Industrial Paper

Failure Prediction of Factory Automation Equipment using the Interaction between Parallel Links

Masanori Haga†, Kazuhiko Tsutsui‡, Katsuhiko Kaji*, Katsuhiro Naito*, Tadanori Mizuno*, and Naoya Chujo*

†Graduate School of Informatics, Aichi Institute of Technology, Japan
‡Mitsubishi Electric Co., Ltd., Japan
* Aichi Institute of Technology, Japan
{Tsutsui. Kazuhiko}@ay.MitsubishiElectric.co.jp
{b19723bb, kaji, tmizuno, ny-chujo}@aitech.ac.jp
{naito}@pluslab.org

Abstract - Maintenance of factory automation (FA) equipment is important for quality assurance in the manufacture of industrial products. In the present paper, we develop a failure prediction method for FA equipment with parallel links.

Recently, predictive maintenance has been considered as a maintenance system for FA equipment. In predictive maintenance, sensors are attached to the equipment. The failure time is estimated based on the sensor data, and maintenance is carried out in advance. Unsupervised learning is the recommended method, because FA equipment is not prone to failures and may not accumulate much failure data. The principal component analysis used in the present study can be used unsupervised, and related studies have shown that principal component analysis is more accurate than other unsupervised learning methods.

The considered method has a simple structure in which links of the same type are arranged in parallel. The considered method is shown to have great potential for enhancing predictive maintenance.

Since each link is connected to one mechanism, when the operation of a particular link is abnormal, the operations of other links are affected. By monitoring these interactions between links, failure prediction for the entire link mechanism can be performed using the measurement data from the sensor of a single link.

Experimental equipment with two links was produced. Time series data were obtained from measurements using the sensor of the servomotor when a load was applied to one link. Using principal component analysis, changes in link classes were observed based on the measurement data of not only the loaded link but also the unloaded link. In the present paper, we confirm the existence of the interaction between the links using an experimental apparatus of the parallel linkage mechanism. These interactions are used to predict failures with a small number of sensors.

Keywords: Predictive Maintenance, Factory Automation, Parallel Link, Principal Component Analysis

1 INTRODUCTION

Recent factory automation (FA) systems support a wide range of industrial products, from electronic devices, such as mobile phones, to transportation equipment such as automobiles. Proper maintenance of FA systems is required in order to ensure the quality of these products. In general, the maintenance cost of an FA system has been reported to be 15 to 60% of the manufacturing cost of the product, and thus is not insignificant [1].

There are two types of maintenance methods for FA equipment. The first is preventive maintenance which involves regularly performing maintenance, regardless of the state of the equipment. Therefore, unnecessary maintenance is performed on the FA equipment, which increases maintenance costs. The second type of maintenance is predictive maintenance, in which maintenance is performed according to the predicted state of the FA equipment. The state of the FA equipment is measured by sensors, and future failure times are predicted. The maintenance cost can be reduced by conducting maintenance based on failure prediction. The International Air Transport Association (IATA) has estimated that the cost of maintenance would be reduced by 15 to 20% if aircraft were to be subjected to predictive maintenance [2]. Failure prediction is required in order to perform predictive maintenance. The installation cost and physical space in a system, including wiring, for the sensor must also be considered [3]. In addition, a communication channel must be secured in order to upload real-time measurement data to the cloud. The purpose of the present paper is to predict the failure of FA equipment. FA equipment consists of a combination of several servo motors, links, and other mechanical components. By attaching sensors to the components in a system, it is possible to accurately measure mutations that lead to component failure. We herein examine a failure prediction method that is suitable for edge computing.

In the present paper, we predict failure for predictive maintenance using the interaction between mechanical parts. Defective components in FA equipment are detected based on changes in the sensor data. We examine the accuracy of the failure prediction using an experimental apparatus while increasing the load on the equipment until failure. We use principal component analysis (PCA) for feature extraction in the failure prediction.

The remainder of the present paper is organized as follows. Section 2 introduces related research. Section 3 presents the considered method for failure prediction. Sections 4 and 5 describe the experimental system, the experimental method, and the obtained results. Section 6 discusses the evaluation results, and a summary is presented in Section 7.

2 RELATED RESEARCH

System diagnostics can be separated into model-based diagnostics and signal-based diagnostics [4]. Model-based diagnosis is used when the theoretical modeling of a target system is straightforward. A deterministic model is created using equations to represent the actual system, and the diagnosis is performed by comparing the output of the system with the output of the model.

Signal-based diagnosis is used when theoretical modeling of a target system is difficult. In this case, we use a model derived from measurements. We extract the characteristics for normal and abnormal operating conditions of the equipment from the measurements and use these characteristics to diagnose faults.

In recent years, a method for signal-based diagnosis using machine learning techniques has been introduced. With the increasing accuracy of sensors and developments in the field of AI, the accuracy of failure prediction is improving. There are also techniques to perform signal-based diagnosis under dynamic conditions, as compared to static conditions alone [5].

