and a rotary joint is integrated in each module.

For the ith module:

\[ I_{mi} \gamma_i \dot{q}_i + f_i(\tau_{si}, \dot{q}_i) + \frac{\tau_{s1}}{\gamma_1} = \tau_1 \] (1)

For the second module from the base, \( i = 2 \),

\[ I_{m2} \gamma_2 \dot{q}_2 + f_2(\tau_{s2}, \dot{q}_2) + I_{m2} \sum_{m=2}^{m=2} z_{m1} z_i \dot{q}_1 + \frac{\tau_{s2}}{\gamma_2} = \tau_2 \] (2)

For \( i \geq 3 \),

\[ I_{mi} \gamma_i \dot{q}_i + f_i(\tau_{si}, \dot{q}_i) + I_{mi} \sum_{j=1}^{j=1} z_{mi} z_j \dot{q}_j + \frac{\tau_{si}}{\gamma_i} \]
\[ + I_{mi} \sum_{k=1}^{j=1} z_{mi} z_j (z_k \times z_j) \dot{q}_k \dot{q}_j = \tau_i \] (3)

These assumptions are established for each module:

Assumption 1: The rotor is symmetric with respect to the rotation axis.

Assumption 2: The joint flexibility is negligible.

Assumption 3: The inertia between the speed reducer and the torque sensor is negligible, and torque transmission does not fail at the speed reducer.

To predict the underlying nonlinear friction for controller compensation, many friction models are proposed [24]. Here, we utilize a friction model that considers for payload dependency, and the friction is modeled as a function of the joint
velocity.

\[ f_i (\tau_{si}, \dot{q}_i) = B_i \dot{q}_i + \left( h_i (\tau_{si}) F_{ci} + F_{si} \exp \left( -F_{ci} \dot{q}_i^2 \right) \right) \text{sat} (\dot{q}_i) \tag{4} \]

where \( B_i \) represents the viscous friction coefficient, \( F_{ci} \) denotes the Coulomb friction related parameter, \( F_{si} \) reflects the static friction related parameter, and \( F_{\tau i} \) is a positive parameter denoting the Stribeck effect. In combination, the sign function is defined as:

\[ \text{sat} (\dot{q}_i) = \begin{cases} 
1 & \text{for } \dot{q}_i > 0 \\
0 & \text{for } \dot{q}_i = 0 \\
-1 & \text{for } \dot{q}_i < 0 
\end{cases} \tag{5} \]

The function \( h_i (\tau_{si}) \) is defined as follows:

\[ h_i (\tau_{si}) \triangleq 1 + h_1 |\tau_{si}| + h_2 |\tau_{si}|^2 \tag{6} \]

where \( h_1 \) and \( h_2 \) are positive parameters used to model Coulomb friction effect with payload dependency.

To apply the proposed OHM scheme to the overall joint, a linearized nonlinear friction model for the friction parameters’ nominal values is provided. In the dynamic model in (3), the Stribeck effect term \( F_{si} \exp \left( -F_{ci} \dot{q}_i^2 \right) \) is a nonlinear function of the parameter \( F_{\tau i} \). In this section, the dynamic model (3) is linearized in the parameter \( F_{\tau i} \). Assuming the nominal values of \( F_{si} \) and \( F_{ei} \) are close to their actual values, we linearize the Stribeck effect \( F_{si} \exp \left( -F_{ci} \dot{q}_i^2 \right) \) at the nominal parameter values \( \hat{F}_{si} \) and \( \hat{F}_{ei} \). By ignoring higher-order terms, we have

\[ F_{si} \exp \left( -F_{ci} \dot{q}_i^2 \right) \approx \hat{F}_{si} \exp \left( -\hat{F}_{ci} \dot{q}_i^2 \right) - \hat{F}_{si} \hat{F}_{ei} \exp \left( -\hat{F}_{ci} \dot{q}_i^2 \right) \tag{7} \]

