Lift Activities Monitoring by using Low-cost Motion Sensors

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***Abstract*— Monitoring the operations of lifts is important for planning for energy saving, operation safety and lift maintenance. This paper presents an approach for lift activities monitoring by signal processing and analysis based on low-cost motion sensors. Methods for automatic time-domain lift trip segmentation together with estimation of presence of lift passengers are proposed. Lift trip activities, such as number of lift trips and lift trips with passengers can then be derived. The proposed methods can be implemented for both offline and online system. Experimental results show the performance of the method and viability of deployment to real applications.**

***Keywords*— condition monitoring, motion sensors, motion analysis**

I. Introduction

A large and rapidly increasing number of lifts operate in the modern world, being in residential or commercial buildings. Monitoring the operational condition of lifts is a pertinent issue for service uptime, ride quality, energy saving, safety, and cost-effective maintenance. To fulfill the objectives, real-time monitoring and evaluation are critical. Thanks to the advance of IoT technology, collection of performance data in particular motion sensing data for remote lift monitoring has become feasible.

In recent years, there have been works conducted by researchers for lift monitoring using motion sensing data. Based on the types of motion sensing mechanism, the work can be put into two categories: smart phone motion sensing and lift mounted motion sensing.

In smart phone sensing approaches, [2] proposed algorithms to recognize elevators by detecting elevator acceleration and calculating the moving distance based on the motion sensors in the smartphone. With the data collected using crowdsourcing, the elevator motion features, such as maximum velocity and maximum acceleration can be used to recognize different types of elevators. In this method, the user needs to manually start and end the phone app before and after each elevator trip. [3] proposed an algorithm to automatically recognize lift ride based on the acceleration data from the smartphones and calculate the travel distances of the trips. The experiments have shown that the error of travel distance estimation can be up to 3 meters for the long rides.

In the lift mounted motion sensing approach, [1] and [4] proposed techniques to combine an inertial measurement unit and a barometric pressure sensor to measure the position and velocity of the elevator. These basic parameters are then used for implementation of predictive maintenance. In the sensor fusion approach, the drifting issue of standalone accelerometers is addressed by the extra barometer sensor.

In this paper, we present an approach for lift activity monitoring based on low-cost lift mounted motion sensors, specifically the MEMS digital accelerometer MMA8451Q with cost below 5 USD. The low-cost sensor has sampling rate of 50Hz and 14-bit precision. Due to the low spec of the sensor, sensor drifting is quite significant, and accurate distance and velocity estimation is not feasible. We propose an algorithm for autonomous segmentation of lift trip based on the noisy acceleration data which is not affected by sensor drifting, and the algorithm for the estimation of the presence of passengers in lift trips. The results are then used to derive statistics of the lift operation. The proposed lift trip segmentation technique can also be implemented for online system to trigger measurement tasks of lift condition monitoring, e.g. the measurement of lift leveling between lift car and the landing floor.

II. The Proposed Method

There are two main tasks in the proposed lift activity monitoring method. The first task is to segment the lift trip in the time domain, i.e. the start and end time of each lift trip. The second task is to detect the presence of passengers in a lift trip. Fig. 1 illustrates the flow the processing for the two main tasks.

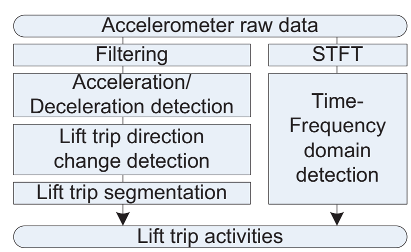


Figure 1: Processing flow

A. *Time-domain processing for lift trip segmentation*

A series of processing and analysis steps was conducted on the raw accelerometer readings for the segmentation of lift trips. The first step is to low-pass filter the raw signal such that detection of acceleration generated by lift operation is more reliable. We used an IIR low pass filter so that the filtering can be implemented very efficiently, as only 3 filter coefficients are needed. Fig. 2 shows an example of raw accelerometer readings after compensation of the gravity in blue and the data after filtering in red. From the plots, we can observe that the acceleration or deceleration caused by lift operation has the magnitude of about 0.1g and duration of about 2 seconds.

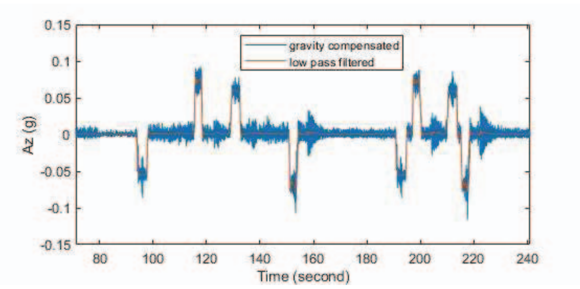


Figure 2: Accelerometer raw data and filtered data

The second step is to detect the event of accelerations and decelerations time periods in the filtered signal, for which a simple thresholding method is used. An acceleration and deceleration time period is detected if the magnitude is above a threshold value (e.g. 0.4g) and with a duration above a threshold value (e.g. 0.5s). Fig. 3 illustrates the detection in red plot.