FA equipment is generally reliable and resistant to failure. However, in real environments, it is difficult to apply supervised learning because of the small accumulation of failure data. Therefore, it is common to use unsupervised machine learning for FA equipment. According to a review paper on FA equipment diagnosis by unsupervised machine learning, methods using PCA provide the best results [6]. The considered method uses unsupervised learning because it is not possible to know the parameters at failure from the beginning. Maintenance is carried out and monitoring the parameters and actually operating the FA equipment and is optimized by adjusting the operation period little by little.

In addition, there is a problem in signal-based diagnosis in that signal-based diagnostics require high computational power for recording and processing large amounts of measurement data. Therefore, it is necessary to apply these methods using cloud computing [7]. In the case of FA equipment, it is necessary to secure a large capacity communication line.

For this reason, it is desirable that the computer on the edge side be able to diagnose faults in the FA equipment. In addition, it is desirable that sensor count be reduced when edge computing is used. There are interactions between components such as the resonance between the components in the FA equipment, and the status of the entire FA system can be diagnosed using a small sensor count with appropriate signal processing. However, as far as we know, methods for predicting failure using the interaction between parallel links in FA equipment have not been studied.

3 FAILURE PREDICTION OF FACTORY AUTOMATION EQUIPMENT WITH PARALLEL LINKS

In the present paper, we examine a method for predicting failure by signal-based diagnosis for FA equipment with parallel links. Parallel link robots [8] are multiple link mechanisms of the same type that are arranged in parallel and operate synchronously. Robots using parallel links use many more shared control components compared to a single-arm robot. Therefore, the manufacturing cost is low, and the mechanism is simple and easy to maintain. For this reason, parallel links have been widely used. Fault prediction is performed by the parallel link mechanism with the installed sensor. Since each link is combined to form a single mechanism, the movement of a link is affected by other links. Therefore, if there is an abnormality in the operation of a certain link, the behavior of other links is expected to be affected. In the present paper, by considering the interaction between parallel links, using only measured data of sensors from a single link, we considered a method to detect an abnormal sign of an FA apparatus with parallel links to carry out its fault prediction. Generally, FA equipment does not change suddenly from the normal state to an abnormal state, and there may be a sign of abnormality due to wear of parts between the normal state and the abnormal state. The considered method measures the time series data of FA devices with parallel links. PCA is performed for these data. Based on the change in the PCA result, a sign of the abnormality is obtained, and the failure time is predicted. The procedure of the considered method is shown below.

- Measurement of time series data during operation of FA equipment
- PCA for measured time series data
- Classification of the data using the plane with the first and second principal components as axes
- Representation of each class by elliptic approximation and extraction of elliptic parameters
- Prediction of failure time from time series variation of elliptic parameters

The concept of fault prediction based on the considered method is shown in Fig. 1. The two axes represent the first and second components of the PCA. An ellipse approximating the measured data is shown. A normal ellipse indicates normal operation. This ellipse gradually changes with various factors to an abnormal state which is indicated by an abnormal ellipse. This change is obtained as an "abnormal sign" ellipse in the middle, which indicates a sign of the abnormality. A class is a collection of data measured at the same timing in an operation of an apparatus. Therefore, classification is possible by collecting data in the order of measurement. In addition, we use curve approximation to predict elliptic parameters. In the next section, we discuss how to verify the degree of abnormal behavior from other links that can be detected.

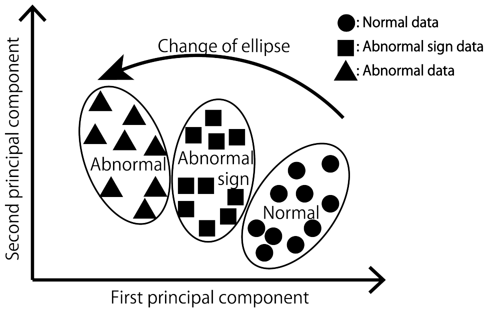

Figure 1: Concept of failure prediction

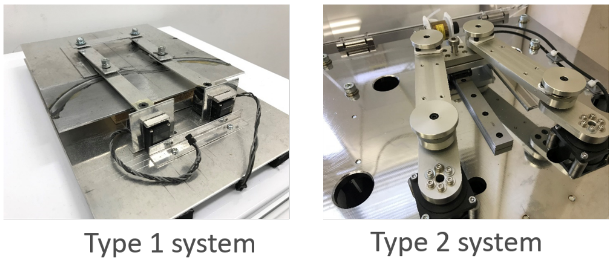

Figure 2: Experimental apparatuses

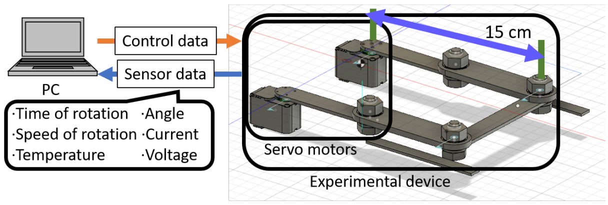

Figure 3: Type 1 experimental system

4 EXPERIMENTAL METHOD

In this section, we describe the experimental apparatus with a parallel link as well as the procedure for using the experimental apparatus. The experiment was carried out in a room in which an air conditioner was set at a constant temperature in order to suppress the change of motor data due to the change in temperature between day and night. An outline of the experiment is as follows. In this experiment, the abnormality of the bearing due to seizure and rusting due to a lack of grease is shown by mounting the weight. This is a fatal failure as a parallel link robot because the movement of the joint is impeded.

