DETECTION AND ANALYSIS OF DETOURS OF COMMERCIAL VEHICLES DURING HEAVY RAINS IN WESTERN JAPAN USING MACHINE LEARNING TECHNOLOGY

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In this study, we detect the detours of commercial vehicles during heavy rains in western Japan using machine learning technology and then analyze the cause of these detours. Due to heavy rains in 2018 in western Japan, road regulation was implemented over a wide area. GPS-generated probe trajectories revealed the detour routes taken. The necessity of taking detours is one of the traffic failures caused by disasters. To identify these detours, a road administrator must visually check and analyze the probe vehicle trajectory, which requires considerable labor. Therefore, in this study, we detected detours during a disaster by learning the probe vehicle trajectory under normal circumstances using a one-class support vector machine (OCSVM). Results of detour detection for Shikoku revealed that vehicles were using distant detour routes even when nearer detour routes were accessible. An analysis of the cause of these detours showed that the “risk” of the traffic failure was one factor.

Key Words: one-class support vector machine (SVM), commercial probe vehicle, the heavy rain event, detour route, risk of traffic failure

1. INTRODUCTION

In this study, we detect the detours of commercial vehicles during heavy rains in western Japan using machine learning technology and then analyze the cause of these detours. Due to the heavy rain event of July 2018, road blockage was implemented throughout a wide area. The road administrator needed a long time to recover the road due to the considerable damage. For example, Kochi Expressway took about one year to fully recover. When such long-term road blockage occurs, passing vehicles are forced to take detours between the disaster and recovery, thereby affecting people’s movement and logistics. In the event of a disaster, identifying the detour route or the cause of the detour will be useful for traffic guidance during the period between the disaster and recovery; it will also aid in developing detour routes in the future. However, at present, the road administrator does not have any information about the detours due to the road blockage caused by the heavy rain event of July 2018. Probe data can identify detours due to road blockages. However, to identify these detours, the road administrator must visually check and analyze the probe vehicle trajectory, which requires considerable labor. In this study, we propose a method of detecting detours efficiently during heavy rains using commercial probe vehicle data1). First, we define detours. In this study, we target detours peculiar to disasters, which have a significant traffic impact. Therefore, a detour is defined as: 1) a long-distance trip, 2) a route with a longer time and distance than normal, and 3) a route that differs from normal circumstances. We detect detours using a one-class support vector machine (OCSVM)2)3), which is a machine learning technology. Anomaly detection for rare events (unsupervised), such as heavy rainfall disasters, is positioned as “unsupervised learning for outlier
(1) Analysis of route choice behavior during sudden events and disasters

Studies have analyzed route choice behavior during sudden events, such as construction, accidents, and traffic jams, (Kusakabe et al.\textsuperscript{10}, Wardman et al.\textsuperscript{9}). Kusakabe et al. investigated traffic behavior by providing information about variable-message signs (VMSs) during sudden events along urban highways using stated preference (SP) surveys. The results of their analysis showed that information about the increasing trend of congestion and fees affects route choice. In the above studies, SP surveys were used to investigate traffic behavior, and the route choice model was built based on the survey results to analyze traffic behavior.

Some studies analyzed route selection behaviors during disasters (Morii et al.\textsuperscript{7}, Asakura et al.\textsuperscript{8}, Fujita and Mitamura\textsuperscript{9}). Morii et al. conducted a web-based questionnaire survey on traffic behavior in the event of heavy rainfalls, assuming that the information would be provided by car navigation systems. Using the results of the survey, they constructed a path choice behavior model using a multinomial logit model. The results of the analysis showed that information about the extent of the heavy rainfall (risk) influences drivers’ route choice (hazard avoidance behavior). Asakura et al. surveyed traffic behavior in Shikoku, where the roads were closed due to typhoon damage, using a questionnaire survey. Their analysis results revealed that 85\% of drivers do not abort their trips but divert them even when they encounter traffic restrictions and that the trip aborting, trip diversion, or waiting for traffic restrictions is affected by the time consumed by such actions. Fujita et al. analyzed traffic behavior during a heavy rainfall in Tokai using a questionnaire survey. Their findings showed that no detours were taken during the disaster because of gridlock (heavy traffic jam).

All of the above studies were conducted on private vehicles; the route choice behavior of commercial vehicles was not clarified. In addition, SP surveys and web questionnaires can lead to problems because the responses depend on subjects’ memories. By contrast, probe data collected from mobile phones and car navigation systems can provide detailed information about routes and speeds. In the next section, research on the traffic analysis of accidents and disasters using probe data is summarized.

