Outlier Detection Method for Equipment Onboard Merchant Vessels

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Abstract: The equipment onboard merchant vessels are essential for safe navigation. If an equipment malfunction occurs during a voyage, it is difficult to repair it with the same speed and accuracy as on land. Therefore, it is important to It is required to be able to repair and replace the equipment with a margin of time by detecting the signs of anomalies. In this paper, we present the results of detecting signs of anomalies from various sensor data collected using One-Class SVM. It also shows the results of interpreting the signs of anomalies and detected locations using SHAP. The results show that the proposed method can detect signs of anomalies at a point about one month before the conventional method. Therefore, the proposed method is shown to be potentially useful for the maintenance of equipment on merchant vessels.

1 INTRODUCTION

In recent years, to maintain schedules and ensure safe operations, efforts have been made not only to maintain and manage safe vessel operations, but also to ensure safe navigation and marine environment conservation from various perspectives. To maintain safe vessel operation, it is important for navigators to conduct proper monitoring and to select the best route in consideration of weather and sea conditions. In the engine room, the condition of the main engine, which propels the ship, and auxiliary engines, such as motors, which are important for operation, are monitored by the engineer, and preventive maintenance management is conducted. To prevent severe damage, these devices are repaired or replaced when anomalies are detected during daily patrol inspections of their operating conditions. Traditionally, vessel monitoring equipment has been minimal and inspections have relied on the human senses. In recent years, with the improvement of technology such as temperature, pressure, and vibration sensors, there have been efforts to detect anomalies through automatic monitoring, but it is still insufficient. Ship equipment is characterized by the fact that once it goes out to sea, it does not return for a long period of time and that repairs that can be done easily on land are difficult to do at sea. Therefore, events that would be detected on land in time after an anomaly is detected must be detected and responded to before that time for vessels.

In this paper, we describe related research in the next section. In the section 3, we explain the subject data. In the section 4, we briefly explain section the proposed method of detecting signs of anomalies in equipment onboard merchant vessels. The experimental results are shown in the section 5. Finally, we conclude the concept of anomaly prediction detection for equipment onboard merchant vessels based on outlier detection methods.

2 RELATED RESEARCH

In the marine field, monitoring the condition of equipment and achieving condition-based maintenance is still a new study. In the past few years, studies have been conducted in supervised learning. (Porteiro et al., 2011) presented a multi-net fault diagnosis system to provide power estimation and fault identification of a diesel engine. (Coraddu et al., 2016) proposed an application of supervised machine learning approaches to estimate the decay status of a naval propulsion plant for improving condition based maintenance. (Cipollini et al., 2018b) and (Cipollini et al., 2018a) proposed some supervised and unsuper-

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vised approaches for condition based maintenance of a naval gas propulsion plant. (Lazakis et al., 2019) investigated a One-Class support vector machine (One-Class SVM) based approach to realize condition monitoring of a marine diesel generator with the noon-report data. (Brandsæter et al., 2019) developed an on-line anomaly detection approach based on multivariate signal reconstruction followed by residuals analysis for anomaly detection of a marine diesel engine in operation. Supervised learning algorithms have been proposed for condition monitoring of marine equipment systems. However, (Tan et al., 2020) said that supervised learning algorithms tend to be unrealistic, because the fact that most of the samples monitored by the shipboard monitoring system are normal samples is ignored and the required labeled samples are not easy to obtain. They proposed the use of a one-class classification technology. Specifically, a comparative study of Condition monitoring of the marine equipment system was conducted using six one-class classification algorithms: One-Class SVM, Support vector data description (SVDD), Global k-nearest neighbors (GKNN), Local outlier factor (LOF), Isolation Forest (IForest), and Angle-based outlier detection (ABOD). The results show that the one-class classification algorithm is applicable to marine equipment.

However, when it comes to actual use in the field, a system that only detects signs of anomaly not be adopted by companies. The reason is that it does not explain what the cause of the problem is. In recent years, the field of Explainable AI has flourished, as can be seen from Figure 1. From figure 1, we can see that companies are demanding evidence for the results of machine learning. In other words, by providing clear evidence for detection results, companies are expected to be more proactive in detecting anomalies using machine learning.

In this study, the one-class classification algorithm was applied to merchant marine equipment to verify whether it is possible to detect predictive signs of anomalies. In addition, we use SHAP, one of the interpretation methods of the one-class classification algorithm, to clarify the basis for the detection of predictive signs of anomaly.

3 MEASUREMENT DATA

In this study, under the collaboration with Furuno Electric Co. we will detect predictive signs of anomalies in equipment onboard merchant ships. Data from equipment onboard merchant vessels is sent via satellite to a data center on land. Then, the data center

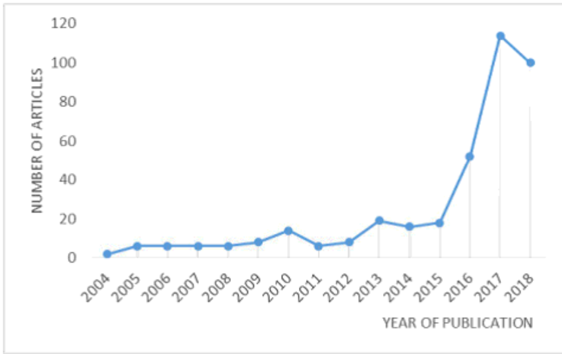

Figure 1: Explainable AI Papers by Year (Adadi and Berrada, 2018).

detects signs of anomalies, and if an anomaly is confirmed, instructions are given for repair or replacement. So, note that we do not perform predictive anomaly detection within the merchant vessel. In the 3.1 section, describes the target equipment onboard merchant vessels, and describes the data of the target equipment in the 3.2 section.

