A.I. REAL-TIME LIFT DOOR INSPECTION SYSTEM

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ABSTRACT

This paper presents a proof-of-concept of the use of A.I. Real-time Lift Door Inspection System which can revolutionize lift maintenance. Lift service interruptions caused by malfunctioning lift doors are unavoidable. Unlike traditional inspection, the fully automated system will greatly reduce the need for lift technicians to conduct inspections inside the lift shaft. The system consists of a versatile stand-alone installation suitable for all types of lifts. The installation involves electronic sensors, cameras, microphones, an edge computer, and a 5G router. As the lift car moves along the shaft, a camera captures the landing doors' images to assess their integrity and alignment. At the stop of each designated floor, another camera monitors the movement of both the car doors and landing doors, while a microphone monitors any abnormal screeching sounds when the doors are in motion. A set of ultrasonic sensors also detects angular misalignments by measuring the distance between the car doors and landing doors. Collected data are then processed by an edge computer and wirelessly transmitted through 5G to a cloud computing platform. Smart analytics on video and audio data are performed to analyze the health of lift doors for predictive maintenance. Alerts are also generated to prompt technicians to take necessary actions. The system offers automated and 24/7 continuous monitoring, enhanced safety for lift technicians and passengers, data-driven predictive maintenance, and improved maintenance quality. This paper will share the experience, effectiveness, and challenges of developing a new concept of system for inspection and predictive maintenance strategy for lift installations.

KEYWORDS

Anomaly detection, IoT predictive maintenance, Real-time inspection

INTRODUCTION

Lift doors are an important safety feature in any building, designed to prevent people from falling into the lift shaft. Lift systems have two sets of doors: the landing doors (also known as hoistway doors or shaft doors) which keep people in lift lobbies and the car doors (or cabin doors) which keep passengers inside the lift car. If these doors

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are not properly aligned or malfunctioning, they can be a serious hazard to both passengers and lift mechanics.

Decades of lift equipment fault incident records published by the government show that a significant number of the incidents were related to mechanical failures in lift doors (EMSD 2024). A study of several thousands of lifts in the city also found that the car door and landing door mechanisms are among the four main causes of lift system breakdowns (Zhang and Zubair 2022). Manual inspection of lifts systems remains the main mode of inspection, which has disadvantages of high time demand, human labour, and disability of real-time detection. Conducting manual inspections on a weekly basis is the common practice in Hong Kong. The A.I. Real-time Lift Door Inspection System bypasses this limitation, allowing 24/7 continuous monitoring.

SYSTEM DESCRIPTION

The inspection system is a standalone device for examining the lift car doors and all landing doors of a lift shaft continuously during normal operation. An installation drawing is shown in Figure 1, left. A main compartment ("1") is mounted atop the lift car that houses an edge computer and 5G router, a laser distance sensor pointing at the lift shaft ceiling and a pressure sensor ("2"), a camera referred to as Camera 1 ("3"), tilting upward, and an LED lamp ("4").