- Applying a load, which assumes an increase in the friction load at a specific link, and measuring the data.
- Analysis of changes due to increased load.
- Comparison of data between loaded and non-loaded links to evaluate the possibility of failure prediction.

4.1 Experimental Apparatuses

The experimental apparatuses are shown in Fig. 2. These apparatuses are systems that predict failure times from data obtained from the servo motors and can cover anomalies in joints such as bearing wear and seizure due to a lack of grease. In this experiment, the method was first examined on an apparatus (Type 1) that imitates FA equipment. By applying the method to an apparatus similar to actual FA equipment (Type 2), we obtain the results reported herein, and the generality to the parallel link mechanisms is confirmed. The Type 1 system is shown in Fig. 3. The Type 1 system consists of a personal computer and parallel link mechanisms using two servo motors. The personal computer transfers control to the servo motors, and the servo motors transmit the data to the personal computer. Six kinds of data can be obtained from the servo motors. The Type 1 sensor data consist of temperature, current, voltage, rotation angle, rotation speed, and rotation time, which can be obtained from the servo motor. The data acquisition frequency is 10 Hz. The temperature data measurements of the servo motor are affected by the temperature of the room. Therefore, this temperature is stabilized in the range of $\pm 1°$c using air conditioning. This method prevents temperature change due to factors other than the heat generated by the operation of the servo motor.

The Type 1 system is approximately 15 cm and is smaller than actual FA equipment. The specifications of the servo motor are listed in Table 1. The Type 2 system consists of an external hard disk drive (HDD) and parallel link mechanisms, as well as a controller using two servo motors. The controller operates the servo motors and transmits the data to the external HDD. Three kinds of data can be obtained from the servo motors. The Type 2 sensor data consist of current, rotation speed, and overshoot, which can be obtained from the servo motor. The data acquisition frequency is approximately 2252 Hz.

The specifications of the servo motor are listed in Table 2.

In the experiment, by operating the experimental apparatus which is similar to FA equipment, we obtain the sensor data necessary for failure prediction by increasing the load on the servo motor. In particular, we increase the load on the link component in order to create abnormal operating conditions. The experimental apparatus is shown in Fig. 4. The joints connect the links of the link components. The guide rails limit the movement of the drive unit. The drive unit is perpendicular to the guide rail.

Table 1: Specifications of the Type 1 servo motor (RS302CD)

Torque (during operation 7.4 V)	5.0 kgf·cm
Current consumption (when stopped)	40 mA
Current consumption (when moving)	125 mA
Working voltage	7.2–7.4 V
Movable angle	150°
Temperature limit	0–40 °C
Communication speed	max 460.8 kbps

Table 2: Specifications of the Type 2 servo motor (MDH-4012-324KE)

Torque	6.1182 kgf·cm
Temperature limit	0–40 °C

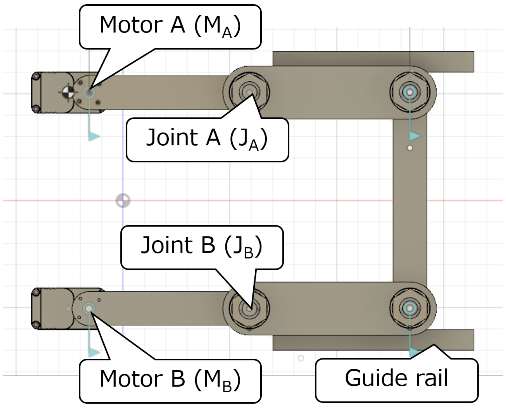

Figure 4: Parallel links

The drive unit moves backward and forward by rotating servo motors A (M_A) and B (M_B) outward. The weights are placed either at Joint A (J_A) or Joint B (J_B).

4.2 Experimental Procedure of Type 1 System

Experiments are conducted to increase the friction between the links. First, we record the sensor output for 20 minutes without placing a load on the system. Second, weights are fixed to J_A for a 30-second interval. Next, we record the sensor output for another 20 minutes under a 70 g load. Weights are fixed to J_A, again. Finally, we record the sensor output for 20 minutes under a 130 g load.

4.3 Experimental Procedure of Type 2 System

Experiments are conducted to increase the friction between the links.The weight on joint A is the same as in the Type 1 experiment. The change is that the motor of the Type 2 system has a stronger force than that of the Type 1 system. We performed measurements from 0 g to 2500 g at 100 g intervals.

This experiment is carried out in order to verify whether the load increase can be observed by only the measurements from M_B when placing a weight on J_A.

