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Paper
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Failure Detection Method using Aggregated Vehicle Detector Data

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Vehicle detectors play an indispensable role in traffic management and control systems (TMCS). The data collected via vehicle detectors are used to fulfill various functions such as signal control and traffic information provision. In Japan, TMCS use mainly ultrasonic detectors. Owing to their aged deterioration, their detection accuracy gradually reduces over many years, and thus their efficient operation and maintenance requires accomplished engineers. In recent years, it has become difficult to maintain great numbers of ultrasonic detectors because of the financial constraints in public resources and shortfall of accomplished engineers. In this paper, we propose failure detection methods, and confirm their validity by using actual data. First, we propose an aggregation method of detector data for classifying installation positions, and validate the method by using large amount of data. Moreover, we propose a few failure detection methods with the aggregated data, and compare their decision results by using the actual data.

Keywords: failure detection, aggregated data, vehicle detector

1. Introduction

Traffic management and control systems (TMCSs), which play a role in social infrastructure, not only collect and provide traffic information but also regulate traffic signals to efficiently control the flow of excessive concentrations of vehicles in city centers [(1)(2)]. In order to adequately grasp the traffic conditions on roads and then appropriately control traffic signals in response to those conditions, it is necessary for the road network extending in all directions across urban regions to include numerous devices called vehicle detectors for detecting the situation regarding passing vehicles. In fact, there are over 130,000 ultrasonic detectors installed mainly in the urban areas in Japan, making up two thirds of the total number of vehicle detectors. To achieve highly accurate data collection from these vehicle detectors, maintenance inspection work is performed regularly to preserve their functionality. However, there are many aging vehicle detectors, maintenance is required frequently, and the existence of units that are already broken cannot be ignored. It is rare for failure information to be constantly transmitted from the vehicle detectors themselves, so maintenance is performed after determining whether or not a vehicle detector in a TMCS is faulty using the method of comparing the gathered data to actual vehicle travel conditions. In addition, there are occasionally cases in which the measurements from ultrasonic vehicle detectors diverge from the actual vehicle transit situation as they deteriorate with age, and so it is difficult to determine whether there has been a breakdown [(3)]. Among previous studies as well, there have only been reports on efforts to detect failure on expressways [(4)] with none considering ordinary roads. Also, although methods for detecting anomalous traffic conditions on expressways have been studied for many years [(5)–(8)], these do not consider vehicle detector failure and so are difficult to put into practice. There are high hopes for the development of an efficient and effective method for quickly detecting breakdowns like those described above in ultrasonic vehicle detectors installed on ordinary roads. This paper investigates methods for aggregating traffic volume and occupancy time data and using statistical values to detect failure.

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2. Methods for Detecting Failure in Vehicle Detectors

Today, TMCSs include vehicle detectors at fixed intervals (ordinarily every five minutes) that collect data on traffic volume, occupancy time, and pulse abnormality count. The detectors use a 50 ms detection pulse as the minimum unit of time for the presence of a vehicle, and measure how many detection pulses correspond to the time that a vehicle is present. Thus, if a vehicle occupies the area beneath a vehicle detector for five minutes, the occupancy time measurement data would be 6,000 counts. A threshold is set for each measurement variable in the measured data at a single point in time, and a value above/below that threshold is judged to be abnormal. The vehicle detectors installed on ordinary roads are affected by parked vehicles, vehicles waiting at stop lights, and the like, and so temporary abnormalities are not uncommon. However, it is infrequent for this abnormality determination to continue to the following measurement time onwards, and so in such cases the determination of whether the vehicle detector itself has broken down is difficult.

In this context, previous studies include efforts on expressways, and Endo et al. have endeavored to generate information necessary for maintenance from error flag information and decreased traffic volume measurement accuracy based on the premise of traffic volume continuity [(4)]. However, on ordinary roads the detectors are of a single-head type, and there are also parked cars, merging at signalized intersections, and inflow/outflow of vehicles at intersections between vehicle detectors. These greatly undermine the premise of traffic volume continuity, making it difficult to apply. There have also been efforts to detect unexpected situation by detecting anomalous data from ultrasonic vehicle detectors [(5)–(8)]. However, what is being detected is not failure of the vehicle detectors themselves but instead is anomalustraffic conditions, and so these are difficult to apply without modification. Also, the measurement characteristics of the vehicle detectors on ordinary roads should be kept in mind. This depends on differences in the length of a green time used in a signal controller within the measurement period, and so a chronological view of the measurement data contains short-term fluctuations as indicated in Fig. 1.

