1. Introduction

Wire bonding is a joining technique in which an electrode on a semiconductor element is connected by a metal wire to an electrode on an external terminal. It has been used for many years; is highly flexible in terms of connection distance, connection direction, wire size (diameter), connection electrode material, etc.; and has shown excellent performance in terms of productivity, yield, and junction reliability. As a result, it is an important technique in semiconductor manufacturing. Destructive testing is traditionally employed for quality inspection of wire bonding, and typically involves a wire pull test in which a hook is attached to the end of a wire and pulled upward to break it, with pass and fail determined by the fracture load and position. Therefore, statistical analysis through sampling inspection is typically employed for quality evaluation. In sampling inspection, the acceptance or rejection of a lot consisting of numerous samples is based on the results for a sub-group of representative samples. However, this method involves a risk of erroneous detection, with defective samples contained in accepted lots and good samples discarded with rejected lots. In addition, as semiconductor manufacturing technology has dramatically improved, the number of junction elements has increased due to a large amount of integration and lamination, and thus the importance of evaluating junction reliability is increasing. In light of this, quality evaluation of individual samples is required, instead of traditional statistical quality assurance through sampling inspection, as a new form of quality inspection for wire bonding.

The main problem in transitioning to such total quality inspection is that the inspection employs destructive testing, and this is self-defeating when applied in an actual production context. Thus, a non-destructive inspection method is required, in order to shift to total quality inspection. Among the non-destructive inspection methods for...
wire bonding, the evaluation of joints by image processing,[1] and measurement of oscillating ultrasonic waves during wire bonding,[2] have been proposed. However, as actual semiconductor manufacturing involves hundreds of different processes, and significant time and cost, inspection methods requiring the introduction of an entirely new inspection process are likely to be avoided. Therefore, it is desirable to use an inspection method that extracts information on the bonding state in the actual manufacturing process, and automatically determines acceptance or rejection based on the extracted information.

In order to achieve strong bonding in wire bonding, the thermosonic method, involving the application of ultrasonic waves, is widely employed. In the present study, we focused on ultrasonic waves applied during joining, with the aim of developing a totally non-destructive method of evaluating the bonded state, utilizing elastic waves propagating through the bonding target. In a previous study,[3] we proposed an elastic wave measurement technique using a thin film AE sensor. The thin film AE sensor is a compact device that can stably operate even in high temperature environments, and enables measurement near the wire bonding joint, which is impossible using traditional methods. This form of measurement makes it possible to evaluate the bonding condition in all relevant products.

However, since measurement and evaluation using AE sensors requires analysis of multivariate factors, it is difficult to establish key criteria such as thresholds; and as it requires expert knowledge, it may be practically difficult to evaluate individual samples directly from the waveforms. Machine learning has attracted attention in recent years as an effective means of addressing such a situation. Machine learning can estimate quality labels for new sensor signals, by modeling their relationships based on feature vectors obtained by analyzing sensor signals and the like, using pairs of associated quality labels. In particular, when a new sample is obtained, anomaly detection for determining whether it is normal or anomaly is a technology in which it is desired to expand application examples. Since anomaly detection directly leads to reduction in maintenance and inspection costs at production sites, the need for such detection is high. Furthermore, as it is generally difficult to collect many anomalous samples at manufacturing sites, an anomaly detection method that can learn from normal samples alone is significantly easier to utilize. The one-class SVM[4] algorithm is a promising tool in this regard, as it utilizes a highly generalizable support vector machine (SVM)[5] for anomaly detection. Establishing an anomaly detection system using a one-class SVM thus enables the efficient and effective evaluation of new samples.