5 EXPERIMENTAL RESULTS

We first describe the observed interactions. Next, we describe the results of PCA using 12-dimensional data. Finally, we describe the results of PCA using six-dimensional data. The data obtained from the servo motors are shown separately in Figs. 5 through 12.

5.1 Changes in Rotational Angle

Figures. 5 and 6 show the rotational angles of the servo motors.In the rotational angle data, M_A indicates that the movement of the horn is faster than usual due to the loading. Figure. 7 shows an enlarged view of the angle data for M_B. The region of the rotational angle data containing abnormal readings are enclosed by a black circle. Figure. 7 shows an enlarged view of the black circle. In M_B, there was an interaction in which the timing of the action was shifted by M_A.

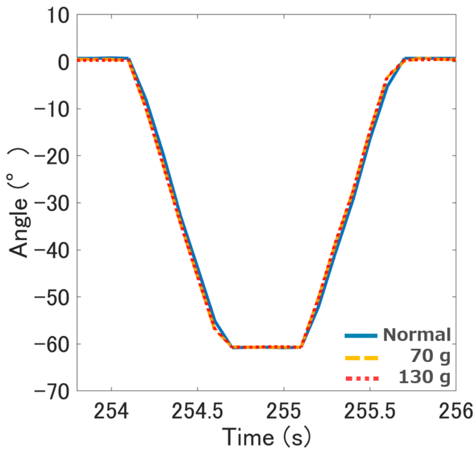

Figure 5: Angle data for Motor A

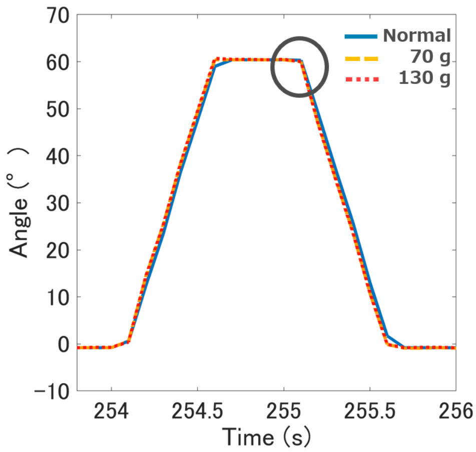

Figure 6: Angle data for Motor B

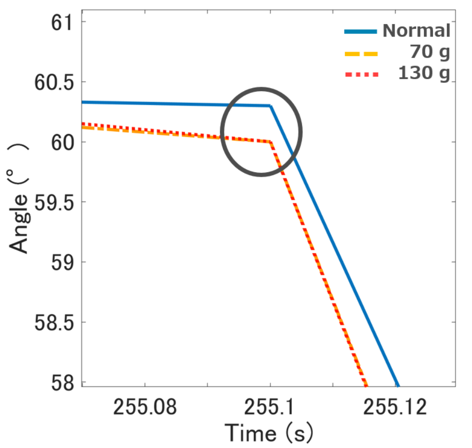

Figure 7: Enlarged view of angle data for Motor B

5.2 Changes in Rotation Time

Figures. 8 and 9 show the rotation times of the servo motors. Rotation time indicates the elapsed time from the start of the movement of the servo horn, and the value is retained until the next movement after arrival at the target angle. The abnormal measurements in the rotation time data are enclosed by a black circle. Figure. 10 shows an enlarged view of the area indicated by the black circle. Here, M_A indicates that the time of movement is clearly earlier than that for the case without a load. Figure. 10 shows an enlarged view of the M_B rotation time data. In addition, M_B is also moving slightly faster than before the load was added.

5.3 Changes in Voltage

Figures. 11 and 12 show the voltages of the servo motors. The three sets of measurements for M_A show that the tendencies in the voltage change do not agree. The M_A voltage under the 130 g load is more stable than that under the 70 g load, probably because the play in the experimental apparatus was suppressed by the weight. The abnormal voltage data are enclosed by a black ellipse. The voltage data for M_B show a small variation, but an abnormal voltage drop was observed due to the interaction.