(2) Traffic analysis using probe data

Several studies used probe data to understand traffic conditions during disasters (e.g., Bengtsson et al.\textsuperscript{10}, Lu et al.\textsuperscript{11}, Hara and Kuwahara\textsuperscript{12}, Kawasaki et al.\textsuperscript{13}). Hara and Kuwahara used probe data from Ishinomaki City, which was affected by the Great East Japan Earthquake in March 2011, to analyze the pro-
cess of gridlock (heavy traffic jam) caused by the concentration of vehicles during the tsunami evacuation. Kawasaki et al. reported that, during the Kumamoto earthquakes in April 2016, the daytime travel time on the alternative route from the Fukuoka area to central Kumamoto increased significantly compared with the normal travel time due to the blockage of the Kyushu Expressway. Therefore, probe data are effective for understanding the traffic state in a disaster.

Next, we describe studies on anomaly detection using probe data. Sekizuka et al.\textsuperscript{14} and Asakura et al.\textsuperscript{15} attempted to detect anomalies in accidents. They estimated the time and location of traffic disturbances by focusing on the shockwave connecting the inflection points of the vehicle trajectory in two dimensions (time and distance) at the time of disturbance. Cai et al.\textsuperscript{16} and Kusakabe\textsuperscript{17} attempted to detect anomalies by clustering probe data. Cai et al. constructed a cluster containing normal and abnormal-behaving vehicle trajectories observed near an intersection. Newly obtained trajectories classified into clusters of abnormal behavior were deemed abnormal trajectories. Kusakabe regarded the tertiary mesh (1 km square) as the minimum unit and created a vector of average trip times per mesh for each day and time of day. Vector clustering using the k-means++ method was performed for each mesh, and the meshes and the date and time of anomaly occurrence were identified. Although several studies have attempted to detect anomalies in accidents and disasters, these studies do not cover the detection of detours during disasters.

Yoshida et al.\textsuperscript{18} and Umeda et al.\textsuperscript{19} attempted to detect detours in disaster situations. Yoshida et al. proposed indexes such as the time–space distance (TSD) and the Levenshtein distance to evaluate the similarity of 3D probe trajectory data between normal and disaster conditions. Umeda et al. proposed a detour rate that regarded the ratio of the normal distance of a route to that of a disaster as an evaluation index for detour detection. However, these studies used the threshold for detour detection as a hyperparameter, and there were challenges in how the threshold should be set.

The present study differs from the abovementioned works in that it utilizes a machine learning technique to systematically detect detours and analyzes the detours of commercial vehicles during disasters.

(3) Contribution of this study

The contributions of this study are as follows:

1) Efficient detour detection: We propose a detour detection method that uses an OCSVM, which is a machine learning technique that can automatically detect detours in case of disasters. A quick understanding of the traffic situation, such as detours, is required when a disaster occurs widely and simultaneously, as in the case of the torrential rains in western Japan in July 2018, and when recovery time is long. Under these circumstances, the efficiency of detour detection using machine learning will aid in the work of road administrators.

2) Investigation of detours of commercial vehicles and causes of detours: The detour detection results confirmed that some vehicles deviated without using the nearest detour, even though the nearest detour was passable in the affected line. The analysis of the detour causes suggested that “risk of traffic failure” was a factor.

3. OVERVIEW OF DISASTERS IN EHIME PREFECTURE

In this section, we outline the damage in the Shikoku region’s Ehime Prefecture, where the damage was particularly severe. First, we describe the rainfall situation. Figure 1 shows the changes in precipitation in Matsuyama City and Uwajima City. Daily precipitation increased from July 4 and peaked on July 6 and 7. In Matsuyama, a maximum precipitation amount of 206 mm/day was observed on July 7, and a special heavy rainfall warning was issued for Ehime and Kochi prefectures on July 8. In this study, on the basis of the daily precipitation trends, the disaster circumstances were set as July 4–10, 2018, and the normal circumstances were set as June 20–26 (before the disaster occurred).