In a previous study,[6] we proposed an anomaly detection method using MT method based on quality engineering method. In the proposed method, feature vectors determined through AE waveform analysis are input, and pass/fail is determined based on the fracture load in wire pull testing. We confirmed its effectiveness experimentally, using bonding samples fabricated using a manual wire bonder. However, since the bonding sample was manually produced, the loop shape of the bonding samples was not constant. Therefore, it was thought that the wire pull test incorporated evaluation bias due to loop-shape variation, such as deviation in the loop length and/or hook position. In addition, since the samples were manually produced, it was difficult to obtain many. In order to introduce the proposed anomaly detection method into the actual manufacturing process, we believe it is necessary to acquire highly reliable data satisfying two conditions: constant loop shape and a large number of samples. Furthermore, in MT method, the user must determine the discrimination threshold, and statistical expertise is required for effective operation. Thus, in order to construct an anomaly detection method that is easy to operate on actual sites, it is desirable to enable automatic determination of the discrimination threshold.

In this paper, then, we propose an anomaly detection system using a one-class SVM and thin film AE sensor, along with equipment that enables automation of the bonding process. Specifically, it will focus on the following two aims.

- With the automation system, we aim to increase the number of samples used for verification, while reducing the evaluation bias due to loop shape.
- Through application of the one-class SVM with high generalizability to unknown data, we aim to construct an anomaly detection system that evaluates pull test quality by evaluating the results of pull testing based on waveform input obtained by the thin film AE sensor.

In this manner, we will examine the effectiveness of the proposed method by conducting experiments in an environment that simulates the actual manufacturing process.

2. Wire Bonding

Wire bonding is a method for forming semiconductor junctions by connecting an electrode bonded to a substrate
with a conductor terminal on a different substrate. Techniques include a thermocompression method using heat and load, and a thermosonic method which additionally employs ultrasonic waves. Among the features of wire bonding, (1) it is flexible compared with flip chip bonding and TAB (i.e., it is able to deal with various patterns); (2) it can enable direct connection to the electrodes of a semiconductor chip, and thus is inexpensive; and (3) it has been studied and implemented for many years, so the process reliability is very high.

There are two types of wire bonding. In ball bonding, the tip of the bonding wire is fused by arc discharge, pressing and bonding the formed ball for a certain period of time. In wedge bonding, the wire is moved onto the lead finger, and pressure is applied through a direct capillary. In this latter form of bonding, ultrasonic energy is transmitted to a wedge tool, and joined by applying load and ultrasonic vibration to a wire. Although wedge bonding can only bond in one direction, bonding using a ribbon or a thick wire can be performed. Also, unlike ball bonding, it is not necessary to melt the wire by skipping a spark, so that aluminum wire can also be used, for example, in addition to gold wire.

2.1 Wire bonding connection reliability evaluation

It is thought that the bonding strength in wire bonding is determined by the true bonding area, irrespective of the bonding components.[7] Effective methods for increasing the true bonding area include increasing the ultrasonic output, increasing the ball hardness, improving the surface cleaning degree, etc. The true bonding area is obtained by applying a gold film of about 0.05 μm thickness to the surface of the electrode, and observing the electrode surface with an SEM after bonding. Therefore, it is difficult and expensive to obtain the true bonding area individually for manufactured bonding samples, and joint strength evaluation through sampling inspection involving destructive testing (such as wire pull or ball shear testing) is generally performed. However, products subject to destructive testing lose their functionality as a result of cracks and breaks, so it is impossible to conduct a full inspection of all target products. Therefore, sampling inspection is performed, in which prepared samples are divided into several lots, and destructive inspection is performed on representative samples from each lot, with each lot’s total samples considered to be of the same quality as its representative samples. Since the number of inspections is less than a total sample inspection, the cost and time required for inspection can be reduced. However, since it cannot be concluded that defective products are not included in the lots that have passed the inspection, there is a risk of cost increases due to distribution of defective products in accepted lots and to discarding of good products in rejected lots. Therefore, an inspection method that can economically estimate the quality of all the products is required.

