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Construction and evaluation of an anomaly detection system using System Invariant Analysis Technology(SIAT) for sound data

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Abstract

Here is a summary of a paper that presents case studies on the application of SIAT, a machine learning technique, for anomaly detection in plants and industrial machinery, with a focus on sound-based anomaly detection as a new application of SIAT:

This paper explains case studies on anomaly detection using SIAT as a machine learning technique. SIAT is specialized in analyzing time-series data and is widely used for anomaly prediction in plants and industrial machinery. In recent years, the application of SIAT has been extended to sound-based anomaly detection, and this paper presents some case studies on this topic.

Specifically, the paper provides several examples of sound-based anomaly detection, such as detecting abnormal sounds or predicting machinery failures. In these cases, SIAT was used to analyze sound data collected from multiple sensors, and anomalies were detected successfully. The results of these anomaly detection methods were then used to take preventive measures such as maintenance or repairs, leading to improvements in productivity and safety.

This paper demonstrates the usefulness of SIAT for sound-based anomaly detection and suggests the potential for expanding the scope of SIAT's applications.

1. Introduction

In recent years, equipment maintenance has become increasingly important in the plant and manufacturing industries. Production stoppages and quality degradation caused by equipment breakdowns and poor maintenance lead to significant losses for companies. Therefore, more advanced equipment maintenance is required, and the use of AI is attracting attention.

However, there are several issues that must be addressed before AI can be used to solve equipment maintenance problems. First, appropriate data may be lacking or of low quality, which may reduce the accuracy of AI and prevent it from providing effective solutions. In addition, AI requires highly skilled engineers and data scientists, which can be expensive to implement. Furthermore, the complexity of AI systems increases and requires proper operation and maintenance, which requires a management structure. Furthermore, ethical issues may arise, as humans will need to make appropriate judgments and take action on the information and analysis results provided by AI.

In this study, we propose an AI-based facility maintenance methodology to solve these issues. Specifically, System Invariant Analysis Technology (SIAT) will be introduced as an AI technology that can be used in the field, and an overview and application examples will be provided. By doing so, we aim to provide an effective method for AI-based equipment maintenance.

2. Overview of SIAT

There are three major factors in utilizing digital technology such as AI in the field of equipment maintenance (Figure 1). These are easy to hit, easy to understand, and maintenance of accuracy.
High expectations for digital technologies such as AI require learning from a large amount of data to derive accurate answers. However, it does not just mean that the result is correct. The second "easy to understand" is important for use in the field of equipment maintenance. If we cannot explain the results that is derived by AI as "why AI made the decision," we cannot take any further action. The third is mainly related to operating costs. In other words, if accuracy cannot be maintained at the field level, the mechanism will not be

used.

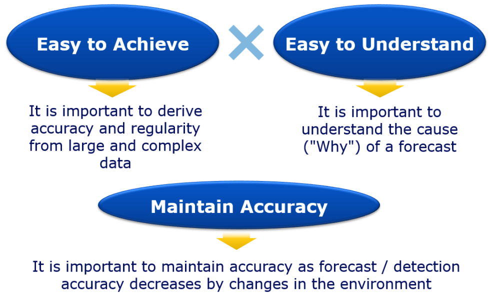

Figure 1. Three important factors in utilizing digital technology

In this way, AI that can be used in the field should not be used only for the purpose of "hit", and it is important to implement these three elements in a well-balanced way.
SIAT is one that satisfies such conditions. This technology was developed with consideration for on-site use from the beginning of development. It is an AI technology that is developed according to the needs and operations of the site, rather than adapting existing technology to the needs. SIAT uses time-series data collected / accumulated by control equipment and monitoring systems. Most of the current manufacturing equipment and plant equipment are automatically controlled by some kind of control system, and these controls are performed based on the monitoring data by the sensor. It is an analysis technology that comprehensively extracts the "invariant relationship" between these sensors from the numerical time series data obtained as these sensor information, and detects the "unusual state" using it as a model (Figure 2)

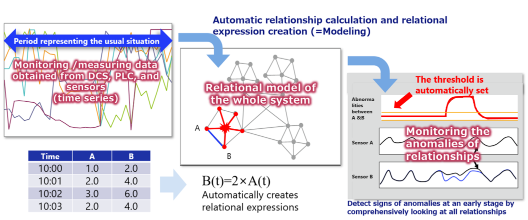

Figure 2. Overview of SIAT

The invariant relationship between the sensors is used as an operation model showing the usual state of the target system by learning (extracting the invariant relationship) from the data of the "normal operating state" of the equipment to be monitored. By monitoring the time and place where the invariant relationship changes in real time, it is possible to detect the "unusual state", that is, a sign of an abnormality at an early stage.
We will explain how to extract relationships and detect anomalies in SIAT. Suppose there is trend data from N sensors. In this case, there is a combination of Eq. (1) in this sensor group. For example, if the number of sensors is 100, there are 4,950 combinations. In all of these combinations, it is automatically generated as mathematical formulas and parameters whether or not there is an invariant relationship between the sensors, what kind of relational expression holds, and how strong the relationship is. An invariant relationship indicates a state in which the relationship is maintained in a given time-series data period (learning period).