Report on road damage: Fig. 2 shows the locations of the restrictions that were implemented between July 4 and 10. As shown in Fig. 2(a), there were many regulated areas over a wide region. According to the Ehime Prefectural Government Office, there were reports as of October 15, 2018 that 16 prefectural roads and 78 municipal roads had been closed...
to traffic. Heavy rainfall on the Matsuyama Expressway caused the Hiji River to overflow at Ozu City, and the Ozu Interchange was inundated (Fig. 2(b)). As a result, the road was closed from July 6 to 8. The Tachikawa Bridge, which is over Kochi Expressway and runs between Ehime and Kochi, was closed before dawn on July 7 due to a large-scale landslide on the upstream side of the bridge (Fig. 2(c)). The section was reopened to two-way traffic on July 13, 2018 using the off-ramp, but it has not been fully restored. The damaged part of Kochi Expressway was then designated by the government as a severe disaster area.

4. TRAFFIC STATE AT THE HEAVY RAINFALL EVENT OF JULY 2018

In this chapter, a basic analysis of trips during heavy rainfalls is conducted using commercial probe vehicle probe data\(^1\). Such data were processed by dividing GPS data into trips at the end of the engine ON/OFF period.

(1) Trip analysis of the Shikoku region

The analysis results of the trips in Shikoku are described here. Figure 3 shows the average daily number of trips under normal and disaster conditions. The number of trips during disasters is lower than that under normal circumstances. Figure 4 shows a histogram and the cumulative distribution of the trip distances and trip times under normal and disaster conditions. The trip distances and trip times are calculated at 5-km and 30-minute intervals, respectively. In terms of trip length during disasters, the number of short-distance trips (less than 100 km) increases in comparison with that under normal circumstances. The assumption prior to the analysis is that, if detours occur during a heavy rainfall, the trip distance and trip time would increase. The presumed reason for this is the avoidance of work related to long-distance trips as a precaution against damage caused by heavy rains. However, if we focus only on the long-distance trips that have to pass through the regulated section at the time of the disaster, we believe that the detour will cause increases in trip distance and time. Therefore, in the next section, we focus on specific origin and destination points.

(2) Analysis focused on specific trips

A large number of long-distance trips (more than 100 km) that were likely to pass through the Kochi Expressway upstream, where the landslide occurred, were selected for analysis. In particular, the trip between Marugame City and Kochi City (secondary mesh numbers 513336 and 503325), as shown in Fig. 2, was examined. Figure 5 shows a histogram and the

Fig. 2 Traffic regulation due to heavy rainfall (July 4–10, 2018).
5. DETECTION METHOD OF DETOURS

In this chapter, we propose a method of detecting detours using probe data. The detection consists of three steps: (1) preprocessing, (2) detection of detour candidates, and (3) inspection of detour candidates. In this chapter, we describe this step-by-step process and define the performance evaluation indicators for...
Preprocessing

In the preprocessing, we performed 1) map matching and 2) exclusion of delivery data. Here, map matching is the identification of a path (road) moved on the road network from location data. The reason for the exclusion of delivery data and the exclusion method are described. A commercial vehicle may stop at several points on its way to its final destination due to delivery operations. Since delivery data consist of a mixture of multiple trips, the impact of deliveries should be minimized to detect detours in accordance with the requirements defined in Chapter 1. Therefore, in this study, vehicles stopped for more than m minutes in the middle of a trip were deemed to be deliveries. In this analysis, the threshold for excluding delivery was set as m = 30 minutes.

Detection of detour candidates

We describe a method for detecting candidates for detours. Previous studies on anomaly detection using an OCSVM\(^{[2,3]}\) included the detection of signs of anomalies at a hydroelectric power plant (Onoda\(^{[21]}\)) and the discrimination of actions by using pedestrian trajectories (Toyoshima et al.\(^{[22]}\)).

First, we describe the outline of an OCSVM. The normal vector data are denoted by \(\mathbf{x}^n\). The OCSVm is illustrated in Fig. 7. As shown in the figure, the OCSVM maps data \(\mathbf{x}^n\) in the input space to the feature space using the kernel function \(K(\mathbf{x}^n, \mathbf{x}^n)\). The mapped data are called a support vector. Next, we estimate the function \(f(\mathbf{x})\) such that the distance from the origin to the support vector (margin) is maximized. The function \(f(\mathbf{x})\) identifies normal/abnormal data. The OCSVM identifies the newly observed i-th data as follows:

\[
\delta_i = \begin{cases} 
0, & f(x^d_i) > 0 \\
1, & f(x^d_i) < 0 
\end{cases},
\]

where \(\delta_i\) indicates the normal/abnormal status of the data; it is defined as normal when \(\delta_i = 0\) and abnormal when \(\delta_i = 1\). For the abnormal status, the image is mapped closer to the origin than to \(f(\mathbf{x})\), as shown in the red circle in Fig. 7.