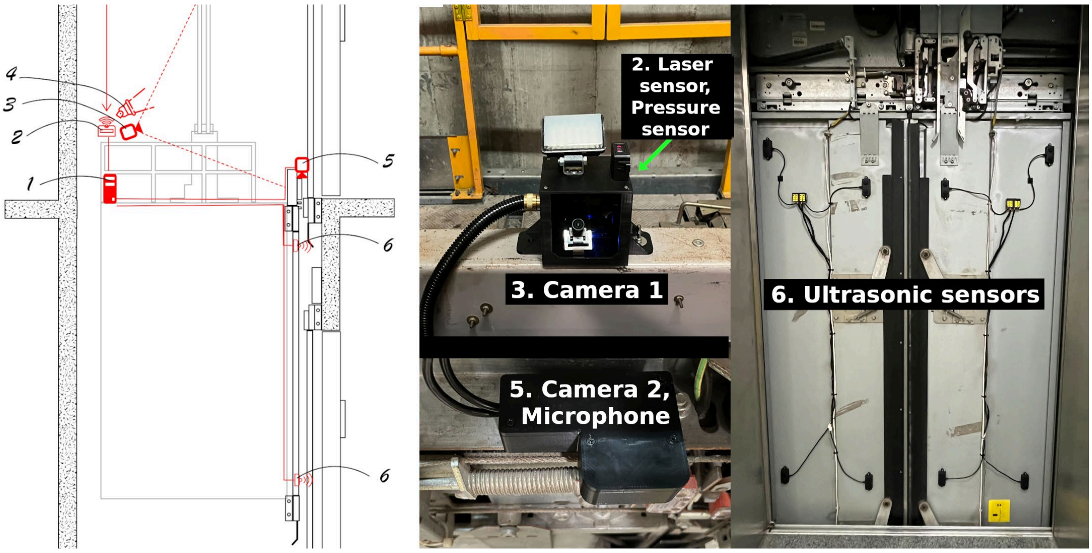

***Figure 1**. Installation drawing and Site 1 installation photos of key devices*

One segment is installed between and above the car doors (Fig. 1, bottom centre). It comprises a second camera referred here as Camera 2 ("5") that is pointing straight down at the car door sill, and a microphone. A final segment comprises eight ultrasonic sensors ("6"), with one sensor installed on each corner of the right and left car door panel. The device sampling rates and their target objectives are listed in Table 1.

***Table 1.** Key devices and characteristics*

Device	*Measurement(s)*	*Sampling Rate*	*Target concern*
Camera 1	Video of landing doors along the lift shaft	4K, 25 fps	Landing door alignment
Camera 2	Video of car door movements	1080p, 30 fps	Car door operation time
Microphone	Audio record of car door operations	48 kHz	Car door operation noise
Ultrasonic sensors	Distance of each corner of landing door to car door	5 Hz	Landing-to-car door alignment
Laser sensor, Pressure sensor	Distance of car to shaft ceiling, atmospheric pressure	20 Hz, 100 Hz	Lift location

METHODOLOGY

Data Description

All data used for analysis and model training in this paper were collected from two installation sites in Hong Kong (Table 2), with key differences in the age of the lift and their frequency of use.

***Table 2.** Installation sites and data collection specifics*

Attribute	*Site 1*	*Site 2*
Building Construction Year	2015	1984
No. of Storeys	22	10
Floors with Landing Doors (Total)	G,1,3, 12-21 (13)	G,1-10 (11)
Lift Type	Passenger	Freight
Sample Period	May to July 2024	August 2024
No. of Weeks Sampled	4	1
Lift Cycles Collected	6,250	216

Preprocessing

Sensor recordings and media files were collectively processed through a data pipeline. Data were first clipped into lift "cycles", which is defined hereon as the period from the first car movement and to the end of the subsequent stationary phase. Using pressure readings, cycles were captured and differentiated into idle and travel phases. A five-minute sample is illustrated in Figure 2, showing 9 idle periods and 8 cycles.

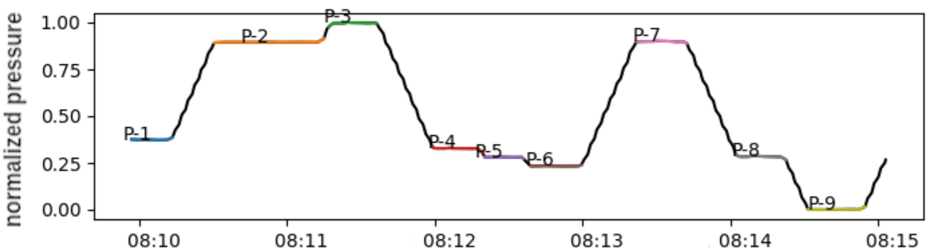

***Figure 2**. Normalized pressure with idle periods ("P") colorized*

A fisheye distortion correction to remove the fisheye effect of the lens, followed by homographic transformation to shift from tilted up to direct frontal view, was applied to all Camera 1 clips to obtain the final rectilinear perspective of the doors (Figure 3).

Figure 3. *Camera 1 perspective before (L) and after (R) transformations*

Failure Simulation

In coordination with both building's registered lift workers, some failure scenarios were simulated (Table 3) in which the door mechanisms were altered in a controlled manner, and the resultant behaviors were recorded by the inspection system on-site. Collected data were separated into training and testing sets. The same analysis methods were applied on both the normal operation data and simulated failure data.

Table 3. *Simulated failure scenarios*

Failure Scenario	*Site 1*	*Site 2*
Landing doors with small gap (<5cm)	✓	✓
Car doors operating slower than normal	*	*
Car doors "stuck" while in opening/closing	✓	✓
Car doors make loud/screeching noise	✓	✓

* prepared by digital manipulation of video FPS of normal operation clip

AI Models

An in-depth literature review of the You Only Look Once (YOLO) family of object detectors proved their applicability in detecting a variety of industrial defects and upholding strict quality inspection, especially for edge devices with constrained computing capacity and real-time requirements (Hussain 2023). Two YOLO models were separately trained on 1,375 annotated frames of landing doors at 4K resolution, and 1,790 labelled 1080p frames of car doors, for 100 epochs. The model architecture was selected for a balance of fast inference time and high accuracy. Failure samples were included in the landing door training set.

