Anomaly Sign Detection for Automatic Ticket Gates by the Histogram Limitation Method

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Abstract

It is crucial to appropriately maintain automatic ticket gates (ATGs) to keep transportation operating smoothly in urban areas. Although the average failure rate of new ATGs is extremely low, continuous operation for many years might lead to unstable performance due to deterioration, and the need for periodic maintenance to avoid fatal faults might halt operations for extended periods. To detect anomalies at an early stage, "anomaly signs" can be utilized to flag ATGs for maintenance by service engineers before anomalies occur. In addition, to minimize the cost of ATG monitoring, the necessary computing resources should be minimized, which means using only light-weight statistical methods rather than deep learning or machine learning. In this paper, we focus on the automatic separation modules inside ATGs that separate multiple tickets by complicated mechatronic controls because this module is the major cause of maintenance calls from station attendants. We propose a simple anomaly sign detection, called the histogram limitation method (HLM). We evaluated the anomaly sign scores over time with maintenance timing and compared them with the conventional fast unsupervised anomaly detection method, Histogram-Based Outlier Score (HBOS) widely used in various domains. The experimental results using real field ATG monitoring data show that HLM successfully detected anomaly signs before a maintenance call was necessary, which is better performance compared with HBOS. Despite being a simple modification based on HBOS, HLM also provides anomaly sign scores that agree adequately with assessments by maintenance service engineers.

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1. Introduction

To smoothly operate public transportation for huge numbers of people in urban areas with highly developed railway transportation networks, it is essential to maintain and monitor automatic ticket gates (ATGs), also known as fare collection systems. Modern ATGs have fewer mechanical parts because e-tickets have become more popular; however, ATGs that use paper tickets must be maintained for at least 10 years into the future as part of the basic railway infrastructure installed at almost all stations in Japan.

In addition to performing scheduled inspections, service engineers (SEs) need to adjust or repair ATGs on-site when they are summoned by station attendants. It is important to prevent ticket jamming failures before they occur because SEs need time to adjust the gap between rollers to fix jams in the separation module; in some cases, they need to replace rollers and/or belts, making the ATG unavailable. When station attendants cannot resolve a jam, they call spot maintenance, which may cause delays for parts procurement and ultimately cause long periods of ATG downtime.

For older ATGs, an efficient, low-cost, and compact monitoring function is required because it is necessary to keep hardware costs as low as possible; otherwise, service fees would increase, and consequently maintenance might be deferred.

To mitigate these problems, we propose efficient and light-weight anomaly detection at an early stage; in other words, a so-called "anomaly sign detection" for predictive maintenance based on condition-based maintenance. Here, an anomaly sign refers to symptoms in the normal operation state before an anomaly occurs. Anomaly sign detection can help prompt preventive action to prepare for part replacement or to summon SEs and avoid fatal defects.

2. BACKGROUND

2.1. Separation Module in ATGs

To date, we have found that the most frequent failure in ATGs is related to the ticket-separation module (Figure 1) operated by complicated mechatronic controls located at the front of the ATG, for which the overall failure rate is about 30%, although the failure rate of a new ATG is extremely low (around 1/10,000) according to our survey. Thus, we focus on the separation modules as the target of anomaly sign detection.

Figure 1. Separation Module in an Automatic Ticket Gate

(https://www.global.toshiba/jp/products-solutions/security-automation/fare-collection/automatic-gate-system.html)

ATGs can automatically separate multiple tickets by feed and reverse rollers at very high speed after these tickets enter the separation module. First, the feed roller and reverse roller rotate in the same direction. When thickness sensors detect multiple tickets, the reverse roller rotates in the opposite direction to send only the upper ticket back toward the entry slot. The feed roller then sends only the lower ticket to the exit slot, and after that, sends multiple tickets down the line once they are aligned horizontally. This process is illustrated in Figure 2.

During maintenance, SEs adjust the gap between the reverse and feed rollers. If the gap is not appropriate, the ATG cannot separate multiple tickets correctly. Some ATGs have an automatic gap adjustment mechanism, but the roller can become enlarged or develop uneven wear due to the presence of fluids such as water and oil. In that case, even ATGs with automatic gap adjustment might require new rollers. In other cases, when the friction between tickets is high, the separation module may need more time to separate them. Furthermore, when an ATG has difficulty separating tickets for some reason, it sends them away from the separation module and attempts the separation again, which increases the amount of time needed to successfully separate the tickets.