Substituting (7) into (3) yields the \( i \)th joint module’s friction parameters estimation-based dynamical equation can be rewritten as [14]:

\[ \begin{align*}
I_{mi} \gamma_i \ddot{q}_i &+ Y_i (\dot{q}_i) \dot{\hat{\theta}}_i + I_{mi} \sum_{j=1}^{i-1} z_{mj}^T \ddot{\tau}_j + \tau_{si} \gamma_i + \\
+ I_{mi} \sum_{j=1}^{i-1} \sum_{k=1}^{j-1} z_{mj}^T (z_k \times z_j) \dot{\tau}_k \dot{\tau}_j &+ \hat{F}_{si} \hat{F}_{ei} \exp \left( -\hat{F}_{ci} \dot{q}_i^2 \right) \text{sat} (\dot{q}_i) \end{align*} \tag{8} \]

where

\[ Y_i (\dot{q}_i) = \begin{pmatrix} \dot{q}_i & h_i (\tau_{si}) \text{sat} (\dot{q}_i) & \exp \left( -\hat{F}_{ci} \dot{q}_i^2 \right) \text{sat} (\dot{q}_i) \\
& -\hat{F}_{ci} \dot{q}_i^2 \exp \left( -\hat{F}_{ci} \dot{q}_i^2 \right) \text{sat} (\dot{q}_i) \end{pmatrix} \]

and the nominal values of joint friction model parameters \( \hat{\theta}_i \) are defined as:

\[ \hat{\theta}_i = \begin{bmatrix} \hat{B}_i & \hat{F}_{ci} & \hat{F}_{si} & \hat{F}_{\tau i} \end{bmatrix}^T \tag{9} \]

Note that the joint friction model parameters are not accurately measured. Nevertheless, their nominal values \( \hat{\theta}_i \) are determined off-line as constant values which are assumed to be close to their actual values.

In order to formulate the dynamic equations in a more compact form, we define:

\[ \delta_i = \begin{cases} 
0 & i = 1 \\
I_{m2}^T z_{i1} \dot{\tau}_1 & i = 2 \\
I_{mi} \sum_{j=1}^{i-1} z_{mj}^T \ddot{\tau}_j + I_{mi} \sum_{j=2}^{i-1} \sum_{k=1}^{j-1} z_{mj} (z_k \times z_j) \dot{\tau}_k \dot{\tau}_j & i \geq 3 
\end{cases} \tag{10} \]

Then, the dynamic equation (8) is expressed as follows:

\[ I_{mi} \gamma_i \ddot{q}_i + Y_i (\dot{q}_i) \dot{\hat{\theta}}_i + \delta_i + \frac{\tau_{si}}{\gamma_i} = \dot{\tau}_i \tag{11} \]

B. ANALYSIS OF UNHEALTHY SITUATIONS

The overall system OHM of an MRR joint module examines its operational health in order to maximize its safety and reliability of operation. Unexpected change in the system dynamics, system parameters, or presence of unknown signals in the robot joint are models for unhealthy situations of MRR [16]. In this work, unhealthy situations include all factors that cause the current commanded joint torque to exceed the MRR dynamic model derived torque estimate in healthy situation, such as typical faults associated with MRR joint modules, including those of actuators, sensors, and harmonic drive gear.

Sensor faults may be caused by incorrect sensing, or problems in transmitting and receiving the sensor signal [25]. In some MRR modules, the torque sensor is considered as a key component. Potential joint torque sensor faults often correlate with strain gauges, signal conditioning, as well as communication. The technique that integrates harmonic drive with torque sensor is promising and improves the compactness of a robot joint. However, as there is very limited space for signal lead layouts, wiring problems are caused by jammed signal leads between the torque sensor signal amplifiers and the harmonic drive [20]. In comparison to sensor and harmonic drive gear, actuators are often associated with more complicated faults. The commanded joint torque is affected by problems in driver, motor, and mechanical transmission [26]. All these situations may affect the commanded joint torque. The commanded torque is usually boosted by the joint controller to maintain, especially when a fault-tolerant controller is employed, which is caught by health monitoring of the module.