Analysis Methods

The landing door AI model was run on each Camera 1 cycle clip, and only frames with full-length landing doors were subjected to video analysis. Knowing the real-world width and the pixel distance of the lift doorway, the bounding boxes coordinates of each door detection were used to calculate the landing door gaps in cm. A combination of brightness threshold and computer vision detection by the car door AI model was applied to analyze each Camera 2 clip. The timestamps at which the car doors move from fully-closed to a fully-opened state (opening phase) and vice versa (closing phase) were identified, and thus operation phase durations recorded. Because duplicate car door operations can be recorded (eg. passenger interruption) in a lift travel, only the first door opening and the last door closing movement were analyzed.

Using the door operation timestamps above, the corresponding audio clips were cut. This was done to keep the audio analysis relevant and also to minimize capturing passengers' conversations. Root-mean-square (rms), a measure of the overall perceived loudness or energy of an audio signal, was used to classify anomalous sounds of a rotating pump using machine learning algorithms analyzing audio features (Intel 2023). Rms was measured here for each phase audio clip.

The sensor readings at each corner of each door panel were collated and their median readings were analyzed individually. The median laser distance measurements during the stationary phase of each lift cycle were calculated and grouped via K-means clustering (N = number of storeys plus ground floor) to determine lift location. For some cases in Site 1 where laser readings were missing, the differences in median pressure readings between the end of one cycle and the end of the previous cycle were gathered and studied to find the reference values corresponding to number of floors travelled, from which destination floor could then be determined.

Postprocessing

All data are organized into clusters based on the destination floor of the operation cycles. The spread of the results were evaluated with standard deviation and interquartile range. Threshold conditions were also applied to alert for possible anomalies. Any outliers or possible anomalous results were reported and saved to separate files according to target issue.

RESULTS AND DISCUSSION

Landing Door Alignment

For Site 1, each floor with landing doors was sufficiently sampled, between 250 to 1,600 times (excluding the rooftop floor). Across the study period, all landing door gaps were measured consistently below 0.3 cm with median readings of 0.2 cm (SD<0.1 cm) per floor, all below the failure condition of 0.6 cm. Due to the very close visual appearance of landing doors from inside the shaft, the low standard deviation was expected for both sites.

Figure 4 shows side-by-side video analysis outputs under normal (left) and failure (right) conditions for Sites 1 and 2. The high resolution of Camera 1 captured sufficiently fine detail for the YOLO object detection model to differentiate between pixels and determine landing door misalignment at very fine scales.