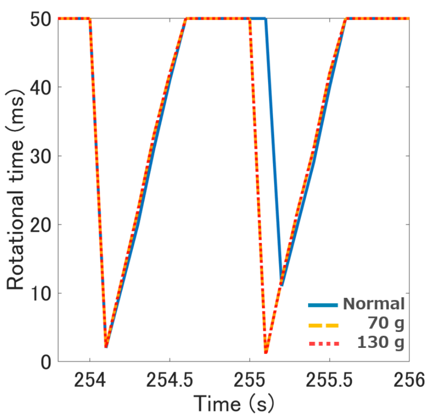

Figure 8: Rotation time data for Motor A

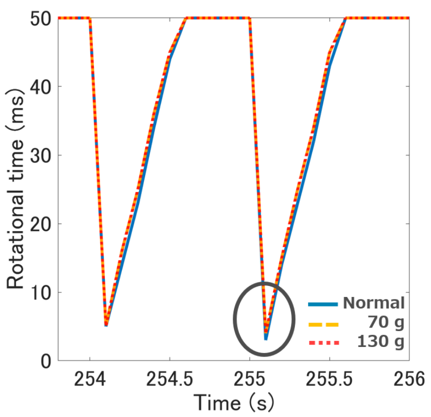

Figure 9: Rotation time data for Motor B

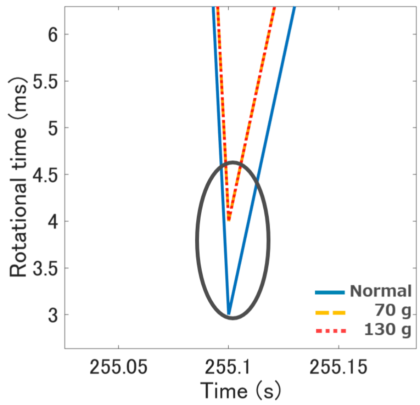

Figure 10: Enlarged view of rotation time data for Motor B

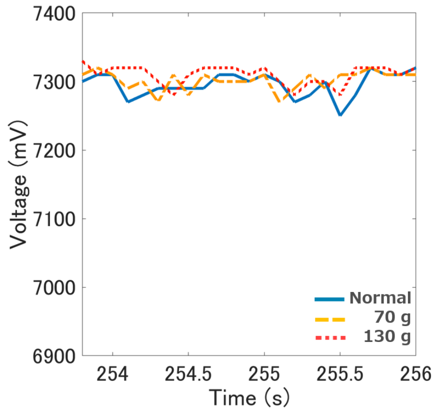

Figure 11: Voltage data for Motor A

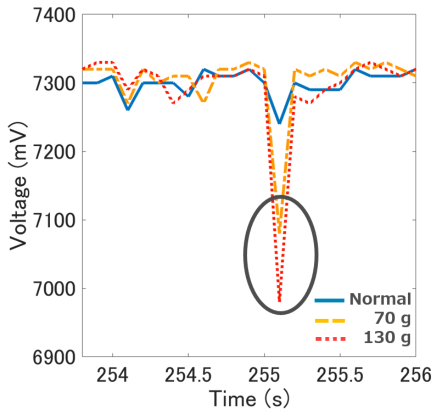

Figure 12: Voltage data for Motor B

5.4 Results of Principal Component Analysis

PCA was performed using 12-dimensional data from both motors. Figure. 13 shows the contribution of the principal components (PCs) of the normal time data. The contributions of the PCs of the loaded data were approximately the same. We can explain less than 50% of the variance in the data in two dimensions.

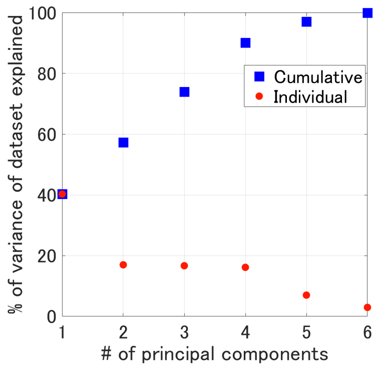

Figure 13: Cumulative explained variance for the principal components

Figures. 14 and 15 show the 12-dimensional data distribution without and with load, respectively. The solid and dashed ellipses indicate the 70 g data and the 130 g data, respectively, in Fig. 15. The class count could be observed to change as the load increased. Classes are formed by grouping points for each operation of the experimental equipment. A given point moves between multiple classes after one movement of the experimental equipment, before returning to the initial class. Classes P_1 through P_4 are highlighted in Fig. 14. Other classes are moving between assigned numbers. The classes are changing as the load increases. In particular, the change of the P_3 class is remarkable.

From the PCA result for the 12-dimensional data, only P_3 was individually analyzed, and the change of P_3 in each state was confirmed. Table 3 shows the change of P_3. We applied a normal distribution to the data and analyzed the average value and the angle of the distribution on the x-and y-axes and the length of the main axis of the distribution. The major and minor axes are the standard deviations for each axis multiplied by a constant. Ellipses represent equal probabilities of 95%. In the 12-dimensional data, the change of P_3 was observed in the x mean value, the angle of distribution, and the principal axis. This is because some of the data for P_3 are located at P_2 in the operation.

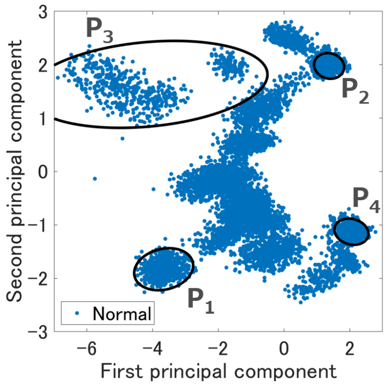

Figure 14: Twelve-dimensional data distribution: without load

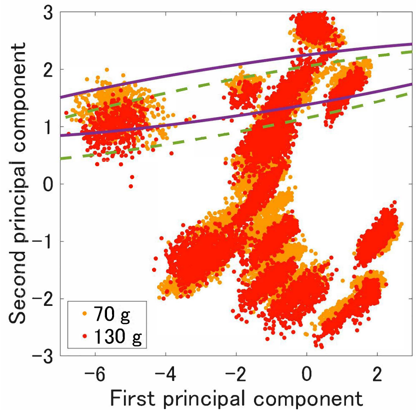

Figure 15: Twelve-dimensional data distribution: with load

Table 3: Twelve-dimensional data change for P_3

	P_3 Center (x, y)	P_3 (Angle)	P_3 (Major, Minor)
Normal	(-4.16, 1.63)	3.02°	(2.99, 0.65)
70 g	(-1.84, 1.65)	5.24°	(6.34, 0.36)
130 g	(-1.90, 1.38)	6.66°	(6.28, 0.38)