III. MODULE SYSTEM OPERATION HEALTH MONITORING

While developing the proposed module system OHM method, it is assumed that a fault-tolerant controller is already implemented, and the controller generates the joint commands to control the robot joint. The commanded joint torque is usually boosted by the joint controller to maintain, especially when a fault-tolerant controller is employed. In some MRR modules, the torque sensor is considered as a key component. Potential joint torque sensor faults often correlate with strain gauges, signal conditioning, as well as communication. The technique that integrates harmonic drive with torque sensor is promising and improves the compactness of a robot joint. However, as there is very limited space for signal lead layouts, wiring problems are caused by jammed signal leads between the torque sensor signal amplifiers and the harmonic drive [20]. In comparison to sensor and harmonic drive gear, actuators are often associated with more complicated faults. The commanded joint torque is affected by problems in driver, motor, and mechanical transmission [26]. All these situations may affect the commanded joint torque. The commanded torque is usually boosted by the joint controller to maintain, especially when a fault-tolerant controller is employed, which is caught by health monitoring of the module.

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situations on the premise that the actuator has infinite input. However, the actuator input is always limited in practice. Based on the actuator input limit, the following OHM method is designed to monitor the health of the system.

To avoid joint acceleration measurement in the OHM scheme, a filtered torque signal, \( \hat{\tau}_{fi} (t) \in R^1 \), is formulated as:

\[
\hat{\tau}_{fi} = f (t) * \hat{\tau}_i (t)
\]

where \( \ast \) denotes standard convolution operation, and the low-pass filter function, \( f (t) \), is expressed as:

\[
f (t) = \alpha e^{-\beta t}
\]

where \( \alpha, \beta \in R^1 \) are constants of positive filter.

The filtered fault signal is delayed from the actual fault as

\[
t = \tau_{ci} - \hat{\tau}_{fi} = f (t) * \tau_{ci} - (\hat{f} (t) * I_{mi} \dot{\gamma}_i \hat{q}_i (t) + f (0) I_{mi} \dot{\gamma}_i \hat{q}_i (t) + Y_i (\hat{q}_i \dot{\hat{q}}_i t - f (t) I_{mi} \dot{\gamma}_i \hat{q}_i (0) + f (t) * \gamma_i^{-1} \tau_{si} (t))
\]

In order to monitor the overall joint module system using the torque estimation-based approach, integration of the magnitude of the torques deviation is utilized to formulate the average torque deviation during a movement from time \( t_1 \) to \( t_2 \) as follows:

\[
\bar{e}_{\tau} = \frac{\int_{t_1}^{t_2} |e_{\tau_i}| \, dt}{t_2 - t_1}
\]

Without losing generality, the time period can be selected \( 0 - t \) to obtain the operation health of the overall joint module system from the beginning to the end of the monitoring period \( t \), and both \( r \) and the beginning time can be arbitrarily selected according to application needs.

Considering that \( \delta_{\tau} \) was neglected and there is a discrepancy between the nominal and actual values of the joint friction, as well as the existence of systematic error, a minimum threshold is defined as:

\[
\bar{\varepsilon}_{\min i} = \bar{\varepsilon}_{\min i}^* + \varepsilon_{\min o}
\]

where \( \bar{\varepsilon}_{\min i}^* \) is the average torque deviations during the monitoring period, which is determined experimentally for each joint module in the healthy situations, and the \( \varepsilon_{\min o} \) is the minimum threshold offset, which is also to be determined experimentally to make the health indicator more precise.

Based on the above considerations, a health indicator that is selected to reflect the operation health of each joint module system is defined as:

\[
\eta_i = \frac{\bar{\varepsilon}_{\tau_i} - \bar{\varepsilon}_{\min i}}{\varepsilon_{\max i} - \bar{\varepsilon}_{\min i}} \times 100\
\]
FIGURE 2. A block diagram of the health monitoring method of MRR.

\[
\bar{e}_{\tau i} = \frac{\int_{0}^{t} \tau_{\text{max}_i} - \hat{\tau}_i \, dt}{t - 0}
\]

is the average torque deviation, which is determined experimentally for each joint module. Specifically, the motor input maximum continuous torque \( \tau_{\text{max}_i} \) during the monitoring period. High motor currents cause excessive winding temperatures, which should be maintained below the maximum rotor temperature through heat dissipation. Consequently, the selected rated current (i.e., torque) should correspond to the maximum constant of permissible current and the set input commanded torque should be maintained below the selected rated continuous motor torque. Throughout the monitoring process, we define that if the motor is continuously operated with a torque greater than the rated continuous motor torque in a certain period of time, the system is completely unhealthy and needs to stop working [6]. Note that motor drivers can provide larger torque than rated continuous motor torque for a short period of time, based on the temperature situation. However, this study does not consider this transient process as we mainly examine MRR’s continuous operating condition when the motor torque is limited by rated continuous motor torque.