3.1 Equipment Onboard Merchant Vessels

There are several types of equipment onboard merchant vessels, each of which plays a key role in ensuring safe navigation. For example, acoustic depth gauges measure the depth of the water, which is important to avoid running aground. Other devices include satellite speed logs that provide information on the speed of merchant vessels, which is indispensable when berthing. Among these various devices, this study focuses on the common parts of the devices called Radar and ECDIS (see Figure 2). A radar is a device that uses the bounce of radio waves to check the movement of other vessels and to confirm the safety of the surroundings. It is especially effective when visibility is poor due to rain or snow and is an especially important device that can hinder the safety of navigation if it is broken. The other is ECDIS, which digitizes and displays paper charts to create ship routes. This is another important piece of equipment that must be equipped. Although there are many target devices, we selected one of them for this experiment. The selection criteria are individuals selected by the experts of Furuno Electric Co. from among equipment whose sensor values were measured to be anomaly.

Figure 2: Equipment on board merchant vessels; left: Radar, Right:ECDIS.

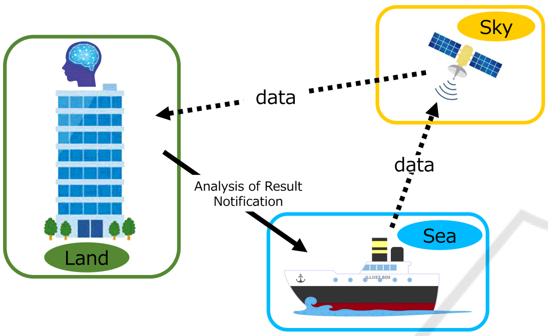

Figure 3: Data flow.

3.2 Used Data

The data of the target equipment described in section 3.1 is acquired as shown in Figure3. Sensor values recorded on the merchant vessel are collected via satellite to a data center located on land. One case of data is obtained every hour. Anomaly detection is then performed at the data center where the data was collected, and if an anomaly is confirmed, the merchant vessel carrying the anomalous individual is contacted. The contacted merchant vessel will take action, such as repairing the anomaly or replacing it with a spare piece of equipment on board, depending on the extent of the anomaly. However, some of the data contain missing data or errors due to satellite communication problems. Therefore, the acquired data cannot be used for experiments as is. Therefore, to address this issue, two data use conditions were established in this study based on expert advice and analysis.

1. If multiple data are acquired in one hour, the first acquired data is used because the later data is error data (Figure 4).
2. If the conditions in 1. are met and the total number of data acquired in a day is less than 15, the data for that day not be used (Figure 5).

The eleven sensors used are listed in the Table 1. These are all sensors that the subject equipment can

1.Data handling at each time		
	Sep. 24, 2022 10:01:00	Sep. 24, 2022 10:02:00
Feature 1	Use it	Not use it
Feature 2		
⋮		
Feature 11		

Figure 4: Data Use Condition(time).

2.Handling of data for each date		
	Number of data/day	Use or Not use
Sep. 23, 2022	24	Use it
Sep. 24, 2022	15	Use it
Sep. 25, 2022	3	Not use it

Figure 5: Data Use Condition(day).

acquire. These 11 items are currently used by on-site inspectors to conduct inspections, so we used these same conditions. The subject individuals had a total of 26,425 data that met the conditions of use, and the acquisition period was from December 2015 to February 2019.

4 ANOMALY PREDICTION DETECTION METHOD

In this section, we describe a model for detecting predictive signs of anomalies in equipment onboard merchant vessel. This study uses One-Class SVM, an outlier detection model, and the Mahalanobis-Taguchi Method (MT Method), a statistical method.

4.1 One-Class SVM

One-Class SVM is an extension of the classical SVM, and it is a common semi-supervised learning tech-

Table 1: Data Summary

Order	Sensor Item	Units
1	CPU FAN RPM	rpm
2	CPU FAN1 RPM	rpm
3	CPU FAN2 RPM	rpm
4	CPU board temperature	degC
5	CPU Core Temperature	degC
6	GPU Core Temperature	degC
7	CPU core power supply voltage	V
8	Battery supply voltage	V
9	3.3V supply voltage	V
10	5V supply voltage	V
11	12V supply voltage	V

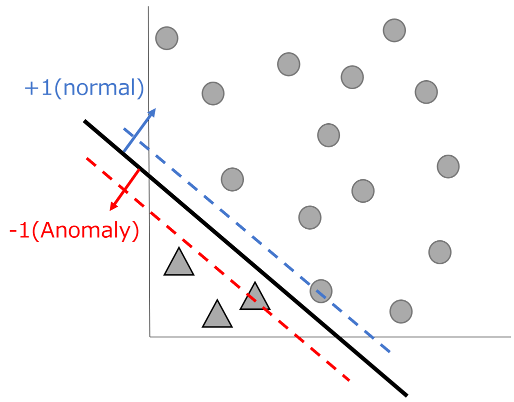

Figure 6: One-class SVM.