The data in this study cover 24 hours on a weekday. Figure 2 indicates the installation locations of the vehicle detectors that measured the data, including an installation at a location approximately 150 m upstream from the stop line at the Kuzugayato Park West intersection. Determining whether there has been a breakdown is difficult from measurement data containing such short-term fluctuations. Thus, we turned to the average traffic volume and average occupancy time at times of day representative for traffic conditions, and used those values (statistically aggregated information) in an attempt to eliminate short-term fluctuations. Furthermore, two-dimensionally visualizing those values could conceivably be used to understand the status of an ultrasonic vehicle detector by eye. In this paper, we propose a method for categorizing ultrasonic vehicle detectors on ordinary roads and for detecting failures using it by aggregating the average values of traffic volume and occupancy time at each time of day using a minimum unit (ordinarily defined as a five-minute period) for the measurement time. As a method for detecting breakdowns, we propose a method taking into account a traffic flow model (Q-k curve) and methods applying mathematical methodologies, and perform a comparative evaluation of the determination results using actual data.

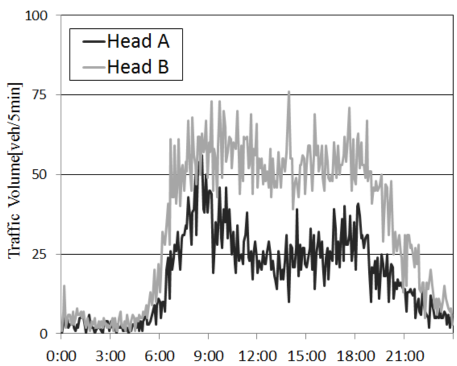

Fig. 1. Example of Detector Data

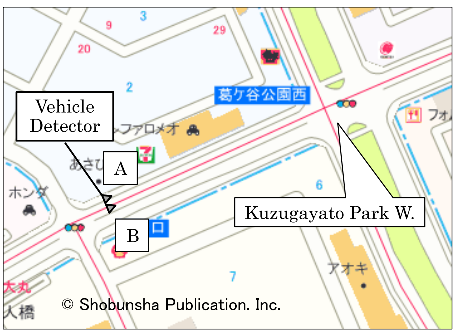

Fig. 2. Location of vehicle detectors

3. Categorizing Vehicle Detectors on Ordinary Roads

3.1 Visualizing Information from Aggregate Vehicle Detector Data Observations of the fluctuations in time in traffic demand over a single day were divided into the five time periods of midnight, morning, noon, evening, and night, and the unit time detector data were averaged for each time period with the results being aggregate vehicle detector information. The definitions for each time period are indicated in Table 1.

We believe that the basic attributes of vehicle detectors on ordinary roads can be discerned using this information. Figure 3 illustrates the result of plotting data for a particular day by unit time. Occupancy times of 0 to 500 counts are distributed linearly, whereas traffic volume for occupancy times of 500 to 5000 counts are distributed in the range of 20 to 40 (vehicles). If the 288 points in time during one day are represented as aggregate vehicle detector information, Fig. 4 is the result.

Furthermore, Fig. 5 depicts one month of aggregate vehicle detector information. There is less scattering of the points in Fig. 5 compared to Fig. 3, and so it can be considered to successfully represent large-scale trends for the detector at this location.

Below, the data is evaluated having been visualized in a scatter plot that, like Fig. 5, tallies one month of aggregate vehicle detector information.

3.2 Information Categorization According to Aggregate Vehicle Detector Information It is common for surveys of the relationship between traffic volume and traffic density to be conducted in relation to expressways. From

Table 1. Time zone of aggregated vehicle detector data

No.	Classification Name	Time Zone
1	Midnight	0:00～6:00
2	Morning	6:00～10:00
3	Noon	10:00~16:00
4	Evening	16:00~20:00
5	Night	20:00~24:00

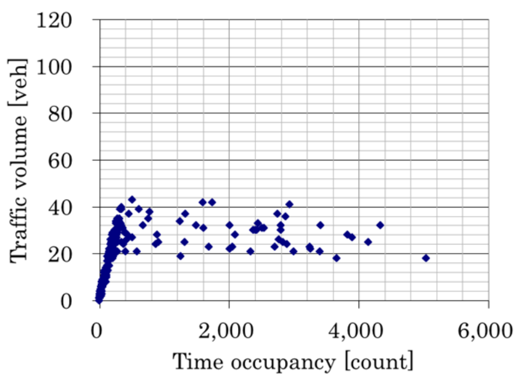

Fig. 3. Scatter plot of the unit data (1 day, 288plots)