A block diagram of the proposed module system OHM scheme is shown in Fig. 2. Actuated by a motor, the considered MRR joint module consists of a harmonic drive gear, a torque sensor, and an encoder. Based on the sensor signal feedbacks, the commanded torque is determined by the controller of each module and is sent to the driver. Connected to the harmonic drive, the motor rotor transfers the motor torque to the side of the payload. When the joint module system is operated in healthy situations, the health indicator is close to zero as \( \bar{e}_{\tau i} \) is close to \( e_{\text{min}_i} \). In an unhealthy situation such as components degradation, the average torques deviation \( \bar{e}_{\tau i} \) increases as the commanded torque increases, providing an indication of the operation health of each joint module system.

IV. EXPERIMENTS AND DISCUSSIONS

The proposed OHM method has been experimentally tested on a 2-DOF MRR (Fig. 3), which was developed in our laboratory. In this experimental setup, each joint is driven by a permanent magnet brushed DC motor from Maxon, with rated continuous motor torque of 190 mNm. The harmonic drive in the setup is SHD-17-100-2SH with gear ratio of 101:1, and rated torque of 16Nm from Harmonic Drive AG. The data acquisition, control implementation, and fault detection were performed using the Quanser Q8 data acquisition card at a frequency of 1 kHz. The link-side position is measured using Netzer absolute position electric encoder (DS-90) with 19-bit resolution and the link-side torque is measured using ATI six-axis F/T sensor, Mini45-ERA. For the experiments, the physical parameters of the Joint 1 and Joint 2 are listed in TABLE 1. The filter parameters are \( \alpha = 1 \) and \( \beta = 10 \). The monitoring procedure using the proposed method consists of the following steps:

Step 1. Define the desired trajectory of the MRR.

Step 2. Applying the controller described in the appendix to complete trajectory tracking control of MRR to obtain a minimum threshold \( e_{\text{min}_i} \).

| Parameters                  | Joint1       | Joint2       |
|-----------------------------|--------------|--------------|
| Rotor inertia (kg m²)       | 0.161 x 10⁻⁴ | 0.161 x 10⁻⁴ |
| Gear ratio                  | 101          | 101          |
| Link mass (kg)              | 0.641        | 0.570        |
| Link length (m)             | 0.55         | 0.45         |
| \( \dot{\theta}_1 \) (Nm s/\( \text{rad} \)) | 0.02         | 0.012        |
| \( \dot{\theta}_2 \) (Nm)   | 0.0015       | 0.0010       |
| \( \dot{\theta}_2 \) (\( \text{rad}^2 \)) | 0.00552      | 0.00152      |
| \( \dot{\theta}_2 \) (\( \text{rad}^2 \)) | 100          | 80           |
| \( e_{\text{min}_1} \) (Nm) | 0.003+0.0003 | 0.003+0.0002 |
| \( e_{\text{min}_2} \) (Nm) | 0.015        | 0.015        |
| \( h_1 \)                   | 4.3          | 4.3          |
| \( h_2 \)                   | 0.5          | 0.5          |
| Driver conversion factor \( k_d \) (A/V) | 4            | 4            |
| Motor torque coefficient \( k_T \) (Nm/A) | 0.321        | 0.321        |
Step 3. Artificially adding faults to the MRR, making the command torque higher than the rated continuous motor torque to complete the same trajectory tracking control, thereby obtaining a maximum threshold \( \bar{e}_{\text{max}} \).

Step 4. According to the proposed method, it can obtain the health indicator \( \eta_i \) at any period to monitor the health of MRR. The closer the health indicator is to 100%, the less healthy the system is.

Step 5. If the desired trajectory of the MRR changes, return to Step 1.