2.2 Elastic wave detection technique for improving wire bonding reliability

In order to estimate the bonding strength with respect to the total number, we focus on ultrasonic waves applied during bonding. Ultrasonic waves applied to wire bonding promote plastic flow and mutual diffusion, and contribute to the generation of newly bonded faces, which is an important factor in improving bonding strength.[8] However, when there are impurities or voids on the target surface to be joined by wire bonding, it inhibits the generation of newly formed surfaces and leads to a reduction in bonding strength. Further, it is also conceivable that the ultrasonic waves do not sufficiently propagate due to insufficient pressure or the like during joining, and the joining strength decreases. In this way, since it is unknown how much of the measured ultrasonic energy in the applied ultrasonic waves actually contributed to the generation of the newly generated surface, in order to evaluate the bonding strength, including the presence or absence of bonding defects, it is desirable to measure not the ultrasonic waves but elastic waves propagating through the target object to be joined.

In this study, then, we adopted a measurement method utilizing a thin film AE sensor[3] and measurement of the elastic waves propagating through the workpiece via the bonding target. Ultrasonic waves applied to the bonding target can be estimated by such elastic wave measurement, and more detailed evaluation of the bonding strength can thereby be expected. In addition, use of the thin film AE sensor enables stable measurement in a high-temperature environment of 800°C or more; and since the detection element is about 5 mm square, housed in a small, 1 cm square sensor of 1 mm thickness, it can be attached to a very limited region. Because of these factors, it can be installed directly on a small region of a workspace being bonded in a high-temperature environment, making it possible to reduce the influence of elastic wave attenuation due to the use of a wave guide or the like.

3. Automation of the Bonding Process

In a previous study, we proposed a good/defective dis-
crimination method based on wire bonding pull test results, using machine learning based on AE waveform input obtained by a thin film AE sensor. In that study, it was difficult to collect many samples because wire bonding was manually performed using a manual wire bonder. In addition, since it is considered that the fracture load in the wire pull test is caused by the loop shape, an abundance of defective samples were obtained. However, since semiconductor manufacturing processes are precision operations, the number of defective samples is, in fact, overwhelmingly small in comparison with the number of normal samples. Therefore, in order to construct an anomaly detection system suitable for an actual semiconductor manufacturing process, it is necessary to decrease the proportion of defective samples while securing more samples.

Therefore, in this study, we automated the semiconductor fabrication process, stabilized the loop shape, and automated the sample fabrication. Automation of the manufacturing process uses an XYZ three-axis robot and an automatic XY stage (Fig. 1). The XYZ three-axis robot can independently control the X, Y, and Z axes. In addition, the Z-axis has a gripper mechanism used for connection with the wire bonder, and through its connection with the manipulator arm of the wire bonder, it is synchronized with the operation of the XYZ three-axis robot and a loop shape is produced. In addition, the manual wire bonder is a special mechanism which enables the Y and Z axes to change in response to angular change in the manipulator caused by the arm movement that accompanies the change in the bonding position. Therefore, since the operation of the wedge as the end effector varies with the X position, correction of the loop locus according to it is required, which complicates the control. Therefore, by installing the work holder on the automatic XY stage, it is possible to move the bonding position without changing the angle of the manipulator arm. Also, by sending a trigger of 5 V in synchronization with the start of operation of the XYZ three-axis robot, we also automate the acquisition of the AE signal.

In this study, we prepared a loop trajectory for the XYZ three-axis robot beforehand. Various shapes are used for the loop shape in wire bonding (such as triangular or trapezoidal), mainly depending on the type of package, and generally a triangular loop shape is adopted, as in the present study (Fig. 2, where H is the height of the loop, and S the length of the hypotenuse). The loop trajectory for forming the target loop shape is shown in Fig. 3. After 1st bonding at point A, it rises 45 degrees forward to point B. This is because the wedge tip of the wire bonder used in this study had a wire path of 45 degrees, and the wire was supplied at a 45-degree angle, so as not to apply a load to the neck section when the wedge ascends. From point B to point C, it moves horizontally in the direction opposite to the 2nd bonding point. This bending process, called a reverse operation, enables a corner to be formed in the triangular loop by hanging a wire. The length of the wire fed out from point A to point C is equal to the height H. Next, it rises 45 degrees forward from point C to point D. The
length of the wire fed out in the movement from point C to D is equal to the length S of the hypotenuse portion. Between point D and E, the trajectory was derived using cubic splines in order to lower the wire to the 2nd bonding junction target without loading the wire.