nology used to solve one-class classification problem (Khan and Madden, 2010). In the classical SVM, it can determine an optimal hyperplane by maximizing the interval between the support vectors of two classes. However, in One-Class SVM, there are only one-class data points involved in model training, which makes it impossible to find the optimal hyperplane like the classical SVM. In fact, it regards the origin as the only negative data point and all training data as positive points. The goal of model training is to make the classification hyper-plane as far away from the origin as possible. After transforming the feature via a kernel, they treat the origin as the only member of the second class. The using relaxation parameters they separate the image of the one class from the origin. Then the standard two class SVM techniques are employed (Vapnik, 1999). One-Class SVM (Schölkopf et al., 2000) returns a function of that takes the value +1 in a small region capturing most of the training data points, and -1 elsewhere. The algorithm can be summarized as mapping the data into a feature space using an appropriate kernel function, and then trying to separate the mapped vectors from the origin with maximum margin (see Figure 6).

4.2 MT Method

The MT method, proposed by (Taguchi and Jugulum, 2002), is a practical method for anomaly detection, developed from Hotelling's T^2 control chart (Hotelling, 1947) by adding ideas such as item selection and item diagnosis. The MT method assumes that only normal data form a homogeneous population. Then, if the new data does not deviate from the formed population, it is judged as normal, and if it does, it is judged as anomaly. This homogeneous population is called the unit space in the MT method. The measurement of deviate level from the unit space is quantified based on the Mahalanobis distance. In actual use, a threshold value is set in advance, and if the value is exceeded, it is judged as anomaly (see Figure 7).

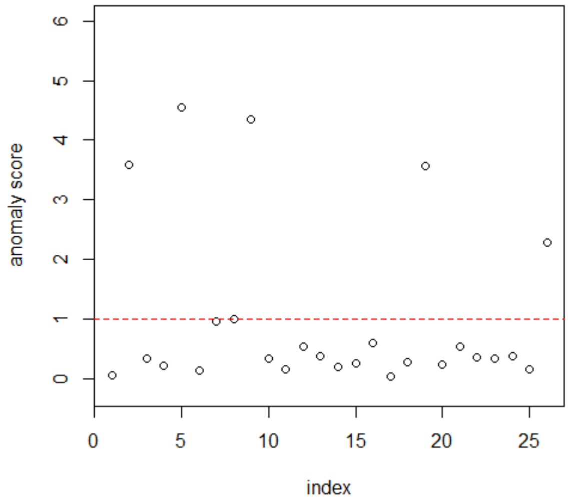

Figure 7: MT Method Sample.

Another feature of the MT method is called Signal-to-Noise (S/N) ratios. This quantifies the contribution of individual variables and allows interpretation of the results of the MT method as to what is due to what. Taguchi empirically introduced an indicator such as Equation 1, which is the S/N ratios for the variable set q. Where M_q in Equation 1 represents the number of variables and a_q represents the anomaly when using a covariance matrix of $M_q \times M_q$ dimensions.

$$SN_q \equiv -10log_{10}\{\frac{1}{N'}\sum_{n=1}^{N'}\frac{1}{a_q(x'^{(n)})/M_q}\} \quad (1)$$

Calculating the S/N ratios in this way yields the contribution of each variable as shown in Figure 8. Figure 8 shows the results for the road data included in the MASS package, and the cities shown are in California. The S/N ratios indicates that a large value is influential. The results show that almost all of the large anomalies in California are caused by fuel. Thus, the MT method not only detects anomalies, but also identifies their causes by a unique method called the S/N ratios.

5 CONTRIBUTION CALCULATION METHOD

The MT method has its own interpretation method as described in section 4.2. On the other hand,

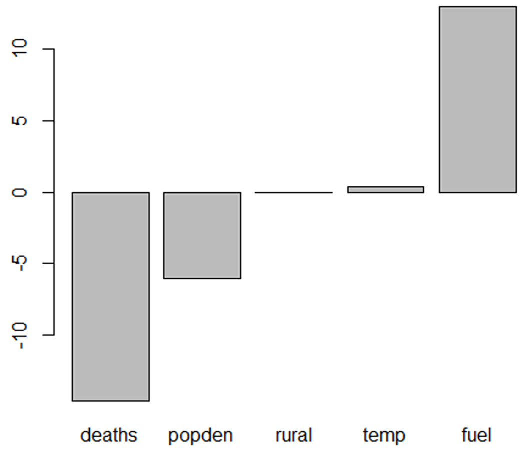

Figure 8: SN ratio Sample.

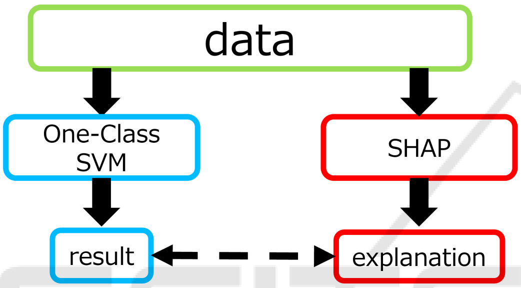

Figure 9: Relationship between One-Class SVM and SHAP.

One-Class SVM can be interpreted by using coefficient in the case of linear kernels, but there is no such method for RBF kernels. Therefore, a different approach must be used for interpretation. Currently, DARPA, which conducts defense research in the United States, categorizes Explainable AI approaches into three broad categories(Gunning et al., 2019). These three approaches are: feature visualization, generation of interpretable models, and approximation by interpretable models. In this study, we interpret One-Class SVM models based on Shapley additive explanations (SHAP), a type of feature visualization. The relationship between One-Class SVM and SHAP is shown in Figure 9 SHAP uses the machine learning model and the data used in the model to measure the contribution of each feature and to add interpretability to the results of the machine learning model. This SHAP was originally based on the concept of the Shapley value in cooperative game theory. Therefore, this chapter describes the Shapley value and SHAP.