5.5 Failure Prediction of Type 1 System

PCA was performed using six dimensional data for each servo motor. Figsure. 16 and 17 show the results of PCA of M_A for the data distributions without and with load, respectively. Since M_A was directly loaded, the transition in the entire class from right to left was remarkable. Figures. 18 and 19 show the results of PCA of M_B for the data distributions without and with load, respectively. A transition was observed in the class. From this result, it is considered that abnormality in the equipment operation can be detected based only on PCA of the data of M_B without applying the load directly.

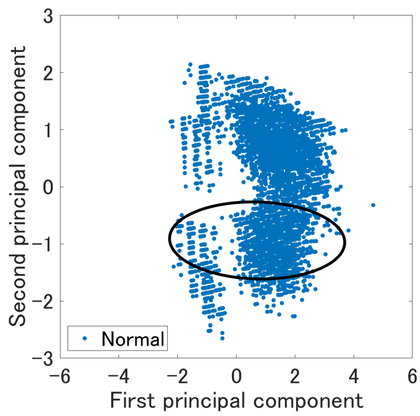

Figure 16: Six-dimensional data distribution for Motor A without load

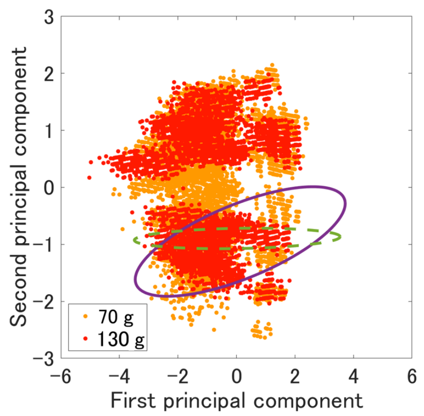

Figure 17: Six-dimensional data distribution for Motor A with load

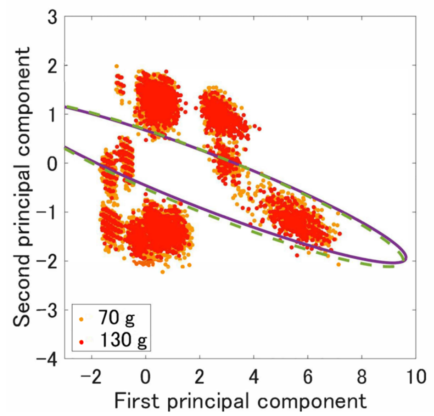

Figure 19: Six-dimensional data distribution for Motor B with load

Based on the PCA result for the six-dimensional data of M_A, only P_3 was individually analyzed, and the change of P_3 in each state was confirmed. Table 4 shows the change of P_3. In the M_A data, the change of P_3 was observed in the x mean value and the angle of distribution. In this case, as in the case of the 12-dimensional data, the data are arranged from P_3 to P_2 by the operation.

Based on the result of PCA for the six-dimensional data of M_B, only P_3 was individually analyzed, and the change of P_3 in each state was confirmed. Table 5 shows the change of P_3.

Table 4: Six-dimensional data (M_A) change of P_3

	P_3 Center (x, y)	P_3 (Angle)	P_3 (Major, Minor)
Normal	(0.71, -0.94)	-0.68°	(8.45, 1.80)
70 g	(0.13, -0.95)	10.9°	(7.41, 1.73)
130 g	(0.02, -0.90)	0.49°	(7.47, 1.62)

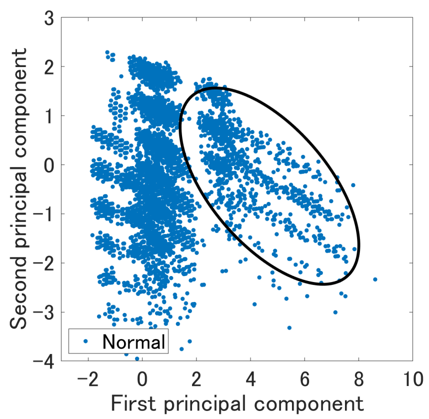

Figure 18: Six-dimensional data distribution for Motor B without load

Table 5: Six-dimensional data (M_B) change of P_3

	P_3 Center (x, y)	P_3 (Angle)	P_3 (Major, Minor)
Normal	(4.70, -0.44)	-24.5°	(2.91, 1.21)
70 g	(2.30, -0.38)	-12.0°	(6.12, 0.47)
130 g	(2.31, -0.42)	-12.4°	(6.04, 0.51)

In the M_B data, the change of P_3 was observed in the x mean value, angle of distribution, and principal axis.In this case, as in the case of the 12-dimensional data, the data are arranged from P_3 to P_2 by the operation.By looking at the long axis of the distribution, it is possible to observe the abnormality even from the motor under no load.