4. Anomaly Detection

The purpose of anomaly detection is to determine whether a new case is normal or anomalous. In such detection, a normal sample is called negative, and an anomalous sample positive. A false positive refers to a normal sample erroneously determined to be anomalous, and a false negative refers to an anomalous sample erroneously determined to be normal. In the design of the anomaly detection algorithm, it is important to balance the false positive and false negative rates. Since the proper balance depends on the specific context, it is necessary, when designing the algorithm, to introduce parameters that can be adjusted so that the required balance can be achieved.

Two main approaches have been proposed for designing anomaly detection methods: unsupervised and supervised detection. Supervised anomaly detection can be regarded as a two-class classification problem in which normal and anomalous values are given as learning data. The SVM enables pattern recognition, and offers a solution for two-class classification in which normal and anomalous values are given as learning data. The SVM can maximize the marginal distance between classes when determining the classification boundary, and determine the appropriate classification boundary; thereby obtaining excellent discrimination performance for unlearned data. One-class SVM is a technique applied support vector machine for unsupervised anomaly detection. By determining the classification boundary similarly to the SVM, anomalies can be detected based on the boundary. Since the data necessary for learning is only normal data, the one-class SVM is an effective method for anomaly detection in systems in which it is difficult to generate anomalies and/or gather anomalous data. However, since only normal cases are given as learning data in the one-class SVM method, it is difficult to assign appropriate classification boundaries. Therefore, in practice, learning rules are often established such that the false positive rate is 1% or 5%. The \( \nu \)-SV classification algorithm\[9\] enables control of the false positive rate. In this algorithm, we use the parameter \( \nu \in (0,1) \) to control the balance between the loss term and the regularization term. \( \nu \) is the upper limit of the ratio of the margin error and the lower limit of the ratio of the support vector. Therefore, it is guaranteed that the following relationship holds:

\[
\frac{\#(M.E.)}{n} \leq \nu \leq \frac{\#(S.V.)}{n}
\]

where \( \#(M.E.) \) represents the number of margin errors, \( \#(S.V.) \) represents the number of support vectors, and \( n \) represents the number of data items. By using this property in the one-class SVM, we can learn the function \( f(x) \) which makes the false positive rate almost \( \nu \).

4.2 Anomaly detection in wire bonding

In this study, quality evaluation was performed based on the fracture mode, confirmed by pull testing. The fracture mode in the pull test is the wire mode with the highest quality, then the neck, the bond. In the wire mode and neck mode, it is considered that the wire is broken before peeling occurs between the wire and plating, because the joint has sufficient bonding strength. Even in the case of being regarded as a bond mode, there is a state in which...
the bonded portion and bonding target adhere at the time of peeling, and the bonding target is broken. In this case as well, it is considered that the bonding strength between the wire and the plating is sufficiently high, so that the peeling of the substrate occurs before the peeling between the wire and the plating. In this study, the results of the wire pull test suggested that the fracture mode was bond mode, the samples displaying peeling of the bonded target from the bonded target were defined as defective, and the other samples were defined as good. Examples of such good and defective products are shown in Fig. 4.

5. Experiment

Two experiments were conducted to examine the effectiveness of the proposed method. First, we measured the shape of wire bonding made using an automated device. Next, an anomaly detection technology based on one-class SVM was applied using the created sample.