The robust fault-tolerant controller described in the appendix is applied for the MRR control. The commanded torque correlates to the commanded voltage \( \upsilon_{ci} \) and other parameters as follows:

\[
\tau_{ci} = K_T \lambda_d \upsilon_{ci} \tag{25}
\]

where \( K_T \) denotes the coefficient of motor torque and \( \lambda_d \) denotes the drive voltage-current conversion factor.

To demonstrate the proposed scheme’s effectiveness, two independent experiments were conducted. In the first experiment, an artificially adjustment was applied in the motor torque constant \( K_T \) for Joint 1, which represents a fault in the motor magnetic field, and used to simulate degradation faults. In this case, the Joint 2 working in a healthy situation and Joint 1’s filtered output commanded torque represented by (25) can be expressed as:

\[
\tau_{cf1} = f(t) \ast \rho K_T \lambda_d \upsilon_{c1} \tag{26}
\]

where \( \rho (0 \leq \rho \leq 1) \) denotes actuator effectiveness factor. The introduction of the artificial factor \( \rho \) in (26) can be equivalently taken as that the motor torque constant has somehow changed to \( \rho K_T \) from its original value \( K_T \) due to whatever reasons that can cause degradation in the motor magnetic field and motor winding. The desired trajectory for Joint 1 is \( q_{1d} = -0.2 \cos(3\pi t/10) + 0.2 \), with a 30s duration and the desired trajectory for Joint 2 is \( q_{2d} = \pi/7 \ast \sin(0.5t) \), with a 30s duration.

Based on (21), the torques deviation of Joint 1 can be estimated as

\[
e_{\tau 1} = f(t) \ast \rho K_T \lambda_d \upsilon_{c1} - \hat{e}_{f1} \tag{27}
\]

Figs. 4-5 show the link-side position, position error, and Joint 1’s filtered output commanded torque represented by (25) can be expressed as:

Fig. 4. Experimental results for Joint 1 under fault free \( \rho = 1 \).

Fig. 5. Experimental results for Joint 2 under fault free.
whereas the tracking performance is satisfied due to the application of fault-tolerant controller. In this case, the health indicator of Joint 1 is 13.5%. However, the tracking performance of the Joint 1 noticeably decreased when factor $\rho$ was changed from 0.7 to 0.3 and the health indicator becomes 71.8%. It is worth noting that from the experimental results as shown in Figs. 6-9, it can verify that the fault in Joint 1 does not affect the tracking performance of Joint 2 due to the application of the distributed control method.

Various $\rho$ values were tested for Joint 1. With the decrease of $\rho$, the torques deviation increases. TABLE 2 lists the experimental results of the health indicator according to the changes of factor $\rho$.

In the second experiment, the resistive torque is injected into the Joint 1 for simulating mechanical degradation and a free-swinging fault is introduced for Joint 2 at $t = 15s$, which represents abrupt fault. In order to further illustrate

| $\rho$  | 1   | 0.8 | 0.6 | 0.4 | 0.27 |
|---------|-----|-----|-----|-----|------|
| $\eta_1$(%) | 0.8 | 4.5 | 20  | 44.9 | 94   |
| $\eta_2$(%) | 0.51 | 0.52 | 0.51 | 0.55 | 0.53 |
that the proposed method is suitable for any desired trajectory, an intermittent desired trajectory has been tested for Joint 1. For the desired trajectory

\[
q_d = \begin{cases} 
-0.2 + 0.2 \cos \left( \frac{\pi t}{3} \right) & 0 < t \leq 6 \\
0 & 6 < t \leq 12 \\
0.2 - 0.2 \cos \left( \frac{\pi t}{3} \right) & t > 12 
\end{cases}
\]

A system monitoring and fault detection technique, based on power efficiency estimation, is developed for MRR, which can effectively monitor the performance of a joint system [20]. However, due to the need to calculate the output power, it is not applicable to all manipulator operations.