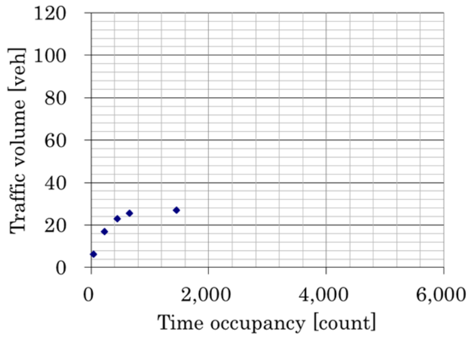

Fig. 4. Scatter plot of the unit data (1 day, 5plots)

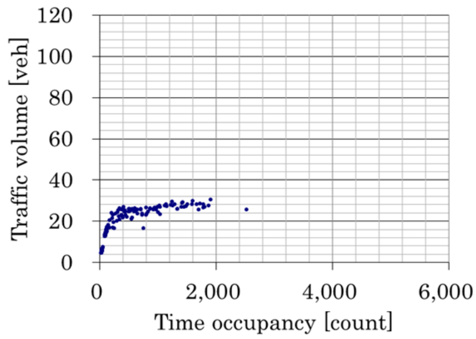

Fig. 5. Scatter plot of the unit data (1 month, 155plots)

Table 2. Categories and conditions of installation location of the vehicle detector

Location	Categories and conditions
A	150m, Approach, Less traffic congestion
B	150m, Approach, Traffic congestion
C	300m, Approach, Less traffic congestion
D	300m, Approach, Traffic congestion
E	Right-turn lane, Less traffic congestion
F	Right-turn lane, Traffic congestion

these survey results, it is known that on expressways, volume and density are in direct proportion during freely flowing conditions, whereas their relationship is markedly scattered during congested flow conditions [9]. However, there are few examples of such studies on ordinary roads. Thus, we confirmed whether aggregate vehicle detection information can be used to categorize installation conditions and the like. Vehicle detectors on ordinary roads are greatly affected by signalized intersections, and so in this study, we checked six conditions focusing on the distance from a signalized intersection, the lane of installation, and whether or not congestion occurred, as indicated in Table 2. Subjects were selected under the conditions that the vehicle detectors had no system abnormalities, and the difference comparing a visual measurement of traffic volume during a specific period and the value measured by the vehicle detector in question was within a certain range. The locations were selected from urban areas with a high density of vehicle detector installation. The locations that were selected were ordinary roads in northern Yokohama City as indicated in Fig. 6.

The upper and middle image in Fig. 6 indicate the surroundings of the intersection with Route 246 at the east side

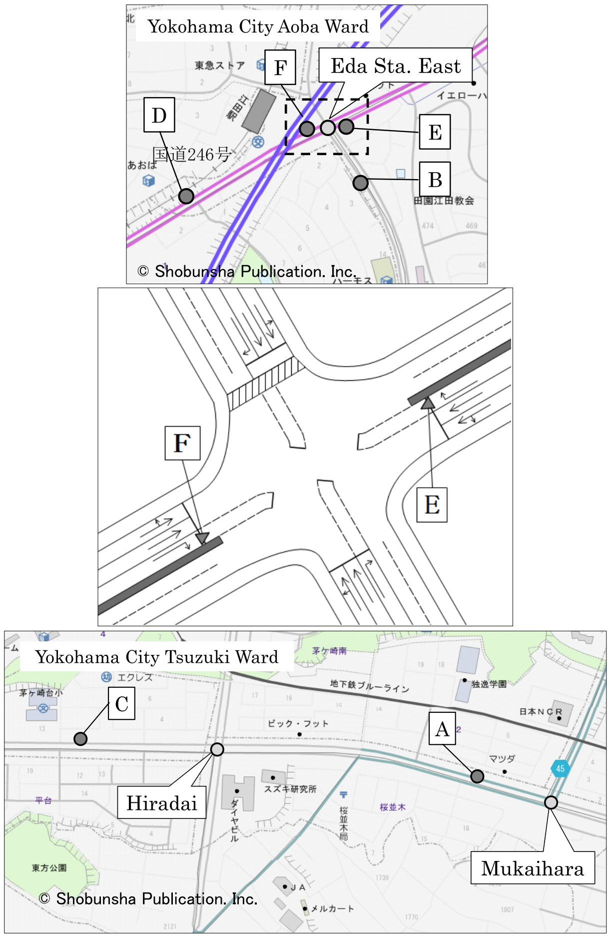

Fig. 6. Selected location

of Eda station. The middle image is an enlargement of the area within the dotted lines in the upper image. At this intersection, congestion occurs both on Route 246, which is the approach of the main road, and the approach of the minor road during a morning rush hour and an evening rush hour. The congestion extends up to approximately 1 km on the main road and up to approximately 500 m on the minor road. The cause of the congestion is traffic demand exceeding the capacity of the intersection. In addition, there is high demand for right turns at the eastward flowing side of Route 246, causing congestion at the right turn lane marked as Location F. On the other hand, the lower image in Fig. 6 indicates the Hiradai and Mukaihara intersections along the Yokohama City Shin-Yokohama Motoishikawa Road. Congestion does not arise around these two intersections. The one-month aggregate vehicle detection information results at the various locations are indicated in Figs. 7 and 8.