5.1 Experimental environment

Figure 5 shows a composite picture of the experimental equipment used in the study. We prepared the loops automatically, using the proposed automation device, and selected a portion for determining feature quantities based on waveform data obtained during bonding. The wire
bonding manufacturing parameters are shown in Table 1, and the thin film AE sensor is shown in Fig. 6. The AE sensor and sample bonding chip were placed on the same work holder, and elastic waves generated in the work holder were observed by means of ultrasonic waves applied by the wire bonder during bonding. Figure 7 shows the AE sensor and sample chips installed on the work holder. A command is sent from the control PC to the XYZ three-axis robot and the automatic XY stage, and the loop is created by the manual wire bonder. The XYZ three-axis robot is connected to the manipulator of the manual wire bonder, and is responsible for forming the loop shape. Figure 8 shows the manipulator connection. The work holder is placed on the automatic XY stage (Fig. 9), and the bonding position is adjusted. The voltage acquired by the thin film AE sensor in the loop creation is amplified by the differential amplifier and stored in the recording PC, using an analog input module (NI9223, National Instruments). The acquisition rate was 1 [MS/s].

We evaluated the bonding condition using a pull tester (PTR-1102/STR-1102 (Ver. 1.0), RHESCA), with the hooking position, between the middle point of the loop and the loop top, being visually confirmed. Key elements of the pull test are shown in Fig. 10. As aforementioned, samples in which the neck broke and samples to whose joint with the bond target has not break were considered good products, and those in which the plating peeled from the wire were judged to be defective.

| Table 1 Bonding parameters. |
|-----------------------------|
| Ultrasonic power [kHz]      | 360 |
| Ultrasonic application time [msec] | 50  |
| Heater temperature [°C]     | 200 |
| Load                        | High (default) |

Fig. 6 Thin film AE sensor.

Fig. 7 AE sensor installation.

Fig. 8 Connection between the XYZ three-axis robot and manipulator.

Fig. 9 Work holder installation.
5.2 Data set summary

The signal transmitted from the XYZ three-axis robot simultaneously the beginning of the bonding operation was recorded continuously until the end of each sample preparation, as the acquisition start trigger. Some bonding samples are shown in Fig. 11, and typical examples of the recorded AE waveforms are shown in Fig. 12. As can be seen in Fig. 12 (a), a signal differing from the background noise appears between the 1st and 2nd bonding. It is thought that the drive vibration of the XYZ three-axis robot, transmitted through the lead wire after the 1st bonding, appears as noise. Since the AE waveform analysis method makes determinations based on the specified threshold, it is necessary to remove the noise in order to accurately measure the AE event. Therefore, noise subtraction was performed using the spectral subtraction method[10] (Fig. 12 (b)). We extracted waveforms from the 1st and 2nd bondings after denoising (Fig. 12 (c) and (d)), and calculated feature vectors by analyzing the time and frequency domains. In the time domain, the raw signal obtained was analyzed using ISO standardized AE parameters (maximum amplitude, rise time, duration, AE count, and RMS), and basic statistics (average, variance, skewness, kurtosis, and rising gradient) were calculated. An overview of the AE parameters is shown in Fig. 13. In the frequency domain, the waveform obtained by FFT was divided equally into eight sections for each frequency band, and statistical analysis was performed on each section, with seven dimensions, including maximum value, minimum value, (maximum value - minimum value), difference sum, difference square sum, average, and variance, being calculated for each section. Therefore, the sample feature vectors had 132 dimensions in total: 20 in the time domain (10 × 2) and 112 in the frequency domain (56 × 2). In order to perform this detection using significant infor-
information, principal component analysis (PCA) was also performed on each feature vector. The full set of input feature vectors are shown in Table 2. In addition, destructive tests were performed on all 1,318 created samples, to determine the quality of the samples; 1,254 were found to be normal, and 64 anomalous (Table 3).

5.3 Experimental results

In this section, we describe the result of shape evaluation based on physical measurement of sample and the result of anomaly detection linking AE waveform and pull test.

5.3.1 Measurement of loop shape

First, we investigated whether the bonding samples created using the automated equipment were of uniform shape. The loop shapes of the prepared bonding samples were measured using a digital microscope (VHX 6000, KEYENCE), and standard deviations were obtained. The measurement items were loop height and loop width. A total of 178 samples were measured using a single sample substrate. In addition, for comparison, bond loops created by non-experts and experts in the use of the manual wire bonder were also measured. The resulting standard deviations are shown in Table 4.