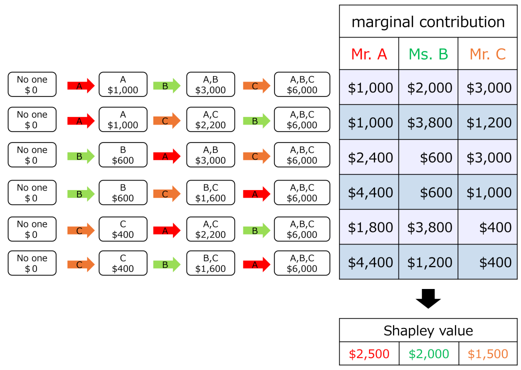

Figure 10: Shapley.

5.1 Shapley Value

In cooperative game theory, the Shapley value is a means used to fairly distribute the benefits in a game in which multiple players cooperate, according to each player's contribution. As an example, suppose we have a situation in which different people participating in a game receive different rewards. The list of rewards is as follows.

- If only Mr. A participates, the compensation is $1,000.
- If only Ms. B participates, the compensation is $600.
- If only Mr. C participates, the compensation is $400.
- If Mr. A and Ms. B participate, the reward will be $3,000 for both of them.
- If Ms. B and Mr. C participate, the reward will be $1,600 for both of them.
- If Mr. A and Mr. C participate, the reward will be $2,200 for both of them.

If the reward for participation by Mr. A, Ms. B, and Mr. C is $6,000, consider the question of how fairly to divide the reward among Mr. A, Ms. B, and Mr. C. First, consider the situation where Mr. A participates from a situation where no one else participates. This raises the reward from $0 to $1,000. In other words, we can say that Mr. A contributed to raising the reward by $1,000. Next, consider the situation where Ms. B is participating and then Mr. A joins him. In this case, the compensation goes up from $600 to $3,000, so Mr. A contributed to raising the reward by $2,400. This contribution is called the marginal contribution, and the average of the marginal contributions of all combinations is the Shapley value. Incidentally, in this example, it is fair to divide Mr. A, Ms. B, and Mr. C into $2,500, $2,000, and $1,500, as shown in Figure 10.

5.2 Shapley Additive Explanations(SHAP)

SHAP is a machine learning application of the Shapley values described in Section 5.1. In SHAP, the Shapley value represents the performance of a feature in the machine learning model. In other words, Mr. A, Mr. B, and Mr. C used in the Shapley value example represent each feature value in SHAP.

SHAP uses an additive feature attribution method, i.e., an output model is defined as a linear addition of input variables(Mangalathu et al., 2020). Assuming a model with input variables $x = (x_1, x_2, \ldots, x_p)$ where p is the number of input variables, the explanation model $g(x')$ with simplified input x' for an original model $f(x)$ is expressed as

$$f(x) = g(x') = \phi_0 + \sum_{i=1}^{M} \phi_i x_i' \tag{2}$$

where M represents the number of input features, and ϕ_0 represents the constant value when all inputs are missing. Inputs x' and x are related through a mapping function, $x = h_x(x')$. Equation 2 is illustrated in Figure 11, where ϕ_0, ϕ_1, ϕ_2, and ϕ_3 increase the predicted value of g(), while ϕ_4 decreases the value of g().

As noted by (Lundberg and Lee, 2017), a single solution exists for Equation 2, which has three desirable properties: local accuracy, missingness, and consistency. Local accuracy ensures that the output of the function is the sum of the feature attributions and requires the model to match the output of f for the simplified input x'. The local accuracy happens when $x = h_x(x')$. Missingness ensures that no importance is assigned to missing features. As $\phi_i x_i'$ implies $\phi_i = 0$, missingness is satisfied. Through the consistency, changing a larger impact feature will not decrease the attribution assigned to that feature. For a setting $z' \backslash i$ when $z_i' = 0$, $f_x'(z') - f_x'(z' \backslash i) \geq f_x(z') - f_x(z' \backslash i)$ implies $\phi_i(f', x) \geq \phi_i(f, x)$. The only possible model that satisfies these properties is

$$\phi_i(f,x) = \sum_{z' \subseteq x'} \frac{|z'|!(M - |z'| - 1)!}{M!} [f_x(z') - f_x(z' \backslash i)] \tag{3}$$

where $|z'|$ represents the number of non-zero entries in z', and $z' \subseteq x'$, and ϕ_i from Equation 3 is the Shapley values. (Mangalathu et al., 2018) suggested a solution to Equation 3 where $f_x(z' = h_x(z') = E[f(z)|z_S]$ and S is the set of non-zero indices in z', known as SHAP values.