Location A and Location C are the locations of detectors installed at main roads where congestion does not occur frequently. However, the graphs for each exhibit a linear distribution from the origin (the 0,0 point), which is a shape close to what is expected for a non-congested area in the Q-k curve. Thus, when the frequency of congestion is low, detectors on a main road exhibit a linear graph with a high slope indicating a free flow regardless of whether it is 150 m or 300 m from the intersection. Location B and Location D are on roads flowing into an intersection with frequent congestion. These graphs

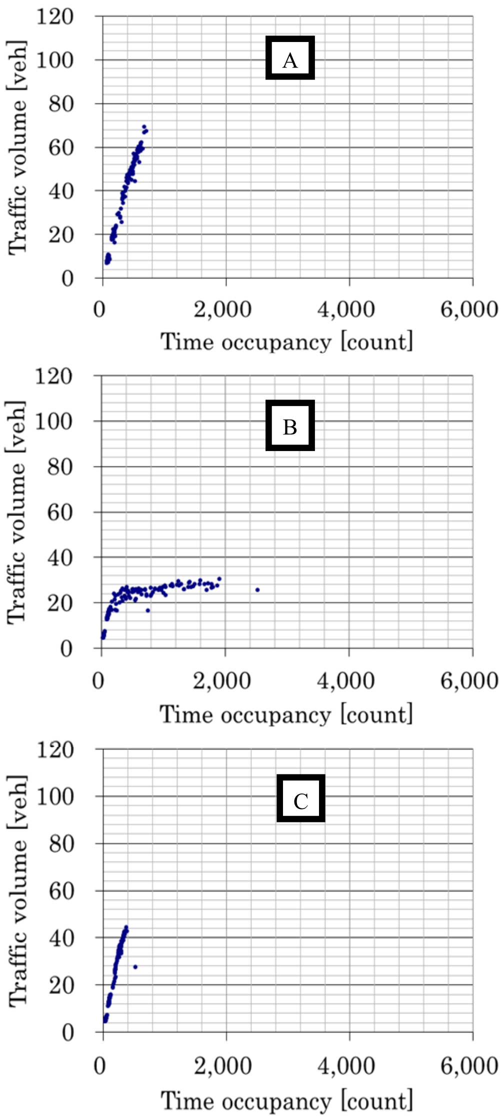

Fig. 7. Aggregated data at each location (1/2)

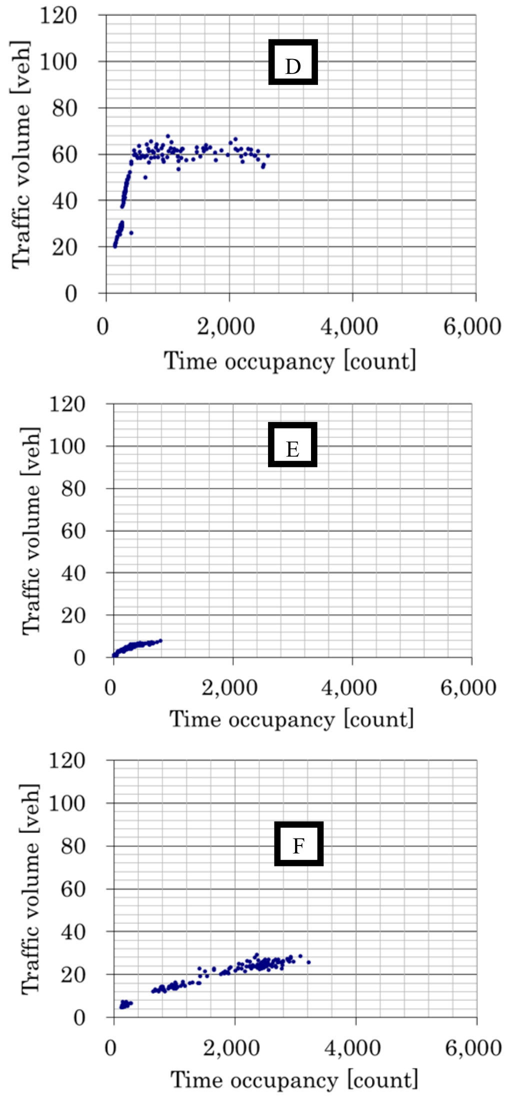

Fig. 8. Aggregated data at each location (2/2)