5.6 Failure Prediction of Type 2 System

In order to confirm the validity of the method, we designed the Type 2 system using high-power motors used in actual FA equipment. Figure. 20 shows that the results of the same data processing for the Motor B data of the Type 2 system. The results of the PCA were categorized on the axis of the plane with the first and second PCs and were approximated as an ellipse. In order to observe the change, 4.5% of the data from the beginning were extracted and defined as class 1.

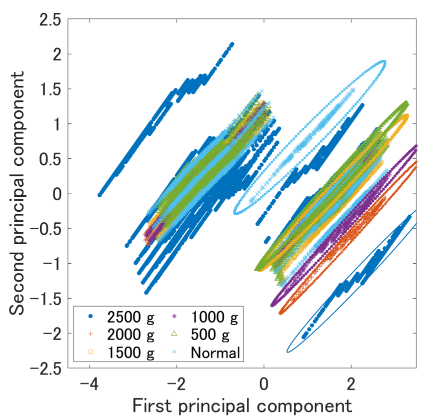

Figure 20: Three-dimensional data distribution for Motor B

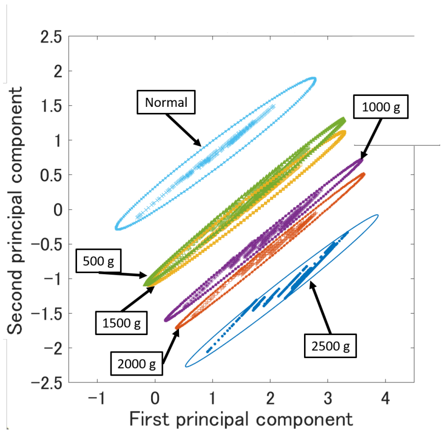

Figure 21: Three-dimensional data distribution for Motor B (class 1)

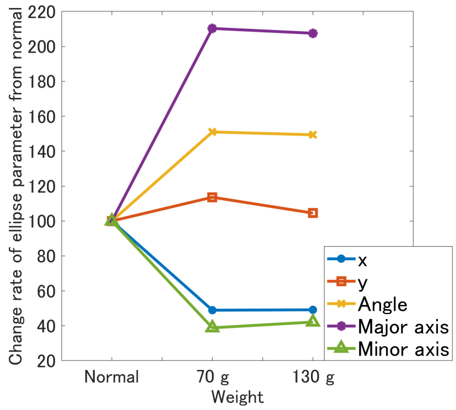

Figure 22: Change of M_B ellipse parameter (Type 1)

Table 6: Type 1 data (M_B) for change of class

	(x, y)	(Angle)	(Major, Minor)
Normal	(1.01, 0.80)	32.1°	(4.08, 0.38)
500 g	(1.55, 0.10)	34.7°	(4.20, 0.18)
1000 g	(1.89, -0.44)	34.3°	(4.14, 0.14)
1500 g	(1.59, 0.01)	33.1°	(4.06, 0.24)
2000 g	(2.00, -0.60)	34.4°	(3.94, 0.14)
2500 g	(2.20, -1.18)	33.2°	(4.00, 0.26)

The results for class 1 are shown in Fig. 21. As shown in the figure, the class 1 data change as the weight is increased. In addition, the parameters of the ellipse are shown in Table 6. In the present verification, it was confirmed that the x and y coordinates of the center of gravity changed with increasing weight, except for 1000 g.

6 DISCUSSION

In the present paper, we considered a fault prediction method for FA equipment with parallel links using the interaction between links. An experimental apparatus for monitoring parallel links using two servo motors was developed. An experiment in which a load was placed on one link was carried out in order to determine whether an increase in friction could be detected from the other link. Based on the results of PCA of 12-dimensional data from the servo motors, it was confirmed that multiple data classes changed when the load was increased. Based on the results of the PCA for six-dimensional data obtained from one servo motor, it was possible to observe changes in the data classes when increasing the load not only in the servo motor with the load but also in the servo motor without the load. This indicates that failure prediction for the robot joint based on the interaction between parallel links of FA equipment is possible.

Changes in the Type 1 M_B ellipse parameter are shown in Fig. 22. The figure shows that the change from 70 g to 130 g is small. It is considered that the equipment has already entered the failure condition from the usual condition, because it has been confirmed that the operation of the equipment stops during the experiment, when the experiment is carried out when the weight exceeds 130 g. In addition, if the data count is low, the evaluation of the parameter prediction will be insufficient.

Therefore, evaluation of the prediction is possible by acquiring more data for the 70 g load from the usual time.