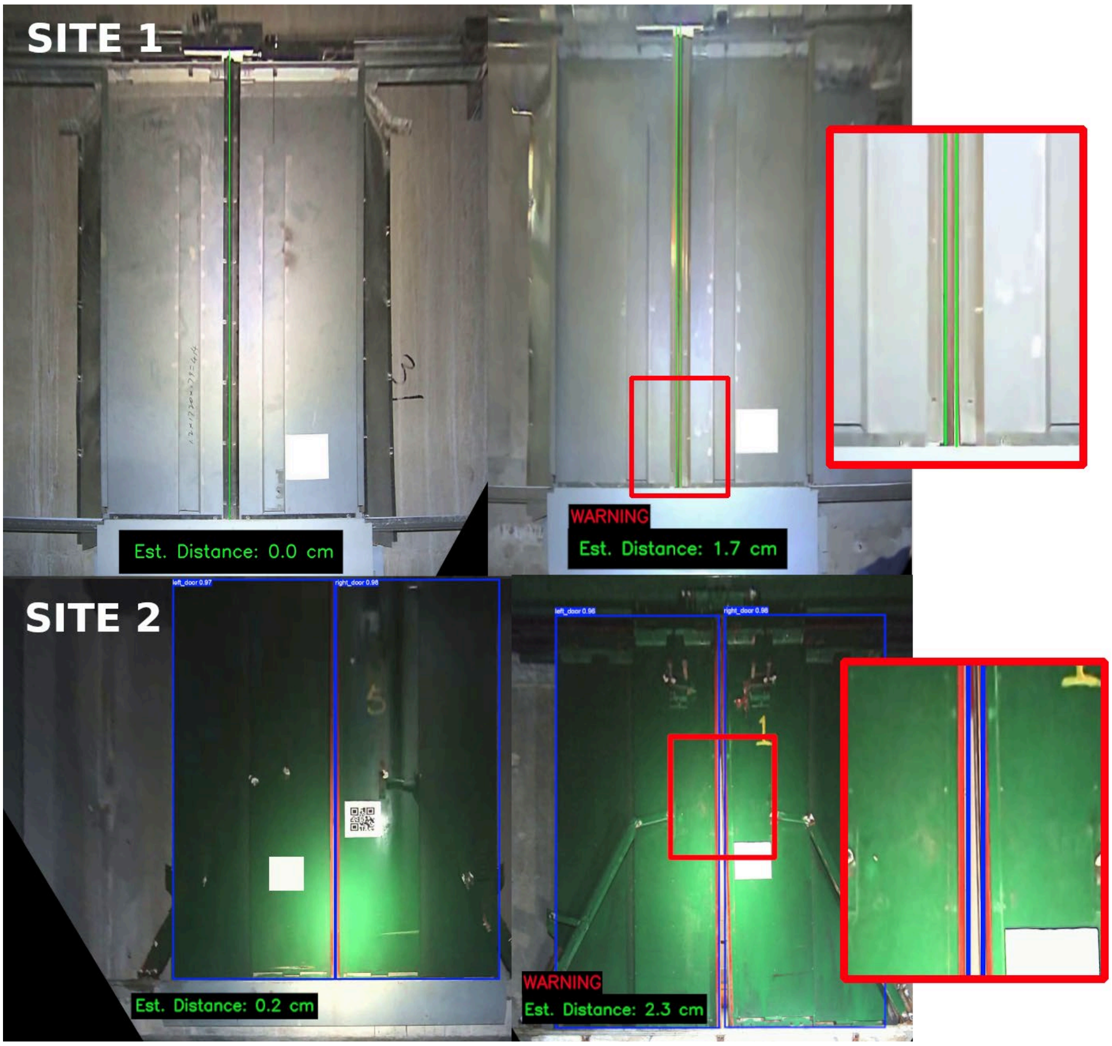

Figure 4. *Landing door misalignment; Box detections in blue, with close-up in red*

Two shapes of simulated misaligned centre-opening doors were tested: parallel and A-shaped. In Site 1 (top right), the model detected the parallel gap and the threshold condition (>0.6 cm) triggered the failure message. For A-shaped misalignment in Site 2 (bottom right), the gap at the door midsection was also detected and triggered the alert. The landing door misalignment detection method was stable and consistent in evaluating the doors' conditions in near real-time for both sites.

Car Door Operation Duration and Noise

The car door opening phase for Site 1 ranged from 2 to 2.2s, while the closing phase was from 3.2 to 3.6s, depending on the floor. Measurements were consistent over the study period (SD<0.1s). Also found were a few false positives, due to the lifts being at parking mode and all the lights inside the lift and the landings are switched off by the building operator on Saturday nights.

Door operation video analyses in Site 2 data found approximately 4.4 to 4.5s and 4.5 to 4.7s for opening and closing duration across different floors, both lengthier than Site 1 as it is a freight lift. Based on these collected observations from normal data, the anomaly thresholds were thus set at 3s for opening and 4s for closing for Site 1, and both 5s for Site 2.

The system was tested on the failure scenarios, with some analysis outputs in Figure 5, involving a digitally slowed clip in Site 1 and for Site 2 where a lift worker manually blocking the doors, adjusted beforehand, so that these would get “stuck” in real-time. The failure video samples triggered the failure conditions (3s for Site 1 and 5s for Site 2), and generated the warning messages. No anomalous cases were found in the normal operation data.