In this study, we decided to use this SHAP to calculate the contribution to the anomaly detection locations. The reason for using SHAP is that SHAP is locally interpretable. In the field of anomaly detection, we do not want to capture overall trends and evaluate which sensors strongly influenced the model. It is necessary to calculate the contribution of each and every location that is determined to be anomaly, and to know and analyze under what kind of influence the anomaly was determined in that location. We thought SHAP desirable because it allowed us to calculate the contribution one location at a time. When calculating the contribution using SHAP, all that is needed is the model and feature data from the prediction and estimation. In this study, the model to be passed to SHAP is the One-Class SVM model, and the feature data is the test data from the tests conducted on the model. However, the test data was limited to only those areas identified as anomalies in the One-Class SVM model. The specific contribution calculation method is as shown in Figure 12. First, the One-Class SVM model and the data of the location that was tested and determined to be anomalies in the model are prepared. Next, each contribution is calculated for each feature of the data in the areas determined to be anomaly as in Figure 13. The expression of not participating in the Shapley value is replaced in SHAP with a value of no impact using the predicted expected value. In this way, the difference between when the feature is affected and when it is unaffected can be calculated. This is done in various combinations and averaged to obtain the contribution. Since this study targets anomaly detection by the One-Class SVM model, the contribution is based on the degree of anomaly, i.e., the distance from the optimal hyperplane.

6 EXPERIMENTAL RESULTS

In this section, after describing the experimental conditions, the results of the anomaly prediction detection and contribution estimation experiments are presented.

6.1 Experimental Procedures

Section 6.1 describes the experimental conditions. Please refer to Figure 14 as you read it. First, the missing data are processed as described in section 3.2. Next, the 11 features for present use in the inspection are selected. Next, extract the data periods to be used in the model. In this case, as shown in Figure 15, one month was used as test data and the last two years of the test period as training data. The reason for this setup is the request of the experts at Furuno Electric Co. to update the model every month with respect to the test data. As for the training data, the experts and I came to the conclusion that using older data would be

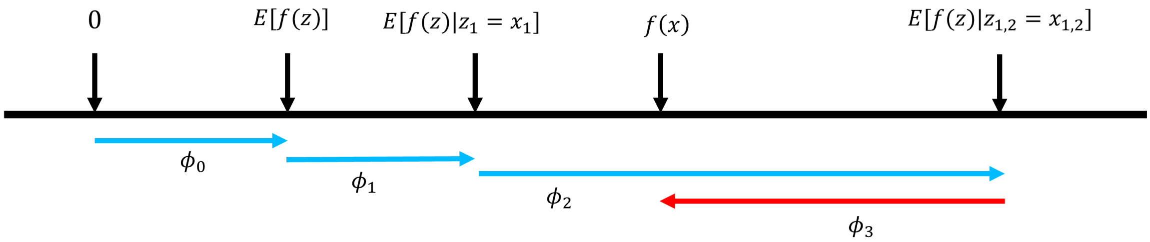

Figure 11: Example of SHAP with 3 variables(Lundberg and Lee, 2017). $E[f(x)]$ is the predicted value assuming all three features were not observed. The measured values are then entered into the features one by one, and the movement of the predicted values is measured as a contribution. In this example, we can see that x_1 and x_2 have a positive contribution and x_3 has a negative contribution.

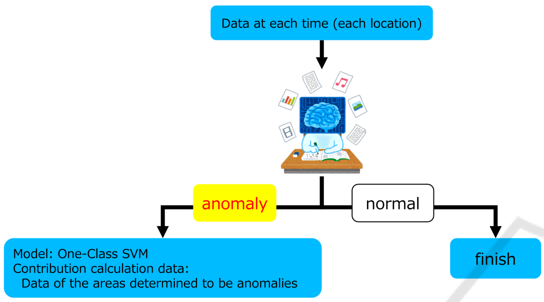

Figure 12: Flow to SHAP.

affected by age-related deterioration, so we decided to use two years. This means that the model was built 15 times in this study. The number of training data at one time is approximately 17,000 and the number of test data is approximately 700. Then, normalization is performed, and models are constructed using training data in each of the MT and One-Class SVM methods. The constructed model is then used to detect anomalies in the test data. Here, the MT method requires a pre-determined threshold value, but in this case, we used 4 as a general guideline. One-Class SVM require a preconfigured kernel. In this study, a Radial Basis Function (RBF) kernel was used. Therefore, it is necessary to set the parameters ν and γ. ν was set to 0.02. On the other hand, for γ, we tried 0.01, 0.1, 1.0, 10 and verified which γ value is optimal. After the anomaly prediction detection experiment, we estimated the cause of the anomaly by using the S/N ratios for the areas identified as anomalous by the MT method and SHAP for the areas identified as anomalous by the One-Class SVM method.

6.2 Results of the Experiment for Detecting Signs of Anomaly

Before presenting results of anomaly prediction detection experiment, we will discuss the areas diagnosed as anomalies in terms of the data mentioned in section 3.1. Figure 16 shows the time series graph of CPU FAN2 RPM for the experiment. This clearly shows that we have recorded something of an outlier in the late August 2018 data. When this data was shown to the experts, the data recorded at 4:00 AM Japan time on August 25, 2018, was found to be anomalous. The goal is to detect this area as an anomaly and how to detect signs of anomalies further down the road. We shall also refer to this part as the defective part. In determining the optimal parameters for the One-Class SVM, this defective part is used as the basis. Specifically, the following equation is used.