$$\frac{(N^2 - N)}{2} \tag{1}$$

In the system, the relationship is often not found at the same timimg due to the difference in response speed. For example, taking water temperature control as an example, there is a slight time lag between the rise of the heater output and the rise of the water temperature. Invariant analysis technology creates and models a relational expression that takes this time delay into account.

It should be noted here is that no abnormal condition is required for learning. This means, SIAT learns the "normal state " in operation of the equipment. In general, there is almost no abnormal state in the operation of equipment, or various abnormalities are assumed, so it is impossible to request the abnormal state as learning data. In addition, it is assumed that the location (sensor) where the collapsed immutable relations are concentrated is the main cause location, and it is possible to identify the abnormal location.
When this technology is applied to factory operation monitoring, it becomes possible to detect abnormalities (silent failure = sign) that occur below the alarm threshold, which was difficult to find with conventional threshold monitoring and rule-based monitoring, so failure becomes apparent. It will be possible to prevent business losses and reduce operating costs by taking early measures before the change.
Also, it is not necessary to specify the objective variable, that is, which sensor value to look at. Some measures have been taken for known and frequently occurring abnormalities in the field, and the original problem is an unknown abnormality. For this reason, the specification of which one to look at is the automation of monitoring so far, which is different from the originally required requirement.
Since SIAT can basically be analyzed as long as it is numerical time-series data, it is possible to handle vibration data and sounds of pumps and motors, for example.
Products that is applied this technology are implemented as "NEC Advanced Analytics - Invariant Analyzer". The several analytical methods are provided according to the usage of the user, such as implementing a user interface for each of the operator in the field, the analyst such as the production engineering department, and the developer such as the IT department. In particular, the interface for operators is designed so that it can be used only with the know-how of on-site op-

eration and maintenance without being conscious of AI or analysis.

3. Case Study

Introducing examples of utilization of SIAT.
SIAT is used in various fields because it handles only time-series data and does not require abnormal data for learning.

3.1. Anomaly detection by sound data

Anomaly detection by sound enables early detection of machine and equipment failures and is expected to be effective for equipment maintenance and productivity improvement. Specifically, abnormal sounds and vibrations generated by machines and equipment can be detected, and their characteristics can be analyzed to detect abnormalities.
On the other hand, there are several challenges in detecting abnormalities by sound. First, since sound includes ambient noise, it is necessary to eliminate the influence of ambient noise for accurate detection. In addition, the frequency bandwidth and intensity of sound vary among different machines and equipment, so building a model for anomaly detection requires customization to suit each machine or equipment. Furthermore, there is the need for specialized knowledge to identify the cause of abnormal noise when it occurs, and the risk of false or omitted detection due to anomaly detection. To solve these problems, it is generally necessary to analyze data using advanced acoustic signal processing techniques and to build an abnormality detection model using machine learning techniques. In addition, accurate understanding of facility conditions requires proper installation of sensors and networks, as well as appropriate data collection and management. Furthermore, when an abnormality is detected, it is necessary to train personnel to quickly implement appropriate countermeasures and develop a system to effectively communicate information on the abnormality. By addressing the above issues, abnormality detection by sound is expected to become a powerful tool for achieving more advanced equipment maintenance and productivity improvement.
SIAT learns the “usual state”. In other words, since peripheral noise is also defined and modeled as “usual state”, it is possible to detect “unusual sound” buried in ambient noise.

Here, we introduce a case study of anomaly detection by sound for detecting predictive equipment anomalies at the High Intensity Proton Accelerator Facility (J-PARC) in the High Energy Accelerator Research Organization (KEK), Japan. (Tomoya Soma, 2018)
In the main ring (MR) of J-PARC, the RF anode power supply has been out of order since mid-May 2018. Therefore, as a test case for anomaly detection, sound was constantly collected by an IC recorder. On May 28, three days after the recorder was installed, an anomaly occurred in the anode power supply, which was recorded by the recorder. This event was used to verify whether it was possible to detect the occurrence of an anomaly in advance.