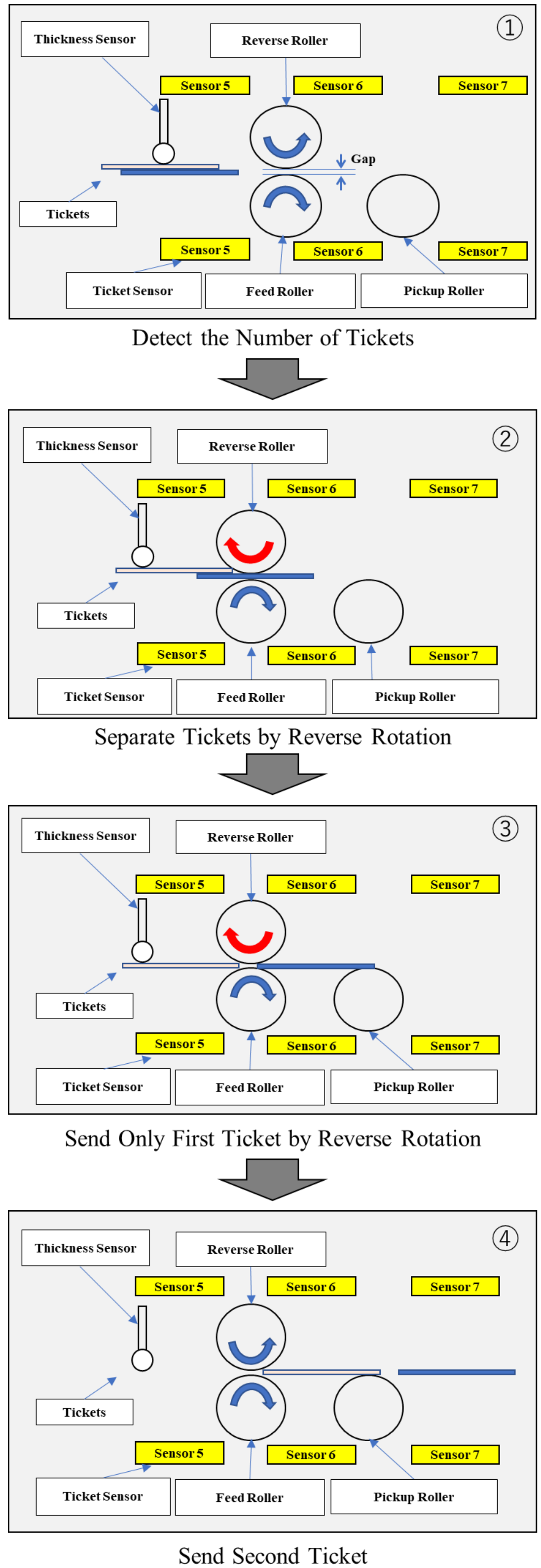

Figure 2. Process for Separating Tickets in the Separation Module

2.2. Related Research

Previous studies have investigated failure prediction for ATGs (Yokoyama, Kono, Matsuda, Shiomi, and Yokoyama, 2023), rule-based diagnosis for ATGs (Shimamura, 2019), and anomaly detection for ticket-selling devices, using deep learning (Xie, Zhu, Wang, Li, and Wang, 2020). Ueno, Ishikawa, Kobayashi, Sunaoshi, and Endo (2023) detected anomalies in ATG control sequences by using a sequential data mining approach to generate common frequent sequential patterns as normal control sequences and applying these normal patterns to monitor control sequences. However, to our knowledge, no existing anomaly detection method for the ATG separation module uses only a single variable to monitor the time it takes the ticket to pass through the separation module. In case that only single variable is available for anomaly sign detection, the anomaly sign score can be easily disturbed by unstable control results, also hard to see the anomaly sign due to low resolution.

Recent studies have reported anomaly sign detection by an autoencoder for power plants (Naito, Taguchi, Kato, Nakata, Miyake, Nagura, Tominaga, and Aoki, 2021) and anomaly sign detection for steel manufacturing facilities (Hirata, Hachiya, and Suzuki, 2021). These approaches are based on multivariate sensor data; therefore, it would be difficult to apply these methods to univariate data.

In the present paper, we introduce our anomaly sign detection histogram limitation method (HLM) for ATGs, in terms of practical anomaly detection system development for infrastructure in urban areas. HLM can remove the effect of unstable control results and improve the anomaly sign resolution by tracking cumulative histogram changes over time.

We describe the basic mechanism of the ATG separation module in Sec. 2. Next, we discuss our anomaly sign detection HLM in Sec. 3. The evaluation results are reported in Sec. 4 and discussed in Sec. 5. Finally, we summarize our research and identify future work.

3. OBJECTIVE OF THE RESEARCH

In this paper, we describe our new anomaly sign detection method enhanced by histogram-based anomaly detection. To compare it with the baseline method, we evaluated the anomaly sign detection performance for separation modules of ATGs based on the following three metrics.

(1) Warning Timing: how early the anomaly sign warning occurs within 2 months before maintenance. Note that only more than two consecutive warnings can be counted to omit uncertainty factors such as slow-release timing of the tickets, or wet or greasy tickets causing bad separation.