$$upper\ limit = anomaly\ degree\ of\ the\ defective\ part\ (distance\ from\ the\ optimum\ hyperplane) \tag{4}$$

$$lower\ limit = upper\ limit \times 0.6 \tag{5}$$

The best parameter is selected based on the trend of the data within this upper and lower limit range. 0.6 was chosen because the lower limit was set on the anomaly side rather than the middle of the anomaly range, which we thought would capture more dangerous signs of danger. Figure 17, 18, 19, 20 and 21 shows the results of applying the MT method and One-Class SVM, with the respective the degree of anomaly represented as time series graphs. The horizontal axis represents time, and the vertical axis represents the degree of anomaly. Anomaly is defined as a value greater than 0 for One-Class SVM and normal for values 0 or less. In the case of the MT method, the anomaly is defined as a location where the anomaly is greater than 4. The colors of the graphs are green for normal, blue for anomaly, and red for results as of 4:00 a.m. on August 25, 2018, with the black line representing the threshold value. The table 2 also shows the number of data contained within the range set in this study for each parameter. From Table 2, $\nu = 0.02$ $\gamma = 1.0$, which records high anomaly values only for one month before and after the failure, is the optimal parameter for the 1-Class SVM in this study. Figure 20 of the optimal parameters show that One-Class

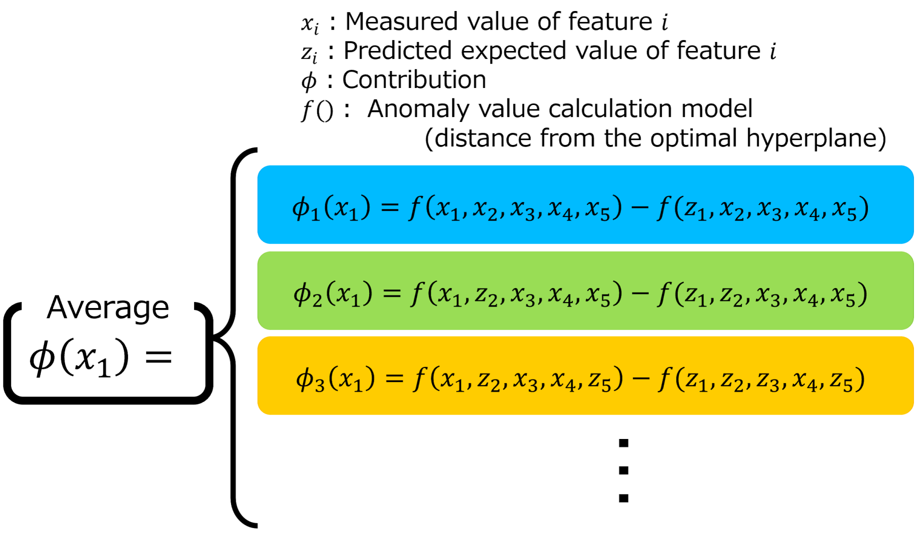

Figure 13: How to calculate contribution in One-Class SVM.

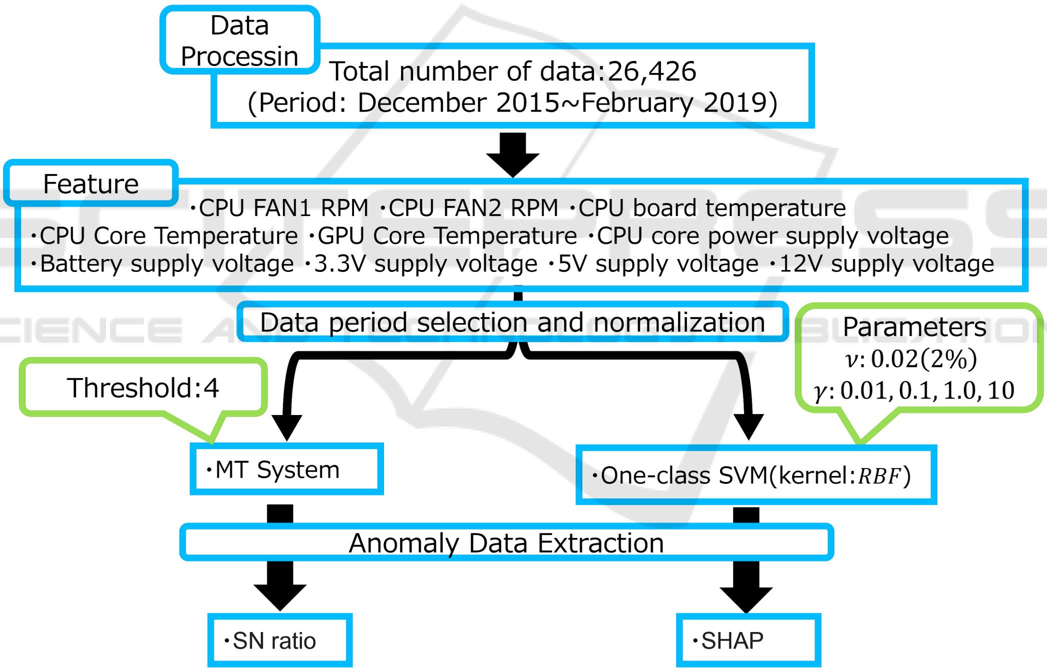

Figure 14: Experimental Procedures.

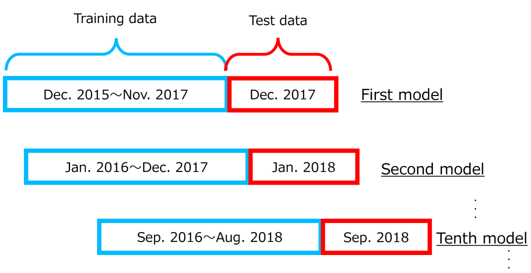

Figure 15: Verification Method.