Next, we define the trip data to be inputted to the OCSVM in this study. We define the trips’ index set as \([n]\). The distance of the i-th trip is denoted as \(l_i\) and the trip time as \(t_i\). The set of trip data under normal conditions is defined as follows:

\[
x^n = (l_1, t_1)^T, \quad x^n = (x^n_1, x^n_2, ..., x^n_i, ..., x^n_T)^T.
\]

Similarly, let \(x^d\) be the trip dataset obtained during a disaster, and denote its i-th element as \(x^d_i \in x^d\). To detect candidate detours, we first learn the parameters of the discrimination function \(f(\mathbf{x})\) using the normal trip data \(x^n\). Then, \(x^d\) is inputted to the parameter-learned \(f(\mathbf{x})\), and those determined to be abnormal are detected as detours. Given that the OCSVM in this study is based on an existing model, the model formulation and parameter estimation are not in the main text but in the Appendix.

Inspection of detour candidates

The processing data in (1) and (2) include delivery data. Thus, data detected as detours are scrutinized to identify any stops (e.g., a temporary stop near a distribution facility or an unnatural U-turn) other than the final destination during the trip. Trips that include such stops are excluded from the data as they are considered deliveries.

Definition of detour detection performance

In this section, we define the evaluation indexes for detour detection by the proposed method. We use precision, recall, and the F-measure as the evaluation indexes for the accuracy of detour detection. Precision and recall are used as indicators of the effectiveness of information retrieval. Precision is the fit ratio that indicates how much data are included in the search results. Recall indicates how much of the total fit data are included in the search results. The harmonic mean of precision and recall is the F-value. In general, there is a trade-off between precision and recall. We define precision, recall, and the F-value as follows: First, we define a detour/normal (no detour) relationship between the model and the actual trip, as shown in Table 1. The True Positive (TP), False Pos-
Table 1: Detour/no detour relationship between the model and the actual trip.

| Model       | Actual trip | Detour | Normal (No detour) |
|-------------|-------------|--------|--------------------|
|             |             | Detour (True positive) | FP (False positive) |
|             |             | Normal (No detour)     | FN (False negative) | TN (True negative) |

F-measure = \( \frac{2 \times \text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \) \hspace{1cm} (3c)

where, TP, FP, FN, and TN in the formula are the number of trips corresponding to each condition.

6. DETECTION AND ANALYSIS OF DETOURS

In this chapter, the detection of detours during heavy rainfalls and the causes of detours of commercial vehicles are analyzed. Trips from Marugame City to Kochi City and from Matsuyama City to Uwajima City are examined. Figure 2(a) shows the positions of the origin and destination points (secondary mesh) of each trip.

(1) Analysis of trips from Marugame City to Kochi City

In this section, we describe the analysis results of the trips from Marugame City to Kochi City. The estimated parameters are \( \sigma = 0.001 \) and \( \nu = 0.01 \). Figure 8 shows the detection results of the trip detours from Kagawa City to Kochi City, as obtained by the OCSVM. The white circles in the figure represent the training data (under normal circumstances). The black and red circles are the data under disaster conditions. The black circles are data with normal labels assigned, and the red circles are data with detour (abnormal) labels assigned. We investigated these detour-detected data and excluded the data of three trips that were considered deliveries, as shown in Figure 9.

Figure 10 shows the vehicle routes under normal and disaster conditions after the inspection. Figure 10(b) shows the red/blue color coding according to the detour (disaster) and normal (no detour) labels. The normal route (Figure 10(a)) shows that commercial vehicle drivers use the Kochi Expressway and National Route 32. During a disaster (Figure 10(b)), a route via Route 194 appears and is marked a detour (anomaly). We consider these routes to be “long-distance trips,” “detour routes that take longer time and distance than usual,” and “routes that differ from the normal route;” thus, they satisfy the detouring definitions in Chapter 1.