(2) Warning frequency: how many times warnings occur within 3 months before maintenance. Note that only two consecutive warnings can be counted to omit uncertainty factors such as slow-release timing of the tickets, or wet or greasy tickets causing bad separation.

(3) Soundness: Anomaly sign scores should return to normal immediately after maintenance is performed.

4. METHODOLOGY

4.1. ATG Log Data and the Target Feature

ATGs record firmware logs of all ticket processing. The logs contain mainly the parts under control and their timing. We obtained monitoring data from five real ATGs at an actual railway station for about 1 or 2 years. We extracted only maintenance records related to separation modules from firmware logs. Through our investigation of the time needed to pass through the separation module, we chose the passing time from just before the separation module to just after. Because our target is the separation module, we focused on processing two ticket combinations: an 85-mm and an Edmonson ticket as well as a pair of 85-mm tickets.

4.2. Anomaly Sign Detection Methods

We employed light-weight detection methods because we have to keep hardware costs as low as possible to avoid maintenance fees for older ATGs. As a baseline method, the Histogram-Based Outlier Score (HBOS) was adopted. To improve anomaly sign detection, we applied our developed anomaly sign detection with the HLM.

4.2.1. Histogram-Based Outlier Score (HBOS)

The HBOS is a widely used conventional unsupervised anomaly detection method (Goldstein., Lewis, and Dengel, 2012), including oil steel industry (Carrasco, Lopez, Aguilera-Martos, Garcia-Gil, Markova, Garcia-Barzana, Arias-Rodil, Luengo and Herrera, 2021), gas industry (Barbariol, Feltresi, and Suusto, 2019), etc. The HBOS is calculated as $HBOS(p)$ with (1). Note that d is the dimension, p means each instance, and *hist* means the height of i-th bin representing a density estimation.

$$HBOS(p) = \sum_{i=0}^{d} log(\frac{1}{hist_i}) \tag{1}$$

Then, based on the HBOS, we calculate the daily histogram-based outlier score *DHOS* by (2). Note that δ represents the date (year, month, and day).

$$DHOS(\delta) = \frac{\sum_{j=0}^{N} HBOS(p_j)}{N} \tag{2}$$

Due to its simplicity, it is even very useful when the target values are close to a normal distribution.

As an extension of the HBOS, recently, the Multi-step HBOS was proposed for steel-plant monitoring (Aguilera-Martos, Garcia-Barzana, Garcia-Gil, Carrasco, Lopez, Luengo, and Herrera, 2023). A histogram-based random forest was also proposed for predicting NO_x sensor failure in heavy-duty trucks (Gurung, Lindgren, and Boström, 2017). Although these approaches are both based on HBOS, they achieve successful results only when they can use multivariate data.

4.2.2. Histogram Limitation Method (HLM)

Our preliminary research revealed that slight anomaly signs tend to appear in the tail of a histogram for passing time during separation (i.e., the time needed for a ticket to pass through the separator). Based on this observation, it seems easy to detect anomaly signs by monitoring the histogram tail. However, the shape of the histogram is also affected by ticket defects such as those caused by bending, folding, and being wet or oily, which make it difficult to decide which area of the histogram should be focused on.

For these reasons, we developed the HLM as a first concept that enables us to calculate the rate of the anomaly score after maintenance by automatically selecting the anomaly sign area (Figure 3) that makes the passing time fastest compared with the one before maintenance in the modeling step. The score can be calculated by the ratio of the calculated anomaly sign area (red area in Figure 4) to the entire area (blue and red areas in Figure 4) in the detection step as follows. Here, we define sets S_1 and S_2 as defined in (3) and (4), respectively. Then, we calculate the daily anomaly sign score *DASS* as shown in (5). Note that the calculated anomaly sign area exists from T_1 to T_2, U refers to the bound for HLM, $|\cdot|$ refers to the number of elements in the set, and δ means the date (year, month, and day).

$$S_1^\delta = \{i \mid 0 \leqq t_i^\delta \leqq U\} \tag{3}$$

$$S_2^\delta = \{j \mid T_1 \leqq t_j^\delta \leqq T_2\} \tag{4}$$

$$DASS(\delta) = \frac{|S_2^\delta|}{|S_1^\delta|} \tag{5}$$

Times T_1 and T_2 can be calculated as follows. First, we choose samples of passing time through the separation module for 1 week before maintenance and define these as S_1^v and S_2^v. Then, we choose samples for 1 week after maintenance and define them as S_1^w and S_2^w. Here, we search L, the best combination of T_1 and T_2 that maximizes the difference $d(L)$ defined as (6) and (7). Note that $\bar{S}$ means the sample mean of S and σ means standard deviation.