SVM is capable of detecting anomalies at defective part and detecting signs of anomalies before and after the defective part. Next, we discuss the results of the MT method. As shown in Figure a, the MT method can detect anomalies in defective part, but it is not as good as 1-Class SVM in detecting signs of anomalies. Therefore, we checked to see if the MT method could predict anomalies by changing the threshold value of the MT method. The Figure 22 shows time on the horizontal axis, threshold 4 in red, threshold 3 in light

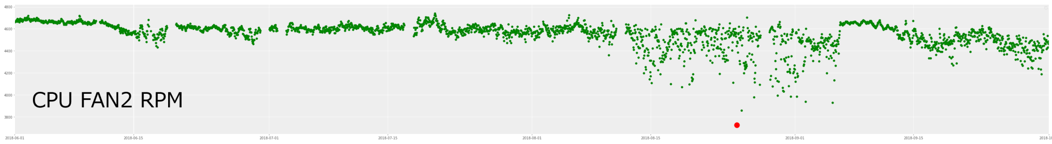

Figure 16: Time series graph of CPU FAN2 RPM. Red dot is 4:00 AM Japan time on August 25, 2018.

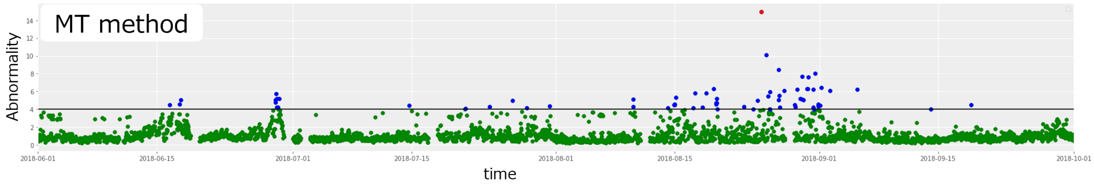

Figure 17: Anomaly Graph (MT method).

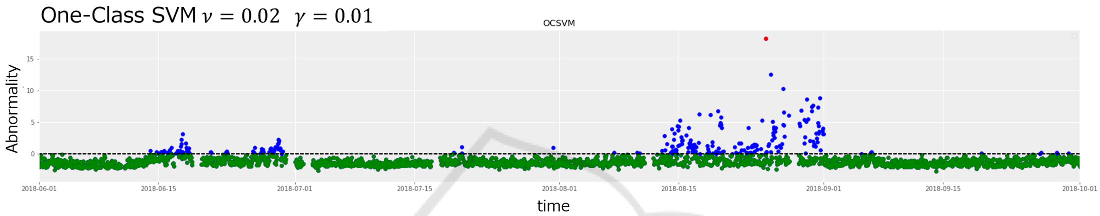

Figure 18: Anomaly Graph (OCSVM $\nu = 0.02, \gamma = 0.01$).

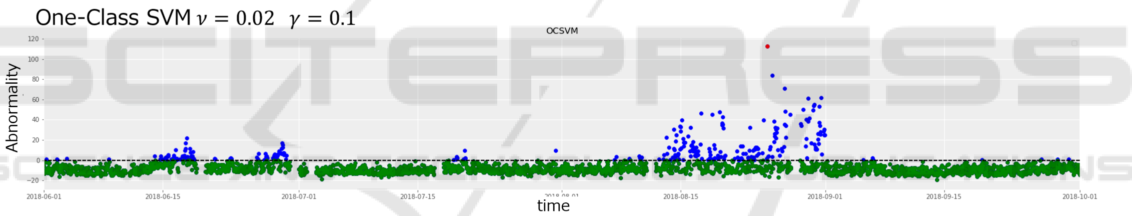

Figure 19: Anomaly Graph (OCSVM $\nu = 0.02, \gamma = 0.1$).

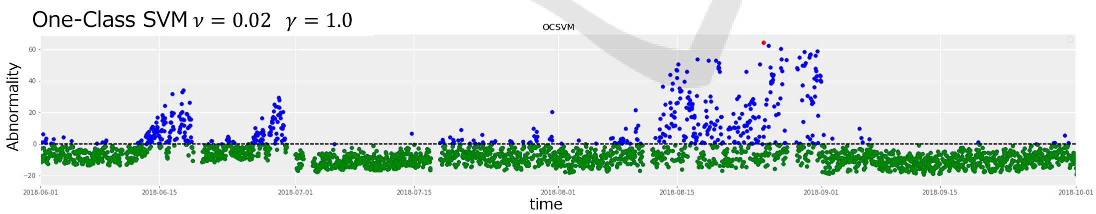

Figure 20: Anomaly Graph (OCSVM $\nu = 0.02, \gamma = 1.0$).

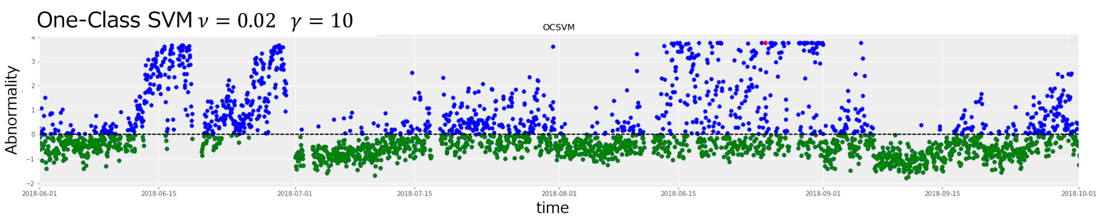

Figure 21: Anomaly Graph (OCSVM $\nu = 0.02, \gamma = 10$).