both include a linear section extending from the origin indicating a non-congested state, and a section with increasing occupancy time without the traffic volume changing. These are similar to example data given in the literature [9]. However, Location D is 300 m upstream from the stopping line, and so more vehicles traverse this location while traveling before reaching the area of congestion than at Location B. As a result, it was found that when congestion occurs frequently, the graph for detectors on main roads exhibit both a linear section with a large slope indicating a freely flowing state, and a section where the occupancy time increases when the number of vehicles is uniform or increases only slightly due to the length of a green time used in a signal controller. In addition, we were able to confirm that locations further from the stopping line had a longer linear section indicating a lack of congestion. Finally, we evaluated data from Location E and Location F, which are located on right turn lanes. The vehicles in the right turn lanes usually pass by the detectors during protected right turns. The signal phases for only right turn traffic are used at both Location E and Location F, but it is green time for a shorter amount of time than the other lights, which can lead to a longer occupancy time. Both graphs indicate that the occupancy time rises sharply with an increase in traffic volume, and so we found that detectors on right turn lanes have a linear graph with a low slope. From the above analysis, we were able to confirm that using aggregate vehicle detector information could be used to categorize installation conditions.

4. Method for Detecting Failures on Ordinary Roads

4.1 Traffic Flow Model Method From the above results, we found that vehicle detectors on main roads could distinguish between free flow and congested flow of traffic via the application of aggregate vehicle detector information. Thus, we propose a method for detecting failures by taking into consideration a traffic model for vehicle detectors at approaches on intersections. As shown in Figs. 9 and 10, different lines were defined for the free-flowing and congested flow regions in order to define regions for measurement results that would correspond to a failure state. If a number of aggregate data fall into these regions, the vehicle detector in question would be judged to be defective (Method 1).