$$d(L) = \frac{\overline{S_w} - \overline{S_v}}{\sigma_w - \sigma_v} \tag{6}$$

$$L = \underset{L}{\operatorname{argmax}}\, d(L) \tag{7}$$

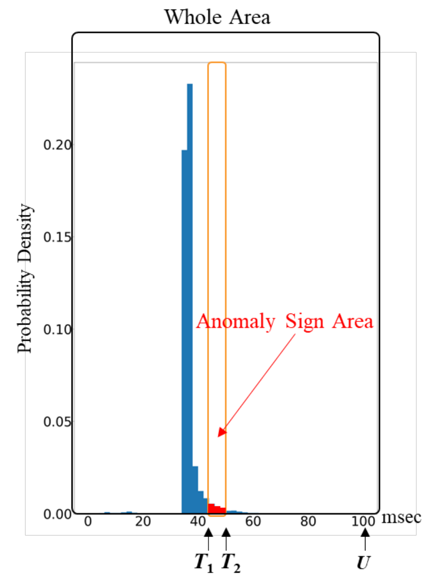

Figure 3. Anomaly Sign Calculation by the HLM in the Model Construction Step

As a result of this evaluation, we found that the $DASS(\delta)$ can partially detect anomaly signs correctly before maintenance. However, the detection results tend to be unstable for a short time (i.e., days) before maintenance, and therefore the SE assessments generally do not agree with the calculated scores. This may be because the method often selects a narrow area, especially when the anomaly sign occurs outside the calculated anomaly sign area, which results in false negatives and is affected by outliers, as shown in Figure 4.

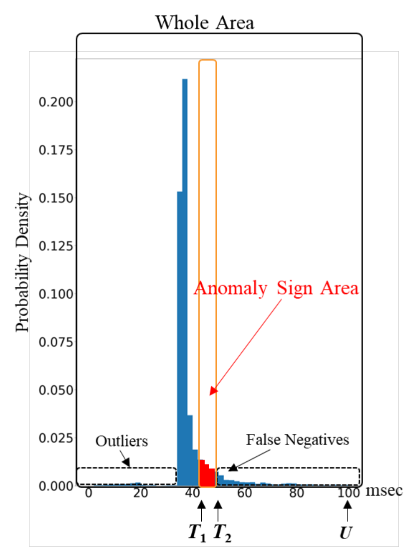

Figure 4. Anomaly Sign Calculation by the HLM in the Detection Step

4.2.3. Improving the HLM

To improve the stability of the anomaly score, we then calculate a stable score by focusing on an area wider than the original HLM, and including almost normal areas on a cumulative histogram (Figure 5). Improved HLM also excludes outlier values caused by complicated ATG mechatronic controls and variations of ticket insert timing and position.

Specifically, first we set the lower percentile A as 10% to remove outliers and set the lower percentile B as 90%, and then calculated the lower values A and B. In this illustrative example, we set the upper value U as 100% (100 msec). In the detection step, we focus on the frequency between A and B. Figure 6 shows an illustrative example to show the difference in the focus area of cumulative histograms between a normal period (about 2 months after maintenance) and anomaly period (about 2 months before maintenance) for the same ATG. The cumulative histogram is steeper than that of the abnormal period. Based on the observation, we revised the HLM as described below.

Here, we define sets S_1^δ and S_2^δ as given in (8) and (9). Then, we calculate the $DASS(\delta)$ as given in (10). Note that $|\cdot|$ refers to the number of elements in each set.

$$S_1^\delta = \{i \mid A \leqq t_i^\delta \leqq U\} \tag{8}$$

$$S_2^\delta = \{j \mid B \leqq t_j^\delta \leqq T_2\} \tag{9}$$

$$DASS(\delta) = \frac{|S_2^\delta|}{|S_1^\delta|} \tag{10}$$

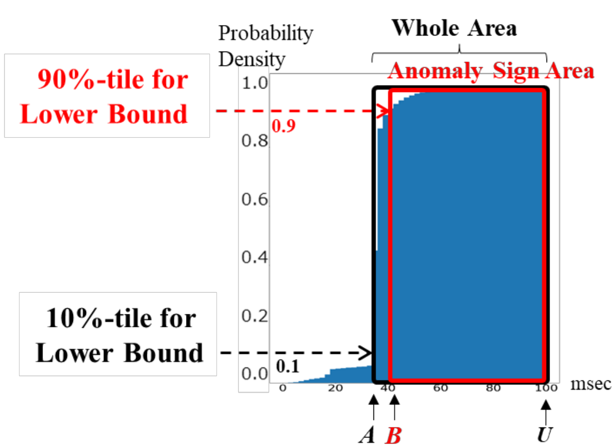

Figure 5. Anomaly Sign Calculation by Improved HLM in the Model Construction Step