In accelerator facilities, maintenance and management of power supply facilities is one of the most important roles, and we installed IC recorders in the power supply building of the J-PARC MR accelerator to collect data. Note that anomalies in inverters and transformers generally appear as sound, and maintenance workers often rely on sound to detect anomalies. Power supply equipment handles extremely high voltages and currents, so it is very difficult to install sensors on the equipment itself. In addition, because the high current flows in a pulsating manner at short intervals (pattern operation), the equipment generates a humming sound. Focusing on this characteristic, we considered installing a vibration sensor on the board containing the equipment to capture the vibration that is the source of the sound. On the other hand, in a large-scale facility such as the J-PARC power supply building, a huge number of vibration sensors would be required and the measurement system would be very large. For this reason, we investigated ”sound” sensing as a method to collect vibration data over a wide area with a small number of sensors. (Figure 3) shows the measurement.

Figure 3. Sound data collection

An invariant model was created based on the collected data. To create the model, the data from one sensor for each of vibration and sound was frequency-resolved by FFT to generate an invariant between each frequency. Our past experience has shown that the relationship between frequency bands by FFT remains the same under normal conditions. We took advantage of this property to model the vibration and sound of pulsating motion such as MR.

(Figure 4) shows the results of the FFT conversion with the RF anode power supply for the acceleration cavity. The frequency range was resolved at 10 Hz intervals. An invariant model was created based on this data. The resulting model diagram is shown in (Figure 5). The model diagram shows that a relatively strong relationship was established between each frequency band, confirming that the model created by sound can be used effectively as a model for anomaly detection by using the model parameters that were verified in this study. For this reason, the model was created using the time period when data was first collected and ambient noise was low.

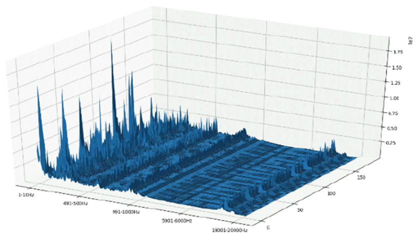

Figure 4. FFT result of RF power supply sound

Figure 5. Invariant model

The failure occurred at around 17:39 on May 28, where a popping sound was recorded. Using the created model, anomaly detection verification was conducted before and after the failure, and the transition of the degree of abnormality (As: Anomaly Score) was confirmed. The recovery only stopped the failed power supply, and no repairs were made.
(Figure 6)shows the time table of the acquired data. An invariant model was created for the modeling period from 16:45 to 17:45 on May 26, which was far enough away from the time when no abnormalities were thought to have occurred.

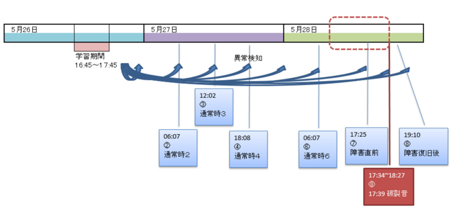

Figure 6. Time table in abnormality detection verification

Using this model, the period from May 27 to around 17:39 on May 28, when the popping sound was heard, was set as the abnormality detection period for confirmation. The As value during normal conditions varied depending on the time of day, but was stable at around As=10 at the highest, indicating that the movement was normal (Figure 7) (Figure 8).

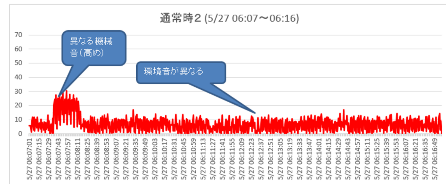

Figure 7. Anomaly score under normal condition

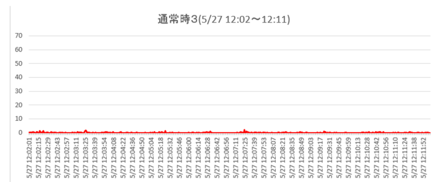

Figure 8. Anomaly score under normal condition

Next, the time period from just before the failure to the recovery period was verified. Just before the failure (Figure 9), the As values were generally high, ranging from 10 to 30, in contrast to the low As values observed in the past. At around 17:32, the As level was even higher, centered around As=30. This condition continued, and at 17:39, a disturbance occurred with a popping sound (Figure 10), and the As level swung widely. After the failure was restored (Figure 11), the As returned to its normal state. This confirms that the accuracy of the invariant model created is at a level that does not pose a problem for anomaly detection.

Figure 9. Anomaly Score just before failure

According to the operation record, beam adjustment was performed from around 10:10 to 17:10 on May 28, 2018, and continuous beam operation was not performed. During beam tuning, the beam was emitting several beams per hour, and all equipment was in constant operation. However, the RF anode power supply is the power supply that supplies power to the cavity that accelerates the beam and is directly related to the

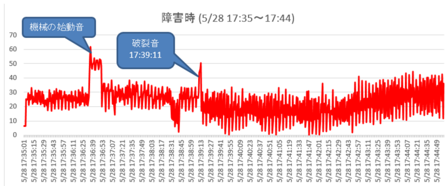

Figure 10. Anomaly score at failure occurrence

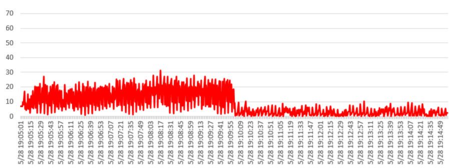

Figure 11. Anomaly score after disaster recovery

beam status. In other words, it is known that the sound of the power supply changes with or without the beam. Therefore, the As values of 10 to 20 seen in (Figure 9) and after may indicate the presence or absence of a beam. This is estimated by the coincidence of the time when the As value dropped below 10 after the failure recovery in (Figure 11) and the time when the continuous beam operation started. This is estimated by the coincidence of the time when the As value dropped below 10 after the fault recovery in (Figure 11) and the time when continuous beam operation started.