In this part of the experiment, the desired trajectory is chosen as \(q_{1d} = 0\) at \(6s < t < 12s\) for Joint 1, which is not within the scope of the [20]. When we use the health monitoring method proposed in [20], the experimental result is that the power efficiency is zero, which means that the system is completely broken. However, it is not the real situation of the MRR system. Fig. 10 and Fig. 12 show the different results obtained by the proposed system OHM method when a resistive torque is applied and not applied to the motor shaft, respectively. When the resistive torque is applied to the motor shaft, the torques deviation increase as the friction is offset by a robust fault tolerant controller, while the tracking performance of Joint 1 is satisfied. The increased joint friction does not necessarily mean joint fault. However, the health
TABLE 3. The health indicator for Joint 2.

| t  | 15  | 15.3 | 15.4 | 15.5 | 15.6 | 15.7 | 15.8 |
|----|-----|------|------|------|------|------|------|
| η₂(%) | 0.55 | 15.7 | 24.5 | 31.2 | 47.4 | 69.4 | 92.5 |

The desired trajectory for Joint 2 is \( q_{2d} = \pi / 10 \times \cos (0.6t) \), the experiment results for Joint 2 are shown in Fig. 11 and Fig. 13. The health indicator for Joint 2 is 0.55% from 0s to 15s. When a free-swinging fault is introduced for Joint 2 at \( t = 15s \), the corresponding performance indicators are listed in TABLE 3 from 15.3s to 15.8s. Notably, with the abrupt fault was injected into Joint 2, the link-side position error significantly changed. Moreover, the torques deviation rapidly increases as the commanded torque increases.

V. CONCLUSION

A distributed OHM scheme has been presented for MRRs. The proposed scheme generates an OHM indicator of the overall joint module system using the deviation between the commanded output of the actuator and the actually delivered. The proposed approach is straightforward and can be applied to MRR modules in any working mode, with promising application potentials especially for robots working in no power output state, such as in stationary state. The effectiveness of the proposed was confirmed with experimental results. It should be pointed out that, even though the reported work has been focused on MRRs, it is straightforward to extend the proposed method to robot manipulators in general.

APPENDIX A

FAULT-TOLERANT CONTROLLER

The following control method is formulated based on the work reported in [14], with consideration of actuator faults. The dynamical equation of each module can be expressed as:

\[
I_m \dot{q}_i + \sum_{j=1}^{n} \sum_{k=1}^{m} z_{mi} \dot{q}_k \dot{q}_j + f_i (\tau_{si}, \dot{q}_i) + \frac{\tau_{fi}}{\gamma_i} + \sum_{j=1}^{n-1} z_{mi} \dot{q}_j + \alpha (t - T_f) \psi_i (q_i, \dot{q}_i, \tau_i) = \tau_i \tag{A.1}
\]

where \( \psi_i (q_i, \dot{q}_i, \tau_i) \) is fault function, \( \alpha (t - T_f) \) is a step function and \( T_f \) is the unknown fault occurrence time. The term \( \alpha (t - T_f) \psi_i (q_i, \dot{q}_i) \) represents actuator fault. \( \tau_i \) is the actual joint torques measured using torque sensors expressed as \( \tau_{fi} = \hat{\eta}_i \tau_{si} + \hat{\sigma}_i \) and \( \eta_i \) and \( \sigma_i \) are sensor gain and offsets, respectively, \( \hat{\eta}_i \) and \( \hat{\sigma}_i \) are the nominal values of \( \eta_i \) and \( \sigma_i \).

By linearizing the Striebeck effect \( F_s \exp (-F_r \dot{q}_i^2) \) at the nominal parameter values \( \hat{F}_s \) and \( \hat{F}_r \), ignoring higher order terms, the “linearized” model of equation (A.1) is obtained as:

\[
I_m \dot{q}_i + \hat{B}_i \dot{q}_i + (\hat{F}_s + \hat{F}_r \exp (-\hat{F}_r \dot{q}_i^2)) \exp (\hat{F}_r \dot{q}_i^2) \dot{q}_i + \hat{\eta}_i - Y(q_i) \hat{\theta}_i + \alpha (t - T_f) \psi_i (q_i, \dot{q}_i, \tau_i) + \hat{\delta}_i \tau_{si} = \tau_i \tag{A.2}
\]

where \( \hat{\delta}_i = \hat{\eta}_i / \gamma_i, \hat{\theta}_i = \hat{\sigma}_i / \gamma_i, \)

\[
Y(q_i) = \left[ \dot{q}_i, \text{sat}(\dot{q}_i) \exp (-\hat{F}_r \dot{q}_i^2) \text{sat}(\dot{q}_i) \right],
\]

and the parametric model uncertainty \( \hat{\theta}_i \) is defined as:

\[
\hat{\theta}_i = \left[ \hat{B}_i - B_i, \hat{F}_s - F_s, \hat{F}_r - F_r, \hat{\delta}_i - \hat{\delta}_i \right].
\]