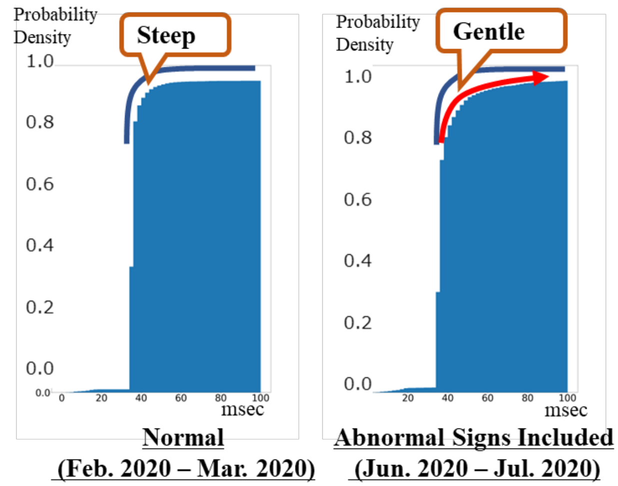

Figure 6. Anomaly Sign Calculation by improved HLM in the Detection Step

In this example, we set the denominator as the frequency between lower value A (35 msec) and U (100 msec), and the numerator as the frequency between lower value B (41 msec) and U (100 msec) based on the observation that the focus area shows slightly different anomaly periods from a normal period in the cumulative histogram. Then, we calculate the fraction as the $DASS(\delta)$.

4.2.4. Monitoring System by HLM

We developed the monitoring system by HLM to detect anomaly signs of real ATGs in operation at train stations in Japan. The process flow of the improved HLM consists of the model construction step (Figure 7) and anomaly sign detection step (Figure 8). In the model construction step, for example, the system calculates A and B based on the data for the set of passing time in the separation module containing normal or abnormal periods for about 2 months before maintenance. Then the system memorizes the parameters A, B, and U, and the anomaly sign judgement threshold TH, which is set by the system user, currently based on our experience. In the detection step, the system calculates the frequencies $|S_1|$ and $|S_2|$ by using A, B, and U. By calculating the fraction described above, the $DASS(\delta)$.

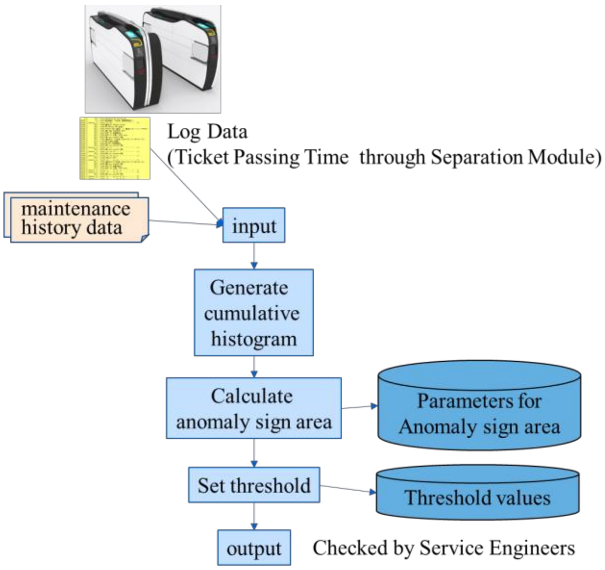

Figure 7. Process Flow of improved HLM in the Model Construction Step

The judgment results on each day can be calculated and visualized on the web page for the improved HLM as shown in Figure 9. We can construct anomaly sign detection models and detect anomaly signs by calculating the score and judge the anomaly sign score with threshold.