5.3.2 Anomaly detection using the one-class SVM

Using the calculated feature vectors (time domain, frequency domain, and time domain + frequency domain) as input, anomaly detection using the one-class SVM was performed. For the three evaluation indices (accuracy, precision, and recall), five-fold cross validation was employed, and the average values were taken as the respective results. In addition, the Lee-Liu metric,[11] an overall evaluation index of the anomaly detection algorithm, was calculated using the precision and recall indices. The parameter $\nu$ for controlling the false positive in the one-class SVM was 5%, and the respective evaluation index was calculated.

6. Discussion

With respect to the shape of the wire loop created using the developed automated device, standard deviations were calculated in order to objectively evaluate the length and height of the bonding samples made using this device. Further, as noted above, for comparison purposes, measurement results for samples prepared by non-experts and experts were also obtained (Table 4). The non-experts learned the wire bonding method immediately before the experiment, while the experts had acquired thorough work experience in manual wire bonding. The results showed that the standard deviation in both loop height and loop width were less in the case of expert workers, and far less in the case of the automated device, suggesting that it is possible to prepare samples with stable loop shape.

Comparing the target and created loop shapes, however, we observed that the vertex of the loop was significantly inclined toward the 1st bonding side. The reason for this
was that the reverse operation employed to shape the wire
during loop creation was too large. It is considered that
various shapes can be produced by controlling the reverse
operation.

We evaluated the wire bonding condition using the pro-
posed method based on the feature vectors obtained from
ultrasonic wave application during bonding. Table 5 shows
the experimental results for the test sample. From Table 5,
we found that the highest accuracy was (roughly 84%)
when both the time and frequency vectors were used. It
was further improved (to roughly 86%) by performing
PCA. In terms of precision, using only the time feature
vector gave the highest result (roughly 95%), and this too
was slightly improved by PCA. Models with high precision
are employed when we seek to minimize false positives,
and the proposed method was shown to be highly effective
this respect. In the case of recall, as in the case of accu-
cracy, the highest result (roughly 89%) was obtained when
both the time and frequency vectors were used, and this
increased slightly (to roughly 90%) with PCA. In the case
of the Lee-Liu metric, using both the time and frequency
vectors yielded a roughly 84% result, which also increased
slightly (to roughly 86%) with PCA. We may conclude that
when the results of PCA with the temporal and frequency
values are used as input for the one-class SVM, the anom-
aly detection algorithm is optimized. The results also sug-
gest that the significant information obtained from the
time feature vector differs from that obtained from the fre-
quency feature vector.

A typical example of a frequency domain waveform
obtained from a normal sample is shown in Fig. 14. In the
normal sample, a power spectrum appears in the same fre-

|                | Accuracy | Precision | Recall | Lee-Liu metric |
|----------------|----------|-----------|-------|----------------|
| Time           | 82.23    | 95.36     | 85.48 | 81.51          |
| Time (PCA)     | 82.99    | 95.58     | 86.12 | 82.31          |
| Frequency      | 84.78    | 94.95     | 88.74 | 84.26          |
| Frequency (PCA)| 85.71    | 94.94     | 89.78 | 85.24          |
| Time + Frequency| 84.79   | 94.96     | 88.74 | 84.26          |
| Time + Frequency (PCA)| 86.31 | 95.06     | 90.34 | 85.87          |

Fig. 14 Typical example of frequency analysis result of normal sample.
frequency band in both 1st and 2nd bonding. A typical example of the frequency domain waveform of the anomaly sample in which the 1st bonding portion is peeled is shown in Fig. 15, and that in which the 2nd bonding portion is peeled is shown in Fig. 16. In the anomaly sample, in addition to the power spectrum of the frequency band obtained in the normal sample, a spectrum appears in a lower frequency band than that. Furthermore, this low frequency tended to be strongly observed in the peeled part (1st or 2d). From this, it can be inferred that the junction strength

Fig. 15 Typical example of frequency analysis result of anomaly sample (1st bonding peeling).