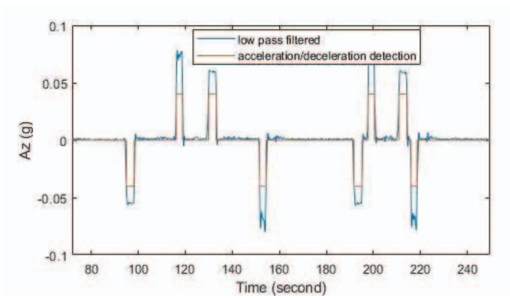


Figure 3: lift acceleration and deceleration detection

Although the acceleration/deceleration events can be detected from the accelerometer data, the lift motion information (i.e. stop/moving, or moving directions) is not directly available. This is due to the nature of the lift operation, where the acceleration is presented for both the starting motion of an upward lift trip and the stopping motion of a downward lift trip. And similarly, the deceleration is presented for both the stopping motion of an upward lift trip and the starting motion of a downward lift trip. As a result, the time period with zero accelerometer reading between any two consecutive events of acceleration/deceleration could correspond to lift in either a stationary status or a moving status with constant speed. Distinguishing the ambiguous cases from the raw acceleration reading is not straightforward.

In the third step, we propose a method to determine the lift motion status by detecting the change of lift trip direction, which can then in turn help distinguish the different lift motion status. The intuition is that when the lift operation changes trip direction, e.g. from an upward trip to a downward trip, two consecutive events of deceleration will be presented with the first deceleration being the stopping of upward trip and the second declaration being the starting of downward trip. The time duration between the two consecutive events of deceleration can be determined to be the lift stationary status, and the following time periods of zero accelerometer reading can be determined as steady moving status and stationary status alternatively. The same principle applies for lift trip direction change from a downward trip to an upward trip.

For example, in Fig. 3, the time period between 120s to 135s shows 2 consecutive acceleration events, which means the time period between these 2 events corresponds to lift stationary status.

If the processing is conducted for offline (recorded) data, the lift motion status before the detected trip direction change can also be determined retrospectively.

With the detection of lift trip direction change, lift trips with moving direction can be segmented in the fourth step. As shown in Fig. 4, the lift trips with moving direction are determined and shown in blue plots, where the upward lift trips are illustrated with positive values and downward lift trips are illustrated with negative values.

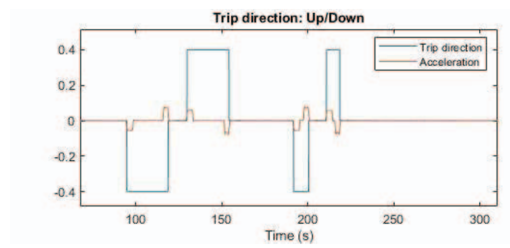


Figure 4: trip segmentation and direction determination

B. Time-frequency domain processing for passenger presence detection

We observed significant vibration signals in the accelerometer raw data that are caused by passengers moving in or out of the lift particularly when right after the lift becomes stationary at the end of a lift trip. For example, in Fig. 2, such vibrational signals are presented at the time point of 125s, 160s, 210s and 225s.

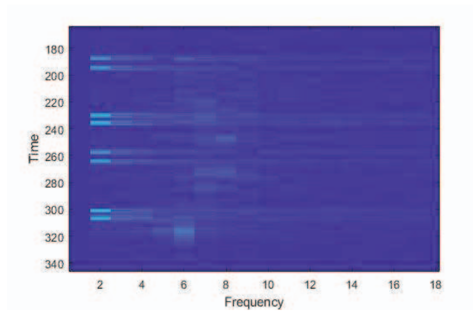


Figure 5: Spectrogram of acceleration data

We could also observe that in frequency domain the vibrational signal is bounded in a certain frequency range, which is perhaps related to the length of the lift rope. By converting the raw accelerometer data into time-frequency domain (i.e. spectrogram) as shown in Fig. 5 and 6, it could be seen that the vibrational signal concentrated at the frequency about 5-8Hz.

The passenger presence detection is based on the detection of signal of magnitude above a threshold value in the time-frequency domain, where the time is at a time interval after the lift becomes stationary and the frequency is within specified range.

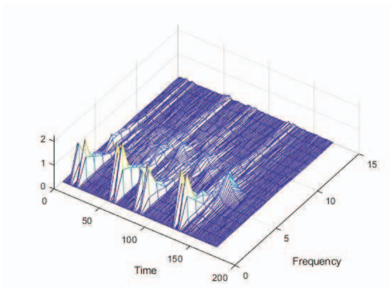


Figure 6: 3D mesh of spectrogram

If the signal is detected, then it is assumed that the lift trip just completed has passengers. It should be mentioned that this heuristic assumption may only provide a rough estimation of the passenger presence. A more rigorous analysis could be adopted by also considering the timing of starting of the following lift trip. However, it should be noticed that the estimation is indirect in nature, as the vibration signal could be cause by passengers moving in or moving out or both.