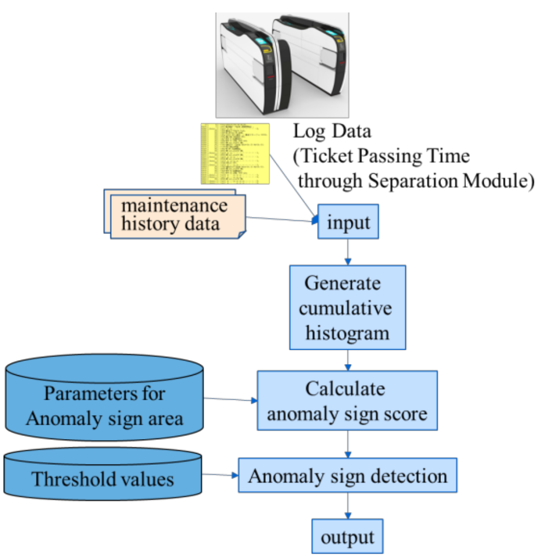

Figure 8. Process Flow of improved HLM in the Detection Step

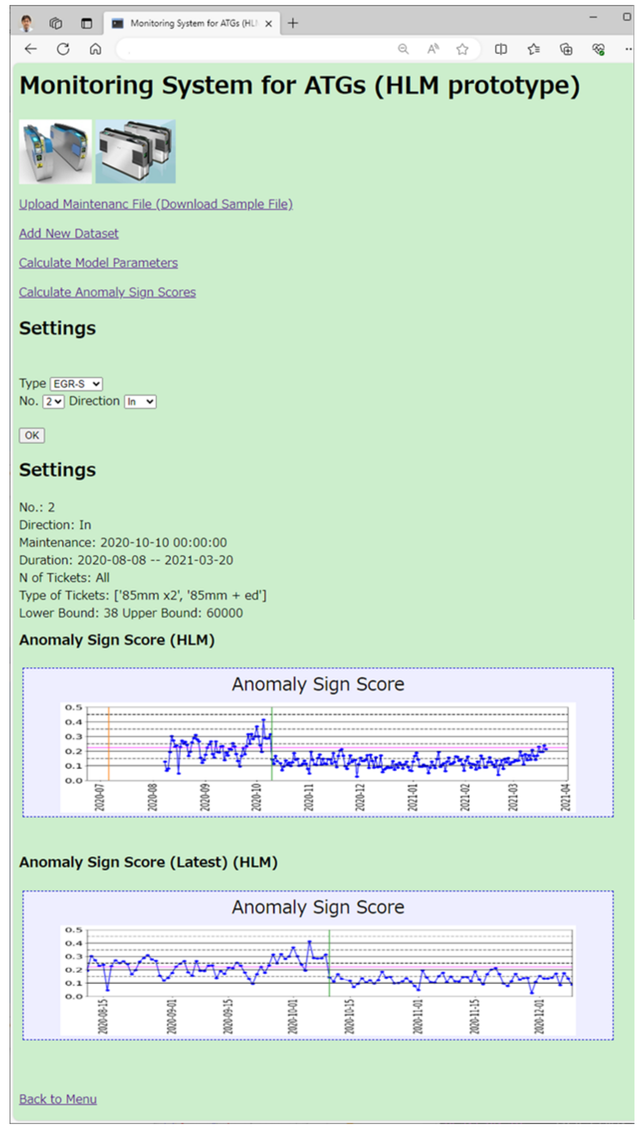

Figure 9. Monitoring Display on the Web Browser

4.2.5. Parameters for Anomaly Sign Detection

For both methods (HBOS and improved HLM) we set the threshold by calculating the 3σ values during a normal period based on our preliminary experiments. We also used $\alpha = 0.1$ for HBOS and B *is calculated based on 90%-tile* for HLM. It may be better to set α as ≤ 0.05 and B based on more than 95%-tile when the monitoring target ATGs are remarkably stable.

5. EXPERIMENTAL EVALUATION

5.1. Results of HLM Improvements

We evaluated the HLM performance focused on the most critical index "warning timing", "warning frequency", and "soundness" as mentioned in Section 3 with the datasets from five real ATGs in operation at train stations. In original HLM, the earliest warning case was seen about 14 days before maintenance (Figure 10). However, the judged anomaly signs were too localized immediately before maintenance.

The result of the improved HLM, shown in Figure 11, shows that the improved method successfully detected four anomaly signs, and the earliest warning was 58 days before maintenance as well as the anomaly sign score gradually increased. As for warning frequency, both methods detect 4 warnings before maintenance, which has no difference. As for soundness, we confirmed that the improved HLM results matched the SEs' evaluation of the field ATG in which operation had degraded before maintenance, while the score tendency of original HLM was not agreed with their evaluation.

5.2. Comparison with Conventional HBOS

Here we compare the anomaly sign detection performance of the HBOS and the improved HLM based on the three metrics described in Sec. 2.2.

5.2.1. Warning Timing

The first metric is how early the warning occurs. The results of Earliest dates for warning (days before maintenance) by HBOS and the improved HLM is shown in Table 1. Note that M means Maintenance timing and number followed by M is maintenance ID within same ATG. From this table, we can see that the HLM detects anomalies sooner than the HBOS by 10 days; however, both methods detect anomaly signs more than 35 days before maintenance on average.

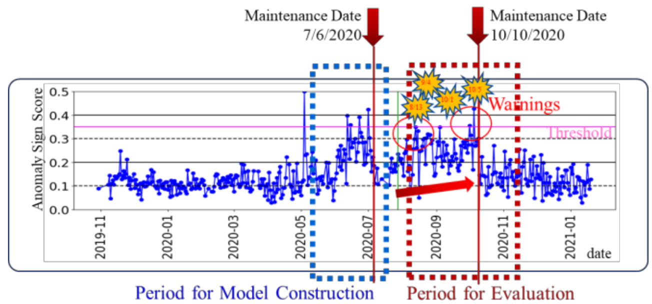

Figure 11. Results of Anomaly Sign Detection by the improved HLM

Maintenance ID	HBOS	HLM
ATG1 M1	33	57
ATG1 M2	74	68
ATG2 M1	32	42
ATG2 M2	16	67
ATG2 M3	16	27
ATG2 M4	24	7
ATG3 M1	32	34
ATG4 M1	53	55
Days Before Maintenance (avg.)	**35**	**44.6**

