Development of Risk-based Railway Track Maintenance Method Using Image Analysis Technology

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A hazard sensing technology has been developed for track maintenance that can extract hazard factors related to the expansion of the damage caused by a derailment accident. In addition, a risk-based maintenance method was developed for track irregularity management using the hazard sensing results and a statistical risk model. As a result, it is now possible to extract the factor of magnification of derailment damage (collision with structures and the public, falls from elevated locations) through image analysis using images recorded from the front of commercially operated trains. In addition, a maintenance and management model was created to calculate the appropriate values of the management value of track irregularity and the inspection cycle time, considering the track maintenance cost and the damage scale of the derailment accident.

Keywords: track maintenance, hazard sensing, image analysis, object recognition, three-dimensional measurements

1. Introduction

In track maintenance and management, the decision whether or not to carry out maintenance is commonly based on a comparison of measured values obtained through inspections with control values established to determine when maintenance is required. Nevertheless, given the growing demand for safety in society, the introduction of "risk-based maintenance" considering cost and safety is being investigated for the maintenance of plant machinery. The concept of "risk-based maintenance" was therefore examined with a view to applying it to track maintenance and management in the wake of a derailment accident. Hazard sensing technology was developed that is capable extracting hazard factors related to the spread of damage from a derailment accident based on images recorded from the front of a commercially operated train. In addition, a risk-based maintenance method was developed for track irregularity management using sensing results and risk estimation models. This paper describes the outline of the developed methods and the results of verification.

2. Overview of risk-based maintenance of track

In conventional track irregularity management, as shown in Fig. 1, it is common to compare measured values with track irregularity management values in order to determine the type of maintenance required. In some cases however, such as a derailment, damage may lead to other consequences, such as an increase in the number of injured individuals. It is considered appropriate from the viewpoint of risk management to raise the priority of maintenance in such locations. Therefore, in order to implement track maintenance and management in consideration of such accident related risk, a flow diagram was created for risk-based maintenance of the track, which prioritizes maintenance based on the magnitude of the risk. An overview of the flow chart is shown in Fig. 2.
3. Development of hazard sensing technology

In hazard sensing, image analysis gives us the factor of the damage expansion at the time of derailment accident. However, in order to evaluate it as a hazard factor, it is necessary to consider the positional relationship between the vehicle and each factor. For example, vehicles after derailment often travel to the outside of the curve, so the assumed damage when the hazard factor is located outside the curve is considered to be greater than inside the curve. Also, if the location of the extracted hazard factor is far from the vehicle, the possibility of the vehicle reaching that location is considered low. Therefore, in the image analysis, the hazard level is evaluated on the basis of distance to the target as well as actual recognition of the hazard factor.

3.1 Image analysis method and result example

In order to obtain the damage expansion factors, the image is analyzed in the procedure shown in Fig. 3. Each item is described in detail below.

3.1.1 Image sharpening

Images photographed from the front of the vehicle in natural light, including mountainous areas and tunnels, can lose clarity depending on light conditions. Images are therefore processed to achieve a quality suitable for the subsequent analysis through image sharpening.
3.1.3 Segmentation

Based on the above three-dimensional measurement results, structures and elevated travel sections are extracted from the image. For these structures, an area with a roughness shape is estimated from coordinate values in a three-dimensional space, and the area is extracted separately from the plane. In addition, for vehicles and people assumed to be potential victims adding to the damage factor, a technique for extracting them directly from a two-dimensional image using object recognition technology was created, so this segmentation processing is omitted.

Figure 5 shows the result of segmentation. The upper figure is the original image, and if processing up to segmentation is performed on this, the structure can be separated as shown in the middle figure. Finally, the output of enclosing the structure in a frame is shown in the lower figure. It can be seen from this figure that the main girder of the bridge and the building on the right side were extracted respectively.

3.1.4 Object recognition

Figure 6 shows the result of hazard factor extraction following object recognition processing, in addition to the above-mentioned processing of the image actually acquired. It can be seen that structures, cars, and workers are properly extracted. These outputs are obtained as a data list combined with distance information and become input data for the risk database.

3.2 Evaluation of precision

The extraction precision of the hazard factor was evaluated using the image taken by the operating line. A sample image for machine learning was created using image data taken in a section (learning section) of about 130 km, and the analysis engine for factor extraction was created using this image. The analysis engine was applied to the image data from a non-learning section (same distance as the learning section) to evaluate the extraction precision of hazard factors. Table 1 shows the precision evaluation results. Note that the table shows the results of the extraction parameters that maximize the recall rate (Indicator indicating the low number of missed detections: "Number of correct factors / Total number of factors actually present") and precision rate (Indicator indicating the low number of false alarms: "Number of correct factors / number of extracted factors").

In all the subjects, the precision was 95.7% when the recall rate was at the maximum, and 76.0% when the rate of precision was at a maximum. In general, since the recall rate and the precision rate are in a trade-off relationship, Table 2 shows the results with parameters in which the recall rate and the precision rate have a high average. As shown in Table 2, the recall rate at this time was 81.8%, and the precision rate was 61.5%.

Overall, the recall rate was higher than the precision rate. In order to improve the recall rate, future work needs to focus on improving the extraction precision of piers and people, and the precision ratio by better extraction precision of buildings, cars and people. Approximately 10000 images were used for machine learning in this study. It is thought that increasing the number of sample images for learning and adding rules, such as limiting the possible range within which people can appear in an image, could further improve the recall rate and rate of precision.