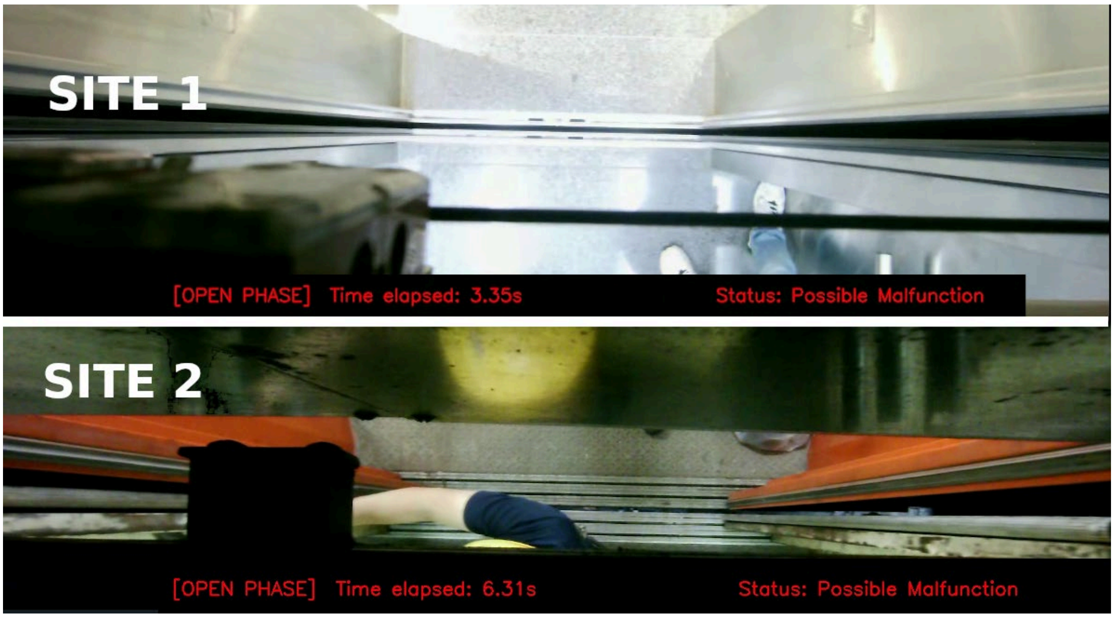

Figure 5. *Analysis outputs of car door failures. Top: slow opening, bottom: “stuck”*

Based on audio analysis by rms, the simulated failure noise created by banging on the landing door and the bumping noise of the adjusted doors on-site triggered the maximum rms threshold condition. Loud screeching noises were also captured during some normal door operations in Site 1. However, the corresponding Camera 2 clips revealed that a person was passing through the lift car right as the doors began to move, and that the high-pitched screeching noise was due to their footwear. More work is needed in differentiating between failure and man-made screeching noise.

Landing-to-Car Door (Angular) Alignment

Results in both sites show an average standard deviation of 0.1cm to 0.3cm, which is acceptable given that the ultrasonic sensors are designed for an accuracy of 1cm. Any readings +/-1.5cm were considered as outliers. All readings were normal, except one sensor in Site 1, in specific floors only, and may be due to some physical obstruction on those specific landing doors not captured on camera. Nevertheless, the measurements were in general consistent across the time period, demonstrating the effectiveness of measuring the car’s angular alignment across the lift shaft.

Lift Location

Lift location was accurately determined for most floors in both sites with low variability (SD<0.03m), with low-traffic floors affected by sample size (SD>0.1m). In Site 1, the laser distance sensor malfunctions at distances beyond 40m, in which case, the consistent pressure differences for every number of floors travelled were used to identify any unknown locations. The study found the laser sensor alone effectively estimated lift car location in Site 2, and was well supplemented by the pressure sensor for tall buildings such as Site 1 with poor ceiling reflectivity and/or unavoidable imperfect laser sensor alignment.

Predictive Maintenance

This study found that equipment degradation in various segments in the lift system could be closely monitored, alerting lift personnel of any suspicious or potential abnormalities and thus preventing breakdowns. Continued collection of operation data and other data sources like historical maintenance records are needed.

CONCLUSION AND IMPLICATIONS

This proof-of-concept study successfully installed the standalone lift inspection system in two sites with contrasting characteristics, achieving automatic recording, extraction, and analysis of lift data in two high-resolution cameras, a microphone, a laser sensor, a pressure sensor, and ultrasonic sensors. Although the findings are limited to the two sites, the results granted firsthand experience into the feasibility of installation and efficacy of detection methods for various anomalies in lift doors and granting potential for early warning alarms, solidifying the technological foundation for the AI real-time lift door inspection system for predictive maintenance. With a combination of threshold conditions, statistical methods and AI approaches, fault detection methods specifically for landing door misalignment, car door movement, landing-to-car angular alignment and lift location were developed. The system facilitates lift engineers to make informed decisions plan their maintenance strategies well in advance, and to achieve their goals of reduced downtime, enhanced safety and maintenance quality.

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