Table 1. Earliest dates for warning (days before maintenance)

Especially for ATG1 M1 around 7/6/2020, the HLM reveals anomaly signs from end of April to the middle of May (Figure 12), whereas the HBOS graphs do not show these signs (Figure 13). It seems much easier for SEs to notice anomaly signs in the HLM graphs. The earliest warning by HLM is 5/10/2020, while HBOS is 6/3/2020. These results suggests that HLM can warn 3 weeks earlier compared to that of HBOS in this case.

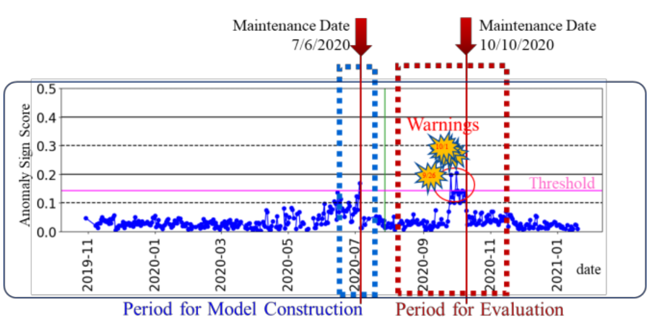

Figure 10. Results of Anomaly Sign Detection by the Original HLM

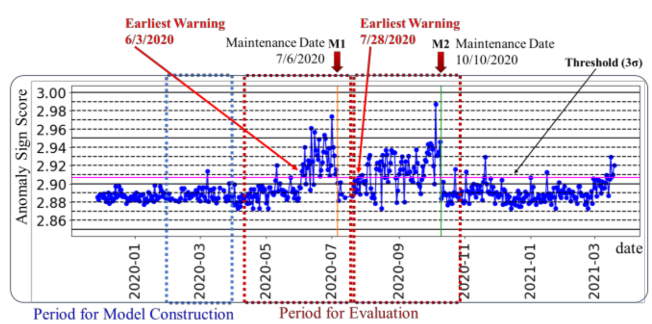

Figure 12. HBOS anomaly sign scores (M1 and M2 in ATG1)

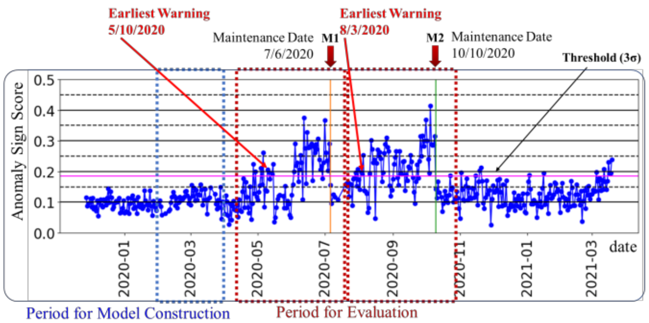

Figure 13. HLM anomaly sign scores (M1 and M2 in ATG1)

According to the valuation results on ATG1 M2 around 10/10/2020, the earliest warning by HBOS is 7/28/2020, while that of HLM is 8/3/2020. The difference of warning timing is less than 1 week. It shows that the warning time by HLM is sometimes slightly delayed compared to that of HBOS, although the average of the warning timing is earlier by 9.6 days.

In another case, for ATG4 M1 around 2020/10/7, the score by HBOS (Figure 14) shows a similar score tendency of HLM (Figure 15); however, the score difference ~~in score~~ between before and after the maintenance by HBOS is smaller than that for the HLM. In contrast, the HLM score shows a remarkably larger difference between before and after the maintenance. The earliest warning by HBOS is 8/15/2020, while it is 8/13/2020 by HLM. It suggests that the timing of warning by HLM is almost the same as HBOS in this case.

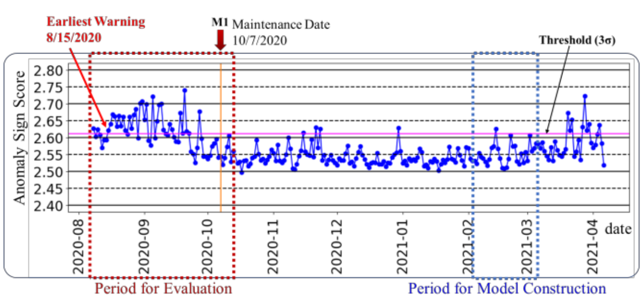

Figure 14. HBOS anomaly sign scores (M1 in ATG4)