Table 3 shows the results of measuring the gauge on the image in a straight section with a gauge of approximately 1067 mm (narrow gauge) to evaluate precision in distance measurement. The error at about 30 m from the camera was within about 2%, which was considered to be sufficiently precise for distance measurement in hazard sensing.
3.3 Development of hazard sensing viewer

A hazard sensing viewer was developed, capable of displaying the results described above, together with the captured image. Figure 7 shows a screenshot of the viewer, which shows the image and the extracted hazard factor list. In addition, the hazard distribution on the map or on the track map can be displayed, and the distribution can be visualized. In the distribution on the track map, it is possible to display the alignment and structure information (crossings, turnouts, stations, bridges, tunnels, etc.) from the ledger data. In addition, it is compatible with track environment data in LABOCS [1] which is a database software widely used in track maintenance.

Fig. 6 Result of extraction of recognized hazard factors

Table 1 Precision of factor extraction by image analysis

|               | Structure | Pier | Elevated location | Car | People | Total |
|---------------|-----------|------|-------------------|-----|--------|-------|
| Number of extracted factors | 284 18 25 131 15 | 295 20 29 132 18 | 473 |
| Total number of factors actually present | 96.3 90.0 86.2 99.2 83.3 95.7 |
| Recall rate (%) | 96.3 90.0 86.2 99.2 83.3 95.7 |

Table 2 Results with average parameters for recall and precision

|               | Structure | Pier | Elevated location | Car | People | Total |
|---------------|-----------|------|-------------------|-----|--------|-------|
| Number of extracted factors | 242 10 25 117 10 | 295 20 29 132 18 | 404 |
| Total number of factors actually present | 82.0 50.0 86.2 88.6 55.6 81.8 |
| Recall rate (%) | 82.0 50.0 86.2 88.6 55.6 81.8 |

Table 3 Precision of distance measurement

| Distance from camera [m] | Actual size [mm] | Measurement size [mm] | Error [%] |
|-------------------------|------------------|-----------------------|-----------|
| 28.6                    | 1067             | 1081                  | 1.31%     |
| 29.0                    | 1067             | 1044                  | 2.16%     |
| 30.6                    | 1067             | 1069                  | 0.19%     |
4. Application to track maintenance and management planning

4.1 Examination of optimal management value of track irregularity

Risk was estimated using the model developed through previous research [2], and the track irregularity management value examined in consideration of risk was performed by calculating the value that minimizes the sum of the cost of risk and track irregularity maintenance. The maintenance period $T$ was calculated by (1) using the management value $z$ for the target location, track irregularity growth $\Delta z$, and the finished value $z'$ after maintenance. The total maintenance cost was calculated by multiplying this reciprocal number (the number of annual maintenance interventions) and the maintenance cost per intervention and the number of years to be considered.

$$T = \frac{(z - z^0)}{\Delta z} \quad (1)$$

Figure 8 shows an example of the calculated maintenance costs for lateral alignment ($T = 25$ years) for a 500m section of rail and the estimated risk for each derailment case. From the figure, it can be seen that maintenance costs increase when the lateral alignment value is managed to in a way that keeps it small.

Figure 9 shows the result of the sum of the calculated maintenance cost and the risk. In each condition, there is the optimal lateral alignment value where the sum of the cost of maintenance and risk is minimized, and the value increases from condition 1 (collision with structure), 2 (fall), to condition 3 (collision with train on adjacent line). This is because the estimated damage increases in the following order: condition 3, 2 and 1. Therefore, it is appropriate to decrease the management value of the lateral alignment in the order: condition 3, 2 and 1.

4.2 Examination of track irregularity inspection cycle

When the inspection cycle is used as a parameter, since track irregularity progresses at a different pace between inspection cycles, the derailment occurrence probability can increase or decrease, and in the same way, risk increases or decreases. Maintenance costs however can be calculated using the above-mentioned calculation method because they do not fluctuate from cycle to cycle. Therefore, it is possible to find the appropriate inspection cycle value by summing the risk and the maintenance cost to calculate the inspection cycle interval that corresponds to the minimum track irregularity.

Figure 10 shows the result of examining the relationship between inspection cycle intervals and the optimal management value of lateral alignment, obtained using the method shown in 4.1. Note that the management value in Fig. 10 is the value to be minimized, i.e. the sum of risk and maintenance cost for each inspection cycle interval. When the inspection cycle interval is the same, the reason condition 3 must be managed to keep lateral alignment small, is the same as the result shown in 4.1. Also, under each condition, the management value of the lateral alignment can be increased by shortening the inspection cycle interval. Furthermore, it can be seen that when the control value is constant, the inspection cycle interval can be shorter for high risk conditions and longer for low risk conditions.
5. Conclusions

A hazard sensing technology was developed for railway track maintenance that can extract hazard factors related to the expansion of the damage caused by a derailment accident. A risk-based maintenance method for track irregularity management was also developed, using the hazard sensing results and the risk statistical model.

As a result, it became possible to extract the magnification factors of derailment damage by image analysis using images recorded from the front of commercially operated trains.

In addition, a maintenance and management model was created to calculate the appropriate values for managing track irregularity and inspection cycle intervals, considering track maintenance cost and the scale of damage from a derailment accident.

References

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