Table 2 shows the results of detour detection. The detour and no-detour labels for the actual trips in the table are assigned by the analyst. As shown in the table, the F-measure = 0.96, precision = 0.92, and recall = 1.00. Therefore, we are able to detect detours with a high accuracy of more than 90%. In the following, we analyze the characteristics of the detours. The share of each route is shown in Figure 11. The sharing ratio is calculated by aggregating the route traffic on the A-A’ cross section in Figure 10(b). In the case of a...
In particular, after the damage to Tachikawa Bridge, the usage rate of Route 194 increases remarkably to about 40%. Figure 12 shows the average time required for each route. The results show that the time required via Route 194 was about one hour longer than that via Route 32 at the time of disaster. As per traffic regulations, the routes of National Road 32 and National Road 194 except Kochi Expressway were unregulated and passable at the time of the disaster. The results show that 40% of the commercial vehicles were diverted to the long (irrational) Route 194 even though Route 32 was passable at the time of disaster. To identify the cause of this detour, we analyze the relationship between the weather, disaster, traffic regulations, and topography as possible triggers for the detour. Figure 13 shows the timeline of each route’s share and incentive data. The figure shows that the share of Route 194 increases after the restriction of Kochi Expressway from July 6 and the damage to Tachikawa Bridge and the issuance of the heavy rainfall special warning on July 7. Figure 14 shows the topography around Tachikawa Bridge. As shown in the figure, National Route 32 is built along a mountain slope and close to Tachikawa Bridge on Kochi Expressway. Based on the above, the detour factors are as follows: The driver knows that Route 32 is passable, but the driver is assumed to divert to Route 194 because he is wary of the risk of traffic failure (road restrictions due to the heavy rain). This result, i.e., risk influences a driver’s route choice, is
Fig. 13 Timeline of sharing ratio and incentives from Marugame City to Kochi City.

Fig. 14 Topography around Tachikawa Bridge.

Fig. 15 Detection of detour candidates for trips from Uwajima City to Matsuyama City.

Table 3 Detection of detours in disasters (after inspection).

| Actual trip | Detour | Normal (No detour) | Total |
|-------------|--------|--------------------|-------|
| Model       |        |                    |       |
| Normal      | 3      | 1                  | 4     |
| Normal      | 0      | 9                  | 9     |
| Total       | 3      | 10                 | 104   |

consistent with the results of a previous study (Morii et al.).

(2) Analysis of trips from Uwajima City to Matsuyama City

We analyzed the detours of trips from Uwajima City to Matsuyama City. The estimated parameters were $\sigma = 0.012$ and $\nu = 0.009$, which were not significantly different from those of the trip from Marugame City to Kochi City. Figure 15 shows the results of the detour detection by the OCSVM. Figure 16 shows the vehicle trajectory under normal and disaster conditions after inspection. The routes detected as detours by the OCSVM do not contain any data that appear to be delivery. In Fig. 15, trips with long times and distances are detected as detours. In our method, if the time required is long, the route will be detected as a detour, even if the route overlaps with that of the normal one. In the future, it will be challenging to process routes that overlap under normal conditions; thus, they will not be detected as detours. The bypass detection results are shown in Table 3. The F-measure = 0.86, precision = 0.75, and recall = 1.00. The F-measure is lower than that of the
7. CONCLUSION

This study detects the detours of commercial vehicles in western Japan during heavy rainfalls and analyzes the causes of these detours. To identify the cause of these detours, we combined the above analysis with various incentive data. The findings are summarized below.

1) The detection of detours using the OCSVM confirmed that commercial vehicle drivers during heavy rainfalls do not always choose reasonable routes with short travel times; instead, they may take large detours. For example, 40% of commercial vehicle drivers on Kochi Expressway were diverted to Route 194, which took a longer time, instead of National Route 32, the nearest detour route to Kochi Expressway.

2) The combined analysis of probe data and incentive data suggests that the risk of traffic failure is a contributing factor to the diversion of commercial vehicles.

The results of this analysis show issues related to road traffic management during heavy rainfalls. Future issues are as follows:

1) In addition to probe data, data that may trigger traffic behavior (such as weather, disaster, and traffic regulations) should be collected and accumulated to analyze the route choice behavior during a disaster in detail. Since there was no dataset related to disasters, it was necessary to collect each of these data by contacting relevant organizations or searching web archives in this study. In the future, it will be necessary to build a system that archives related data efficiently and centrally.

2) Currently, traffic information at the time of a disaster is mainly based on facts, such as traffic congestion, travel time, and regulations. In the future, in addition to facts, information about the risk of traffic failures should be provided to help drivers choose routes. For this purpose, it is necessary to examine how to index the risk of traffic failures and provide information.