In order to present the fault tolerant control law, the following variables are defined as:

\[
e_i = q_i - q_{id} \tag{A.3}
\]

\[
r_i = \dot{e}_i + \lambda_i e_i \tag{A.4}
\]

\[
a_i = \dot{q}_{id} - 2\lambda_i e_i - \lambda_i^2 e_i \tag{A.5}
\]

The compensator \( u_i \) is designed to compensate for the subsystem actuator fault \( \psi_i (q_i, \dot{q}_i, \tau_i) \) as follows:

\[
u_i = \begin{cases} 
-\rho_i \frac{r_i}{|r_i|} & |r_i| > \varepsilon_i \\
-\rho_i \frac{r_i}{\varepsilon_i} & |r_i| \leq \varepsilon_i
\end{cases} \tag{A.6}
\]

where \( \varepsilon_i \) is a positive control parameter, \( \rho_i \) is the boundary of subsystem actuator fault function.

Typically, due to temperature and lubrication variations in practice, the parametric model uncertainty of \( \hat{\theta}_i \) may not
always be constant. To incorporate the compensation for variable parametric model uncertainty, \( \hat{\theta}_i \) is decomposed as:

\[
\hat{\theta}_i = \hat{\theta}_i^c + \hat{\theta}_i^v
\]  

(A.7)

where \( \hat{\theta}_i^c \) is a constant unknown vector, and \( \hat{\theta}_i^v \) is variable and bounded as follows:

\[
|\hat{\theta}_i^v| < \rho_i^v, \quad n = 1, 2, 3, 4, 5, 6
\]  

(A.8)

For the \( i \)th joint, the terms \( u_{F_c}^i \) and \( u_{F_v}^i \) are designed to offset the parametric uncertainty \( \hat{\theta}_i^c \) and \( \hat{\theta}_i^v \) respectively as follows:

\[
u_{F_c}^i = -k_1 \int_0^t Y(\dot{q}_i, \tau_{si})^T r_i d\tau
\]  

(A.9)

\[
u_{F_v}^i = \begin{cases} -\rho_i^v |\hat{\theta}_i^v|, & |\hat{\theta}_i^v| > \varepsilon_i^v, \quad n = 1, 2, 3, 4, 5, 6 \\ -\rho_i^v |\hat{\theta}_i^v|/\varepsilon_i^v, & |\hat{\theta}_i^v| < \varepsilon_i^v, \quad n = 1, 2, 3, 4, 5, 6 \end{cases}
\]  

(A.10)

where \( \varepsilon_i^v = Y(\dot{q}_i, \tau_{si})]^T r_i \), and \( \varepsilon_i^v \) is positive control parameter.

The term \( I_{mi} \sum_{j=1}^{i-1} Z_{mj}^T \dot{q}_j \) in Eq. (A.1) can be expressed as:

\[
I_{mi} \sum_{j=1}^{i-1} Z_{mj}^T \dot{q}_j = - \sum_{j=1}^{i-1} \left[ I_{mi} \hat{\beta}_j^i I_{mi} \right] \left[ \ddot{q}_j \hat{\beta}_j^i \dot{q}_j \right] = - \sum_{j=1}^{i-1} J_j^i D_j^i
\]  

(A.11)

where \( \hat{\beta}_j^i \) denotes the dot product of the unit vectors \( z_{mj} \) and \( z_j \); and \( D_j^i \) denotes the alignment error, calculated by the dot products differences between nominal and actual direction vectors.