Changes in the Type 2 M_B ellipse parameter are shown in Fig. 23. In this verification, it is confirmed that the process applied to the Type 1 parameter can be applied to Type 2 parameter. Therefore, it is conceivable that this method can be applied in the same manner to other parallel link mechanisms to predict anomalies. The considered method does not look for learned patterns, but rather predicts gradual changes in the data. This method is applicable to anomalies other than bearing seizure. For example, it is possible to predict failures due to aging and wear. For these anomalies, we need to conduct verification experiments.

On the other hand, there is a limitation in the considered method in that it cannot predict failures in which gradual changes in the data cannot be observed. Such failures include chipping of bearings due to sudden overloads.

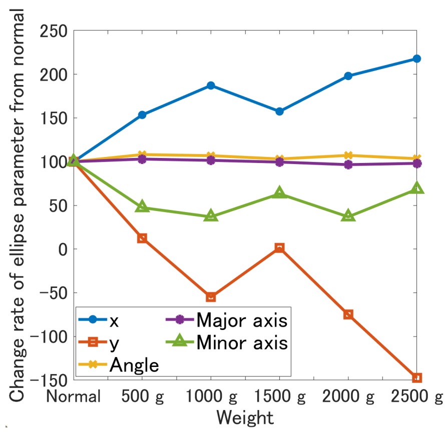

Figure 23: Change of M_B ellipse parameter (Type 2)

7 CONCLUSION

In the present paper, we considered a failure prediction method for FA equipment assuming there exists an interaction between parallel links. The experimental apparatus of the parallel link was developed, and the abnormality of the bearing used for the joint was expressed in the load quantity. The sensor output data were then measured. PCA of the time series data confirmed that multiple data classes changed as the load increased. In the analysis of the measurements for each servo motor, it was possible to observe the change in the data classes under increasing loads, i.e., not only in the servo motor with a load but also in the servo motor without a load. This indicates the possibility of fault prediction based on observation of the interaction between links.

Two experimental systems, Type 1 and Type 2, were designed in order to simulate actual parallel links of FA equipment. As a result, it was confirmed that the considered method applied to both systems can predict failures in which gradual changes in the data were observed. Future issues include verification experiments of the considered method for other kinds of anomalies, such as ageing and wear.

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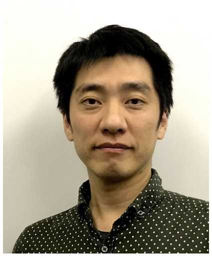
Masanori Haga received his B.E. degree in information science from the Aichi Institute of Technology, Japan in 2019. His research interests include analyzation of machine information. He is a member of Information Processing Society of Japan.

Kazuhiko Tsutsui received the B.E. and M.E. degrees in Mechanical Engineering from Kumamoto University, Japan in 1990 and 1992 respectively. In 1992, he joined Mitsubishi Electric Corp. Since when he joined Mitsubishi Electric Corp, he has been engaged in development of Servo and Spindle drive system.



Katsuhiko Kaji received a Ph. D. in information science from Nagoya University in 2007. He became a RA at the NTT Communication Science Laboratories in 2007 and an assistant professor at Nagoya University in 2010. He has been an associate professor of the Faculty of Information Science, Aichi Institute of Technology since 2015. His research interests include indoor positioning and remote interaction. He is a member of IPSJ and JSSST.

Katsuhiro Naito received the B.S. degree in Electronics Engineering from Keio University, Japan in 1999, and received the M.S. and Ph.D. degrees in Information Engineering from Nagoya University, Japan in 2001 and 2004, respectively. From 2004 to 2014, Dr. Naito was an assistant professor in the electrical and electronic engineering department of Mie university. He was a visiting scholar in the computer science department of University of California, Los Angeles (UCLA) in 2011. Since 2014, he has been an associate professor in the information science department of Aichi Institute of Technology. His research interests include 5G technologies, vehicular communication systems, Internet of Things (IoT) and Machine to Machine (M2M) systems, overlay networks, and network protocols and architectures.

Tadanori Mizuno received the B.E. degree in Industrial Engineering from the Nagoya Institute of Technology in 1968 and received the Ph.D. degree in Engineering from Kyushu University, Japan, in 1987. In 1968, he joined Mitsubishi Electric Corp. From 1993 to 2011, he had been a Professor at Shizuoka University, Japan. From 2011 to 2016, he had been a Professor at the Aichi Institute of Technology, Japan. Since 2016, he is an Affiliate Professor at the Aichi Institute of Technology, Japan. His research interests include mobile computing, distributed computing, computer networks, broadcast communication and computing, and protocol engineering. He is a member of Information Processing Society of Japan, the Institute of Electronics, Information and Communication Engineers, the IEEE Computer Society and Consumer Electronics, and Informatics Society.

Naoya Chujo received his B.E. degree in applied physics and M.S. degree in information science, and Ph.D. degree in electrical engineering from Nagoya University in 1980, 1982, and 2004, respectively. He joined Toyota Central R&D Labs. in 1982. He has been a professor at the Aichi Institute of Technology since 2010. His research interests are in the area of embedded systems and automotive electronics. He is a member of IEEE, IPSJ, IEICE, IEEJ, and Informatics Society.