III. Experiments and Discussion

Experiments of the proposed methods were conducted on accelerometer data of residential lifts, which were operating for buildings of 12 levels and 25 levels. The data were collected continuously for about 1 month (26 days). The data for each lift were split into separated files, with each file for 1 day (24 hours).

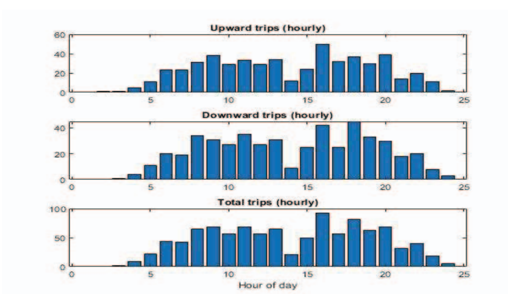


Figure 7: Hourly lift trip statistics for a 25-level-building

The algorithm can segment all the lift trips (i.e. the start/end timing of a trip, trip direction) accurately. The passenger presence detection, however, can only be a rough estimation and it is difficult to verify since there is no ground truth labels.

Fig. 7 shows the hourly lift trip statistics for a lift serving 25-level-building. The x-axis is the hour of the day, and the y-axis is the number of trips. This figure shows upward trips, downward trips and total trips for each hour of a day.

Fig. 8 shows the hourly lift trip statistics for a lift serving a 12-level-building.

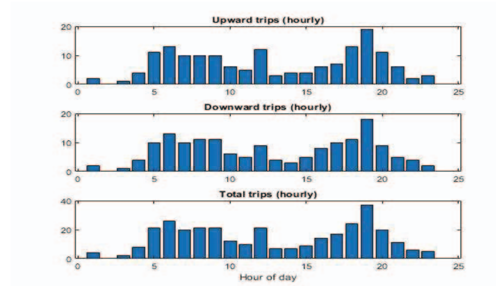
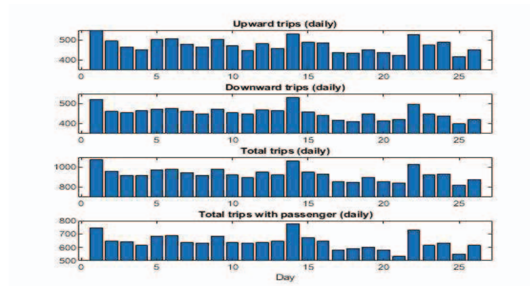


Figure 8: Hourly lift trip statistics for a 12-level-building

Fig. 9 shows the daily lift trip statistics of the 25-level-building, where the x-axis is the day of the month (1^{st} – 26^{th}). The plots show the upward trips, downward trips, total trips and



total trips with passengers.

Fig. 10 show the daily lift trip statistics of the 12-level-building.

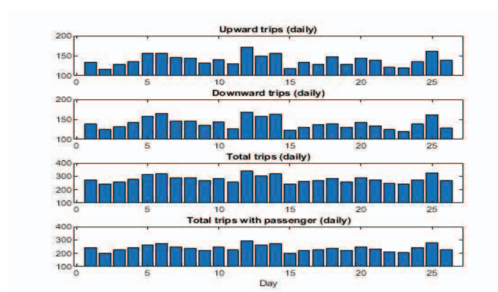


Figure 10: Daily trip statistics for a 25-level-building

Besides the offline processing of lift-mounted accelerometer data, we have also implemented an online application of the lift trip segmentation algorithm. The algorithm is used to automatically detect the timing of lift becoming from a moving state to a stationary state in real-time. The detection is used to trigger a lift leveling measurement device. The triggering is meaningful since the leveling measurement only make sense when the lift is at a stationary state and the measurement only need to be done for a short period of time. Without this trigger mechanism, there would a lot of useless measurement when the lift is moving, and a lot of redundant measurement when the lift keeps in stationary state for a long period of time. This implementation is being used for a site trial of lift monitoring system.

IV. Conclusion

We presented an approach for lift activity monitoring using low-cost motion sensors. We proposed techniques of lift trip segmentation in time domain and lift passenger presence detection in the time-frequency domain. The experiments showed that the proposed methods can be used to produce lift operation statistics, which is useful in applications of lift operation planning. In addition, the online implementation of the lift trip segmentation can be used for real-time lift condition monitoring.

Acknowledgment

This research is supported by the Singapore Ministry of National Development and the National Research Foundation, Prime Minister's Office under the Land and Liveability National Innovation Challenge (L2 NIC) Research Programme (L2 NIC Award No. L2NICTDF1-2017-3).

Any opinions, findings, and conclusions or recommendations expressed in this material are those of the author(s) and do not reflect the views of the Singapore Ministry of National Development and National Research Foundation, Prime Minister's Office, Singapore.

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