Table 2: Number of anomalies within the set range.

Parameters	Within one month before the defect	Within one month after the defect	Except for one month before and after
$\nu = 0.02, \gamma = 0.01$	0	1	0
$\nu = 0.02, \gamma = 0.1$	0	2	0
$\nu = 0.02, \gamma = 1.0$	18	35	0
$\nu = 0.02, \gamma = 10$	75	61	177

Table 3: Results of interpretation.

Order	Sensor Item	SHAP	S/N ratio
1	CPU FAN RPM	0.0056	-5.2943
2	CPU FAN1 RPM	0.0022	-5.9090
3	CPU FAN2 RPM	1.5895	24.8710
4	CPU board temperature	0.0130	-2.4760
5	CPU Core Temperature	0.0073	-0.7549
6	GPU Core Temperature	0.0033	-3.8500
7	CPU core power supply voltage	0.0409	6.4065
8	Battery supply voltage	0.1265	-1.7516
9	3.3V supply voltage	0.0195	-14.6852
10	5V supply voltage	0.0697	-3.3031
11	12V supply voltage	0.1258	-1.4185

Table 4: Results of interpretation

	Number of anomaly detection	Number of CPU FAN2 RPM
S/N ratios	23	16
One-Class SVM	204	198

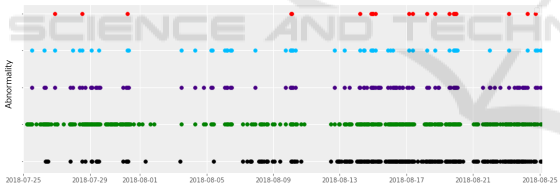

Figure 22: Difference by Threshold.

blue, threshold 2 in purple, threshold 1 in green, and One-Class SVM in black. Plotted locations are those where anomalies are detected. As a precondition, the detection must be continuous in order to be recognized as a predictive sign of anomaly. Considering this, the threshold value must be set to 1 in order to detect signs of anomaly using the MT method. However, if the threshold is set to 1, 30% of the total data will be detected as anomaly. This is inappropriate for an anomaly detection model. From the above, we conclude that it is difficult for the MT method to detect signs of anomaly in the present data. On the other hand, the One-Class SVM was continuously detected as an anomaly, indicating that it may be effective as a model for detecting predictive signs of anomalies approximately one month in advance.

6.3 Contribution Estimation Experimental Results

Next, we applied the S/N ratios for the MT method and the SHAP for the One-Class SVM to the defective part (Table 4). First of all, let me explain how to look at Table 4. As for the S/N ratios, as mentioned earlier, larger values contribute to that result. On the other hand, with respect to the SHAP values, they are essentially both positive and negative. This positive or negative value can measure whether the data is influenced by a small or large value. However, in the field of anomaly detection, the most important question is whether the anomaly is influenced by, or could be the cause of, the anomaly. Therefore, in this study, SHAP values were converted to absolute values to make it easier to understand which sensor is influencing. The results of applying the S/N ratios and SHAP both showed that CPU FAN2 RPM took the highest value, consistent with the experts that CPU FAN2 RPM was the cause of the anomaly. This indicates that both the MT method and One-Class SVM are suitable for the defective part. Next, we check the results of the application for data before 4:00 a.m. on August 25, 2018: anomaly detections for the last month as of 4:00 a.m. on August 25, 2018 are shown in Table 4. Number of anomaly detection in Table 4 indicates the number of times anomaly was detected out of a total of 723 cases from July 25, 2018 to August 25, 2018. The Number of CPU FAN2 RPM indicates the number of times that CPU FAN2 RPM contributed the most out of the Number of anomaly detections. From the above, it was found that the cause of the signs of anomaly is almost the same as the cause of the defective area in both the MT and One-Class SVM methods. In particular, One-Class SVM is able to detect continuously, making it possible to take action one month before the expert's decision.

7 CONCLUSIONS

The equipment onboard merchant vessels are essential for safe navigation. However, these devices cannot be repaired or replaced with the same speed and accuracy as when on land. Therefore, it is necessary to detect the signs of anomalies and act with a margin of error. This paper examines the feasibility of using the MT method and One-Class SVM to detect signs of anomalies in equipment on board merchant vessels. It was shown that both methods can detect the points pointed out by the person in charge of the equipment. In addition, One-Class SVM was able to continuously detect anomalies before the point pointed out by the person in charge of the model, indicating the possibility of detecting predictive signs of anomalies. In addition, by applying SHAP to One-Class SVM, it became possible to calculate the influence of each sensor and to identify which sensor value was the cause of the anomalies. In summary, the proposed method has the potential to be useful in the maintenance of equipment onboard merchant vessels.

There are two major issues to be addressed in the future works. First, the results of this study are limited to a single individual. This is partly due to the fact that, at this point in time, there is still a paucity of data with records of defects. This is a future issue, including data collection. The second is the application of SHAP to other methods. In this study, SHAP was applied only to the RBF kernel of the One-Class SVM. In the future, we will apply SHAP to other outlier detection methods to establish the usefulness of this study.

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