3) The detection of detour candidates by the OCSVM showed a route that was mistakenly detected as a “detour” because it took a long time, even though it overlapped with the normal route. A possible solution to this problem is to add an index reflecting the overlap rate with the normal route to detect detours.

4) In this study, bypass detection was conducted for two trips in Shikoku during a heavy rainfall. The F-measure results of the evaluation showed that detours could be detected with high accuracy. However, additional cases of future disasters should be analyzed to verify the robustness of the...
proposed method.

5) In this study, analysis was conducted on commercial vehicles. In the future, data on private vehicles must be examined to analyze the differences in route choice behaviors between commercial and private vehicles.

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APPENDIX A FORMULATION OF OCSVM

This section outlines the formulation of the OCSVM shown in Chapter 5. For details, please refer to References²,³.

First, define the kernel function \( K(\mathbf{x}^a, \mathbf{x}^s) \). Among the many kernel functions that have been proposed so far, we use the Gaussian kernel function of the following equation:

\[
K(\mathbf{x}^a, \mathbf{x}^s) = \exp(-\gamma \| \mathbf{x}^a - \mathbf{x}^s \|^2), \quad (A.1)
\]

where \( \gamma \) is a parameter. The identification function \( f(\mathbf{x}) \) is defined as follows:

\[
f(\mathbf{x}) = \mathbf{w}^T \phi(\mathbf{x}^a) - \rho, \quad (A.2)
\]

where \( \mathbf{w} \) is a weight vector and \( \phi(\cdot) \) is a function that maps the data from the input space to the feature space. The margin, which is the distance between the boundary \( f(\mathbf{x}) = 0 \) and the origin of the detected anomaly, is expressed as \( \rho / \| \mathbf{w} \| \). Therefore, the larger the \( \| \mathbf{w} \| \) and the smaller the \( \rho \), the larger the margin. Therefore, the main problem of the OCSVM is defined by the following equation:

\[
\min_{\mathbf{w} \in \mathbb{R}^2} \frac{1}{2} \| \mathbf{w} \|^2 - \rho + \frac{1}{n'} \sum_{i \in [n']} \max\{0, -(\mathbf{w}^T \phi(\mathbf{x}^a) - \rho)\}. \quad (A.3)
\]

The first and second terms of the above formula are intended for increasing the margin. The third term corresponds to the hinge loss function in the SVM. The proportion of the parameter \( \nu \in (0, 1] \) remains on the origin side (outlier side) of the training data.

Equation (A.3) is a complex optimization problem with a mixture of minimization and maximization terms. For simplicity, we consider the dual problem of Equation (A.3). The kernel function \( K(\mathbf{x}^a, \mathbf{x}^a) \) is introduced in equation (A.1). Then, the dual problem is defined by the following equation:

\[
\min_{\alpha \in \mathbb{R}^n} \frac{1}{2} \sum_{i \in [n]} \sum_{j \in [n]} \alpha_i \alpha_j K(\mathbf{x}_i, \mathbf{x}_j), \quad (A.4a)
\]

s.t. \( 0 \leq \alpha_i \leq \frac{1}{n'}, \forall i \in [n], \quad (A.4b)\]

\[
\sum_{i \in [n]} \alpha_i = 1. \quad (A.4c)
\]

Here, \( \alpha_i \) is a dual variable and \( \nu \) is a hyperparameter. The OCSVM uniquely determines the discrimination function \( f(\mathbf{x}) \) by solving equation (A.4a) given \( \gamma \) and \( \nu \). If the output of the disaster data \( \mathbf{x}^d \) input to the identification function is \( f(\mathbf{x}^d) < 0 \), it will be detected as a detour.

APPENDIX B PARAMETER ESTIMATION OF OCSVM

This section describes a method of estimating the parameters \( \gamma \) and \( \nu \). On the basis of previous studies, \( \gamma \) is estimated such that the variance of the Gram matrix (the matrix in which the kernel function is computed in all samples) is maximized. The parameter \( \nu \) is estimated by grid search, which involves inputting all combinations of pre-enumerated parameters into a model and taking the best combination of these parameters as an estimate. The detours detected in this study are routes that are not selected under normal conditions. To satisfy the conditions for these detours, we apply grid search to determine all normal data as normal (no detour) and to search for the value with the maximum \( \nu \) as the estimated value. The above parameter estimation method has been described in previous literature. For details, see References²,³ or related research papers.

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