For including the uncertainty of variable parametric in the term \( I_{mi} \sum_{j=1}^{i-1} Z_{mj}^T \dot{q}_j \), \( D_j^i \) in Eq. (A.11) can be decomposed into a constant plus a bounded variable term as:

\[
D_j^i = D_{jc}^i + D_{jv}^i
\]  

(A.12)

where the variable term \( D_{jv}^i \) is bounded as:

\[
|D_{jv}^i| \leq \rho_D^i
\]  

(A.13)

Applying decomposition-based control design, an adaptive compensator \( u_{jc}^i \) is designed for the constant uncertainty term \( D_{jc}^i \) and a robust compensator \( u_{jv}^i \) for the variable part \( D_{jv}^i \):

\[
u_{jc}^i = -k_2 \int_0^t J_j^iT r_i d\tau
\]  

(A.14)

\[
u_{jv}^i = \begin{cases} -\rho_D^i |\dot{\theta}_i^v|/\varepsilon_i^v, & |\dot{\theta}_i^v| > \varepsilon_i^v \\ -\rho_D^i |\dot{\theta}_i^v|/\varepsilon_i^v, & |\dot{\theta}_i^v| \leq \varepsilon_i^v 
\end{cases}
\]  

(A.15)

where \( \dot{\theta}_i^v = J_j^iT r_i \), and \( \varepsilon_i^v \) denotes positive control parameter.

Comparably, for the \( i \)th joint, \( I_{mi} \sum_{j=2}^{i-1} Z_{mj}^T (\dot{z}_k \times \dot{z}_j) \dot{q}_k \dot{q}_j \) can be rewritten as:

\[
I_{mi} \sum_{j=2}^{i-1} Z_{mj}^T (\dot{z}_k \times \dot{z}_j) \dot{q}_k \dot{q}_j = - \sum_{j=2}^{i-1} \sum_{k=1}^{i-1} \left[ I_{mi} \hat{\phi}_j^i I_{mi} \right] \left[ \ddot{q}_j \hat{\phi}_j^i \dot{q}_j \right] = - \sum_{j=2}^{i-1} \sum_{k=1}^{i-1} J_{jk}^i P_{jk}^i
\]  

(A.16)

where the term \( P_{jk}^i \) can be decomposed as:

\[
P_{jk}^i = P_{jk}^i + P_{jk}^i
\]  

(A.17)

and the variable part \( P_{jk}^i \) is bounded as:

\[
|P_{jk}^i| \leq \rho_{jk} \rho_{vj}
\]  

(A.18)

Similar to the above, applying decomposition-based control design, an adaptive compensator \( u_{jk}^i \) is designed for the constant uncertainty term \( P_{jk}^i \) and a robust compensator \( u_{jk}^i \) for the variable part \( P_{jk}^i \):

\[
u_{jk}^i = -k_3 \int_0^t J_j^iT r_i d\tau
\]  

(A.19)

\[
u_{jv}^i = \begin{cases} -\rho_D^i |\dot{\theta}_i^v|/\varepsilon_i^v, & |\dot{\theta}_i^v| > \varepsilon_i^v \\ -\rho_D^i |\dot{\theta}_i^v|/\varepsilon_i^v, & |\dot{\theta}_i^v| \leq \varepsilon_i^v 
\end{cases}
\]  

(A.20)

where \( \dot{\theta}_i^v = J_j^iT r_i \), and \( \varepsilon_i^v \) is a positive control parameter.

The fault tolerant control law is defined as:

\[
\tau_i = I_{mi} \dot{y}_i + \dot{\hat{\theta}}_{qi} + \sum_{j=2}^{i-1} \sum_{k=1}^{i-1} J_{jk}^i (u_{jc}^i + u_{jk}^i) + \dot{\hat{\theta}}_{qi} (u_{jc}^i + u_{jk}^i) + \dot{q}_i + u_i + (\dot{\hat{\theta}}_{ci} + \dot{\hat{\theta}}_{si} \exp(-\dot{\hat{\theta}}_{ci}^2)) \sin(q_i)
\]  

(A.21)

The control law (A.21) can ensure that, in each joint, the tracking error is ultimately uniformly bounded, which has been proved but the proof is omitted here as the focus of this paper is health monitoring.
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