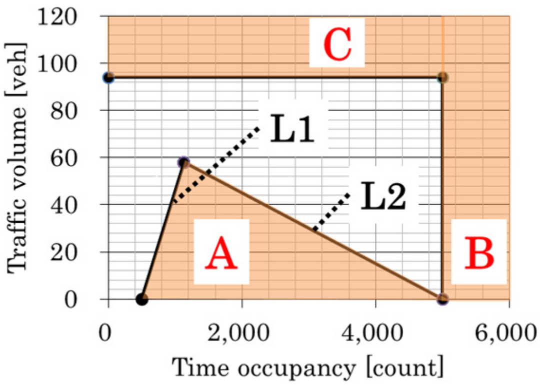

Fig. 9. Region of failure data

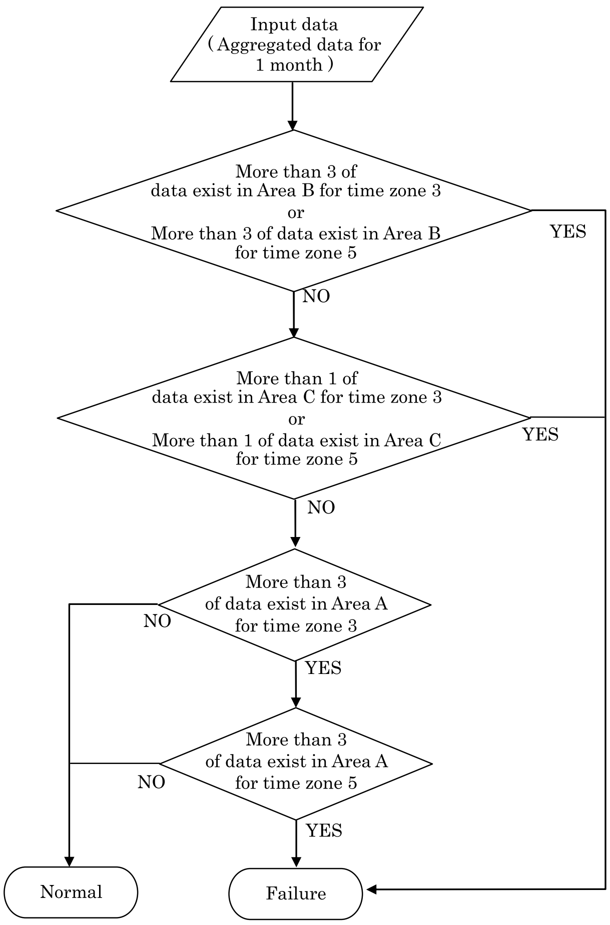

Fig. 10. Flowchart of the proposed method

The definition of the regions in Fig. 9 are explained as follows. The slope of L1 is equivalent to when a vehicle with a length of 4.5 m passes by the detector at a speed of 30 km/h. This value was used because it was nearly the same as that obtained from the average speed during 12 daytime hours in Kanagawa Prefecture [10]. Based on Fig. 7 and practical experience, L1 demarcating the breakdown region was the line shifted by 500 counts of time occupancy, because correct aggregate vehicle detector information is expected to be plotted on a line extending from the origin of the graph. L2 is the line linking the point on L1 with a traffic volume of 60 vehicles, which is approximately 20% less than the critical point of traffic volume, and the point at an occupancy time of 5000 counts and a traffic volume of 0 vehicles, which can be considered the saturation point. Here, the critical point was 75 vehicles calculated from an average thoroughfare-side split of 60% and a saturated traffic flow rate (1440 vehicles/hour) that is used in practice. Region A defined by L1 and L2 focuses on the phenomenon of the occupancy rate remaining high, which is one breakdown state for vehicle detectors. Next, Region B was defined from the fact that when the occupancy time according to the aggregate vehicle detector information is 5000 counts or higher, there is a high likelihood of a breakdown, as well as the fact that the occupancy time in the right turn lane where congestion is believed to have the longest occupancy time has a maximum of about 4000 counts (Fig. 8, Location F). Region C was set to detect the phenomenon of the traffic volume diverging from reality in the upwards direction. This used as a threshold the maximum traffic volume (94 vehicles/5 minutes) that can be observed based on the practical upper limit cycle length (150 s) [11], a split value (78%) close to the functional upper limit, and the saturated traffic flow rate (1440 vehicles/hour) used in practice for control adjustment.

Next, Fig. 10 shows a flowchart for the specific determination process. To simplify the judgment, it was performed using data from the noon time period (time period 3) and the night time period (time period 5), which exhibit different conditions but have relatively stable traffic patterns.

The number of data points for making a determination regarding Region A and Region B in the flowchart is 3, but this number could easily be reached by data from external causes such as parked cars in the vicinity of the vehicle detector, and so the determination standard is actually 10% or more of the number of data points for a period of one month.

4.2 Mathematical Method In recent years, mathematical methodologies for two-class pattern recognition have been studied in a variety of fields. Here, a support vector machine (Method 2-A) and a neural network (Method 2-B) were used. Support vector machine (SVM) is a method combining an optimal hyperplane method and a kernel method, and finds many applications due to having a high ability to discriminate as well as theoretical support for the structure of the discriminant machine. Neural networks have been used for pattern recognition for many years, but has returned to the spotlight as a basic technique for deep learning for big data analysis. Here, we used a common hierarchical network consisting of an input layer, an output layer, and hidden layers. These two methods have as inputs the same one month of aggregate information as the traffic flow model method, but even just the traffic volume data is 150-dimensional (5 time periods × 30 days). Thus, there are a large number of information types compared with the amount of prepared data, which runs the risk of an unstable learning process. We focused on the categorization results in the previous section that considered the data from detectors operating normally to have characteristic features. Thus, we performed principal component analysis on only data from detectors operating normally, and performed dimensionality reduction by applying a coefficient matrix to all input data. Specifically, the traffic volume and occupancy time in the aggregate vehicle detector information from a functioning vehicle detector were used as data in the format shown in Table 3, and then centered and normalized using the average and standard deviation for each column. In

Table 3. Input Data (Before principal component analysis)

Det No.	Date#1 Time#1	Date#1 Time#2	…	Date#N Time#5
1	20	34	…	5
…	…		…	
M	18	21	…	3

Table 4. Settings of Method 2-A

Kernel function	Parameters
Linear	—
Gaussian	0.1, 1.0, 10, 100
Polynomial	2, 3

Table 5. Settings of Method 2-B

Number of hidden layers	Activate function	Error function
1	Sigmoid	Binominal
	Softmax	Binominal
	Softmax	Multinominal
2	Sigmoid	Binominal
	Softmax	Binominal
	Softmax	Multinominal

Table 3, "Det No". indicates unique numbers for the vehicle detectors in the TMCS, while "Date#i Time#j" indicates data from time period j on day i in the month in question. Then, eigenvalue decomposition was performed using a variance-covariance matrix to derive a coefficient matrix. Data conversion was performed using the coefficient matrix on all the input data contained in the failed detector data, and dimensionality reduction was performed.