Fig. 16 Typical example of frequency analysis result of anomaly sample (2nd bonding peeling).
is lowered when some low frequency signal is input at the time of peeling.

In addition, the pull test results showed some ambiguity in the fracture mode (Fig. 17), and there were cases where it was difficult to judge whether a given sample was good or defective, solely on this basis; a situation also encountered in actual manufacturing sites.

The waveform of this sample is as shown in Fig. 18. As a characteristic part, a spectrum is generated in a lower frequency region than the abnormal sample shown in Fig. 15. From this, it is possible that the joint surface may be damaged due to damage to the device. As described above, it was suggested that the junction state could be estimated by frequency analysis.

7. Conclusion

In this study, we developed an anomaly detection system using a thin film AE sensor and one-class SVM, developed and utilized an automated device attached to a manual wire bonder, and experimentally confirmed the effectiveness of the proposed anomaly detection system using production samples. The results showed that the experimental environment could generate an abundance of samples with little variation in loop shape; the maximum discrimination rate was roughly 86%, and the Lee-Liu metric (used as an evaluation index of the anomaly detection system) was as high as roughly 86%.

In order to introduce the system into actual production lines, however, the method of determining whether samples are good or defective must be further refined. We
have proposed an anomaly detection system that focuses on the fracture mode in wire pull testing; but it is likely that the fracture load and/or mode will change when the hook location changes, and thus it is important that the hooks are always located in the same position. In the proposed system, since the operator visually confirms the hook position and conducts the tensile test, the results of the tensile test may not always be accurate.

In addition, there are cases where the quality of the sample cannot be determined only in the fracture mode as Fig. 17. Verification using another indicator (e.g., breaking load, etc.) that determines the quality of such samples is also important.

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Yasutake Koishi received the B.S., M.S., and Ph.D. degrees in engineering from Kyushu Institute of Technology, Fukuoka, Japan in 2014, 2016, and 2019, respectively. He is currently a postdoctoral researcher at National Institute of Advanced Industrial Science and Technology (AIST), Japan. His current research interest is the application of machine learning technology to manufacturing.

Shuichi Ishida received the B.S., M.S., and Ph.D. degrees in engineering from Kyushu Institute of Technology, Fukuoka, Japan in 2008, 2010, and 2013, respectively. He is currently a researcher at National Institute of Advanced Industrial Science and Technology (AIST), Japan. His current research interests are anomaly diagnosis in manufacturing process and machine learning.

Tatsuo Tabaru received the B.S., M.S., and Ph.D. degrees in engineering from Tohoku University, Miyagi, Japan, in 1992, 1994, and 1997, respectively. He is a leader of a research group at Advanced Manufacturing Research Institute, the National Institute of Advanced Industrial Science and Technology (AIST), Japan. His current research interests include anomaly detection in manufacturing process and analysis of material degradation.

Wataru Iwasaki received the B.S., M.S., and Ph.D. degrees in engineering from Kyushu University, Fukuoka, Japan in 2008, 2010, and 2013, respectively. He is currently a researcher at National Institute of Advanced Industrial Science and Technology (AIST), Japan. His current research interests are fabrication of MEMS devices and biochemical sensors for animal health monitoring.

Hiroyuki Miyamoto received the B.S., M.S., and Ph.D. degrees in biophysical engineering from Osaka University, Osaka, Japan in 1985, 1987, and 1998, respectively. He was a member of research staff of Department 3, ATR Human Information Processing Research Laboratories, Kyoto, Japan. Since 2001, he has been an associate professor of Graduate School of Life Science and System Engineering, Kyushu Institute of Technology, Kitakyushu, Japan. His main interest is in the area of brain-like intelligent machines.