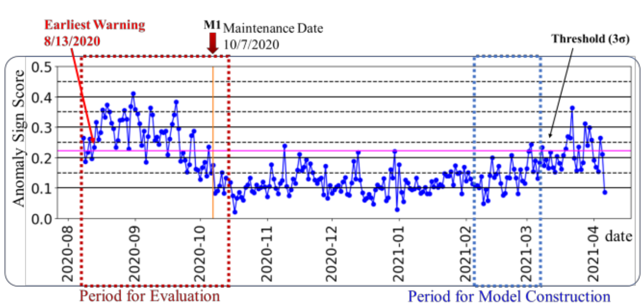

Figure 15. HLM anomaly sign scores (M1 in ATG4)

Maintenance ID	HBOS	HLM
ATG1 M1	30	32
ATG1 M2	50	47
ATG2 M1	9	12
ATG2 M2	14	17
ATG2 M3	12	16
ATG2 M4	11	6
ATG3 M1	17	20
ATG4 M1	28	40
Number of Warnings (avg.)	**21.4**	**23.8**

Table 2. Warning frequency
(number of warnings up to 3 months before maintenance)

5.2.2. Warning frequency

Next, we evaluated the warning frequency, which means the number of warnings within 3 months before maintenance. We found that each method provided more than 20 warnings on average; however, HLM provided slightly more warnings by 2.4 in average. Note that in ATG4 M1 the difference of warning frequencies between HBOS and HLM is 12 which is the largest among all cases for evaluations. As shown in figure 13, the score for HBOS tend to decrease below the threshold continuously in Sep. 2020, which leads to be lower warning frequency in HBOS.

5.2.3. Soundness

We found that anomaly sign scores almost successfully return to normal levels immediately after the maintenance almost every time for both methods. Especially for M1 in ATG4, we found that anomaly sign scores gradually decrease 1 month before maintenance date both by HBOS and HLM. However, the scores keep the difference between before and after maintenance. In other words, the scores are high before maintenance and low after maintenance in both methods.

6. DISCUSSION

As a practical monitoring system for ATGs in urban areas, we developed HLM as an anomaly sign detection method and evaluated its performance compared with the conventional method HBOS. HLM showed good performance, especially when roller gap adjustments are needed. Only occasionally did anomaly sign scores go up and then down without any maintenance (Figure 15). This might have been caused by reduced ticket quality due to sweat, rainwater, or some seasonal factors. It is difficult to identify the cause more precisely because the ticket quality was not recorded.

As shown in Sec. 5, the results suggest that HBOS performs well as an anomaly detection method; however, it does not detect anomaly signs before an anomaly occurs. In contrast, HLM successfully detects anomaly signs before an anomaly occurs, with earlier warnings and much stronger warnings. It also provides warnings without any mechanical factors, such as releasing tickets slowly or receiving greasy tickets.

Another benefit of the HLM is that SEs can much more easily understand its score value in comparison to the HBOS. The HLM score value is a simple probability (0-1); however, the HBOS may change depending on the ATG, which SEs would find hard to discern.

In the ATG monitoring task, it is hard to use deep learning or machine learning with high computational power due to cost limitations; however, some other applications in this framework can permit the use of these methods.

In another aspects for anomaly sign detection, HLM can be used with more sophisticated method like machine learning, deep learning, and other statistical methods in case with the better computing resources because HLM generate new feature values by using input variable into the advanced learning algorithms. It is possible to obtain higher accuracy or sensitivity by combining HLM and other advanced methods. Note that it is not possible to generate new feature like anomaly sign score without feature generation like HLM.

Among deep learning method, LSTM (Braei, and Wagner, 2020) or its variant dLTSM (Maya, Ueno, and Nishikawa, 2019) seems plausible for the ATG monitoring task because of its sensitivity and accuracy, however, these methods need much more data and computing resources for learning sufficient anomaly detection models.

In our evaluation it was no big problem to simply use 3 sigma values of anomaly sign scores during model construction period, however, I think we probably need to learn the optimal threshold for other applications especially for complicated systems.

7. CONCLUSION

In this study, for a practical anomaly detection system for infrastructure in urban areas, we developed HLM as an anomaly sign detection method for ATGs and evaluated its performance with five real ATGs. In particular, the HLM detected anomalies 6 weeks on average before the maintenance day, and furthermore, SEs agreed with the results. Despite it being a very simple approach, HLM successfully detected anomaly signs for ATGs. To understand anomaly signs, SEs can perform predictive maintenance to avoid breakdowns. We are now applying HLM to real ATG monitoring at several sites.

For future research, we plan to apply the method to other infrastructure facilities in urban areas and increase the number of ATG monitoring sites for effective and preventive maintenance, and to improve the method in the aspects of practicality and scalability.

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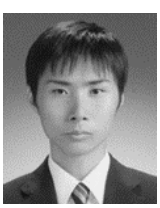

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