4.3 Numerical Experiment A numerical experiment was performed in order to check the state of detection of failed detectors using the proposed methods. Out of 840 detectors centered in Yokohama City, Aoba Ward and Tsuzuki Ward, detectors determined ahead of time to be functioning according to the survey described above as well as detectors known from to have been treated as broken according to maintenance records were used as the subjects. The data used for the verification was from August, 2014, and included those from detectors that broke down between August 1 and August 31, 2014, as well as from those that had already failed by August 1 according to maintenance records. As a result, 10 detectors operating normally (normal detectors) and 6 failed detectors were used for data. Method 2-A and Method 2-B require learning data, so detectors different from those selected for the verification data were chosen, and data from different dates (July 1 to July 31, 2014) were used. For the learning data, 12 normal detectors and 28 failed detectors were used. As a result, the effective dimensionality of the input data was reduced using the aforementioned dimensionality reduction to 22 (11 traffic volumes, 11 occupancy times). In addition, Visual Mining Studio (ver. 8.1) made by NTT DATA Mathematical Systems Inc. was used in Method 2-A and Method 2-B. In Method 2-A, the kernel function type and its parameters must be set, while in Method 2-B, the output layer activation function type and error function type must be set. The settings used for the numerical experiment are shown in Tables 4 and 5.

Table 6. Result of judgement with proposed method

Judgement / Actual Condition	Normality	Abnormality
Normality (10terminals)	10 (100%)	0 (0%)
Abnormality (6 terminals)	1(17%)	5(83%)

Table 7. Settings of each method in calculating the best result

Method	Parameters
1	—
2-A	Linear
	Polynomial: 2
2-B	Hidden Layer : 1 Activate function : Softmax Error function : Binominal
	Hidden Layer : 1 Activate function : Softmax Error function : Multinominal

Table 6 shows the best results obtained for differentiation using the verification data.

At this time, all three methods yielded the same results. However, the results in Table 6 were only obtained from Method 2-A and Method 2-B when certain settings were used. Those settings are shown in Table 7.

The correct response rate for normal detectors was 100%, while the correct response rate for failed detectors was 83%. Although it was not possible to detect unresponsive detectors (indicating 0 vehicles and a count of 0), these are considered detectable by current TMCSs. Thus, relatively good results were obtained overall. The discriminant results using settings other than those indicated in Table 7 are described as follows. When the kernel in Method 2-A was a Gaussian function (parameter: 0.1), the correct response rate for normal detectors was 20%, while it was 100% for failed detectors. When the kernel in Method 2-A was a Gaussian function (parameter: 10, 100), the correct response rate for normal detectors was 0%, and the correct response rate for failed detectors was 100%. When the kernel in Method 2-A was a polynomial function (parameter: 3), the correct response rate for normal detectors was 70% and for failed detectors was 83%. For all other settings for Method 2-A and Method 2-B, the correct response rate for normal detectors was 80% and the correct response rate for failed detectors was 83%. This demonstrated the relationship between settings and differentiation results in Method 2-A and Method 2-B. First, Method 2-A combines an optimal hyperplane method and a kernel method as stated earlier. Table 7 includes the case when the kernel function was linear, which was equivalent to using only the optimal hyperplane method. This suggests that the distribution of aggregate vehicle detection information used as input data is in a state that can be separated in linear space. Even when a polynomial function was used for the kernel, it is a second-order polynomial rather than a third-order polynomial that is included in Table 7. In Method 2-B, the best results were obtained with one hidden layer and Softmax as the activation function. Since the distribution of the aggregate vehicle detector information can easily be used to separate the normal