On the other hand, the oscillations above As=30 may capture the oscillatory sound change of the power supply. We also consider it important to accumulate knowledge. It is known that this failure was a rupture of the inverter. If it becomes possible to link various causes of abnormalities and abnormal sounds to them, it is expected to contribute not only to shortening the time required for normal restoration, but also to investigating the causes and taking countermeasures against failures.

In addition, since anomaly detection by sound can be realized with simple equipment, various applications are expected. The scope of applications currently being verified and examined are shown below.

- Reducing the burden of patrol inspection
- Early anomaly detection
- Mechanization of sensory test
- Prevention of oversight in inspection
- Detection of signs of product quality deterioration
- Optimizing tool replacement time

3.2. Applications in the space field

Invariant analysis is also used for development purposes. One of them is the spacecraft Orion (Figure 12) (*Orion Spacecraft*, n.d.) used in the Artemis program in the United States.

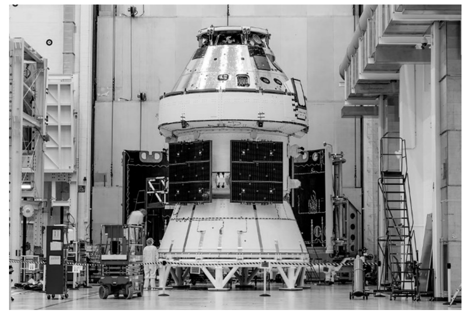

Figure 12. Orion Spacecraft
(*Orion Spacecraft*, n.d.)

Orion's development is short-term period, but it's a long-term human ride, so we can't reduce inspections. The conventional method in which a person sees and analyzes the information acquired from 150,000 sensors takes a very long time.
Invariant analysis only shows the differences that occur between tests and the changes from what is defined as normal, so it presents only the points that one should see. Therefore, the time required for data confirmation is greatly reduced.
Lockheed Martin, a manufacturer, focuses on to this point and integrates SIAT into the analysis platform T-TAURI. It will also be used for monitoring the operation of artificial satellites in the future.

4. For the future

Since invariant analysis uses only time series data, it can be used for various objects. To date, more than 300 verifications and actual introductions have been carried out in power generation, food manufacturing, steel, etc. We believe that it will continue to be applied to new targets.
We are also developing technologies to solve problems in the field, such as "model-free analysis technology," which is AI that does not create models, and "skill acquisition learning," which learns the invisible operational know-how of skilled engineers. Sensing technologies are also being developed, one of which is a technology that uses optical fiber as a sensor medium to continuously measure vibration and temperature over a wide range and without power supply. Combining these analysis technologies with sensing technologies will enable early detection of abnormalities in an unprecedented manner and at an unprecedented speed.

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BIOGRAPHIES

Tomoya.Soma Graduated from Ichinoseki National College of Technology in 1988 with a degree in Chemical Engineering. Joined NEC Solution Innovators, where he was involved in the design and project management of communication network management systems for electric power companies, focusing on high-speed processing and utilization of large volumes of data and designing systems ahead of their time. He started applying AI to industrial sites after applying AI to a real-time monitoring system for large volume/high speed data generated at a nuclear power plant. Currently, he is involved in the research and development of technologies that can be used immediately at industrial sites, such as sensing technology and analysis technology for acquired data, as well as the social implementation of these technologies, including serving as the chief of the JEITA Smart Security Study Group, secretary of the Japan-Thailand Smart Security Consortium, and steering committee member of the Aircraft Life Cycle DX Consortium, He also serves as a member of the JEITA Smart Security Committee, a secretary of the Japan-Thailand Smart Security Consortium, and a steering committee member of the Aircraft Lifecycle DX Consortium..

Akiko.Sasaki Joined NEC Solution Innovators in 2011 and engaged in system development for electric power companies as a system engineer. She was involved in the system design, implementation, and project management of applications in the smart energy domain and service development using machine learning technology on power demand. Currently, as a data scientist at NEC Corporation, she analyzes user data and supports the implementation of optimizations to maximize the potential of AI and meet the needs of complex and evolving industries.