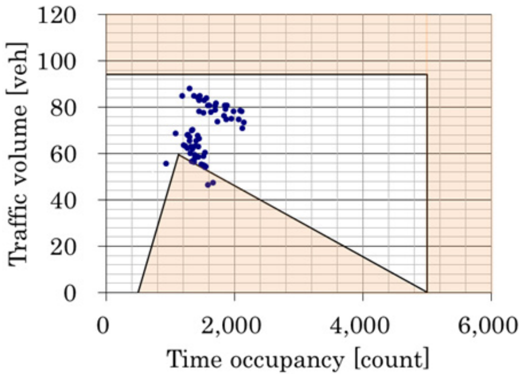

Fig. 11. Aggregated data on location G

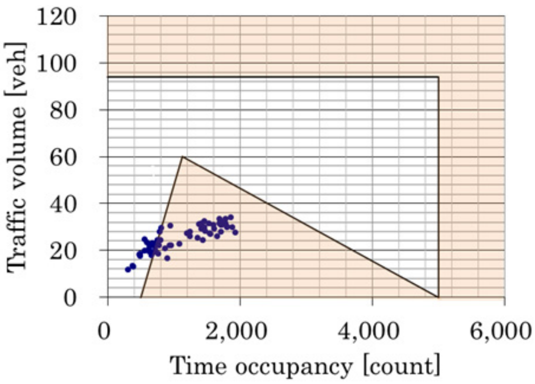

Fig. 12. Aggregated data on location H

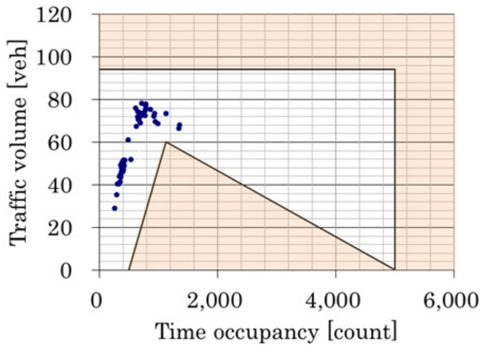

Fig. 13. The aggregated data at location G after repair

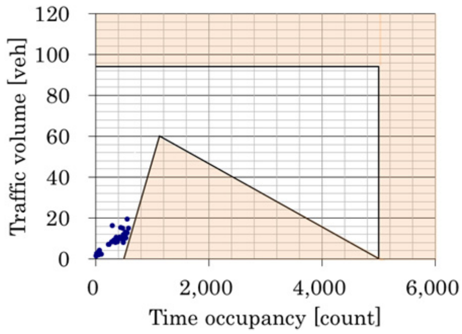

Fig. 14. The aggregated data at location H after repair

detectors and failed detectors, is was more suitable to have fewer hidden layers. On the other hand, we believe that from the perspective of optimizing parameters using a reverse error propagation method, the broad search space of Softmax yielded favorable results. Although all three methods obtained favorable results, we consider Method 1 to be the most desirable. Since being able to indicate the operating condition of a device is needed when it breaks down in a social infrastructure system, performance being equal among the three methods, Method 1 can actually be explained. Also, the need to select the functions and parameters used in Method 2-A and Method 2-B ahead of time can also be considered an issue.

Next, in order to apply the method to numerous detectors to check the detection results, Method 1 was implemented for all 840 detectors described above. As a result, 65 terminals (7.7%) were judged to have broken down. In order to check the condition of the identified detectors on a priority basis, they were sorted by the pulse abnormality count detected within the vehicle detectors themselves and transmitted to the TMCS, and the top five terminals were selected for investigation. Of those, three had already been determined to be faulty according to maintenance records. The remaining two were installed respectively at Location G and Location H, and the aggregate vehicle detection information (time period 3 and time period 5) used for the determination according to Method 1 are shown in Fig. 11 and Fig. 12, respectively.

The unit at Location G was determined to be faulty due to two data points in Region A and one data point on line L1 in Fig. 9. The unit at Location H had numerous data points in Region A as can be seen in Fig. 12, and so was determined to be faulty. At both locations, the data deviated from the traffic flow model, and so the units were suspected of a breakdown and were subjected to maintenance work. The unit at Location G was malfunctioning, and was restored by regulating the power source voltage. The unit at Location H is a vehicle detector that simultaneously detects three lanes. Interference between the ultrasonic transmission/reception heads was suspected and so their orientations were adjusted. The data after the maintenance work at the respective locations are indicated in Fig. 13 and Fig. 14. In them, it can be seen that the data after maintenance for both detectors did not stray into the failure detection regions and variance decreased. In addition, it was confirmed that repeating Method 1 would result in a discrimination as a normal detector.

5. Conclusion

We visualized vehicle detection information on ordinary roads using aggregate vehicle detection information, and it was suggested that it is possible to categorize installation conditions. This categorization was achieved between the three broad categories of approaches on intersections with frequent congestion, approaches on intersections with infrequent congestion, and right turn lanes. Next, we proposed a method for detecting failure using aggregate vehicle detection information by using the relationship between traffic volume and occupancy time in the traffic flow model to set failure regions, and we attempted to apply discrimination methods using mathematical methodologies that have been used more frequently in recent years. All the methods achieved relatively good results, with a correct response rate of 100% for functioning detectors and 83% for broken down detectors. Furthermore, implementing the method using the traffic flow model to 840 detectors resulted in 7.7% of them being selected as failure. When the five detectors with the highest priority were checked, they were found to already be registered as failure or found to be failed in an on-site inspection. From this, the effectiveness of the proposed methodology could be confirmed. In the future, we would like to make further improvements towards practical application through many more numerical experiments.

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