Non-invasive Method for Elevator's Movement Monitoring Based on MEMS Sensor and Kalman Filter

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***Abstract*—Elevator has been indispensable in modern cities, yet a great number of elevator-related accidents have caused considerable harm to people's welfare. In response to the situation, this paper proposes a non-invasive method for elevator's movement monitoring using MEMS sensor and Kalman filter. Specifically, the method could automatically determine elevator's status and use Kalman filter to yield accurate estimation of elevator's displacement, especially short range displacement, without intervening elevator's operation. The method could potentially be used in a considerable range of scenarios, such as automatic mechanical anomaly detection and monitoring of daily or weekly usage pattern for power conservation and information services.**

***Keywords*—elevator surveillance, MEMS sensor, movement monitoring, Kalman filter**

I. Introduction

ELEVATOR has been an integrate part of modern society and its number has been climbing worldwide. It was estimated that by the end of 2016 there were 4.5 million elevators in China alone [1]. However, along with the increasing scale of the industry occur a large number of accidents, which reveals the lack of effective means for elevator's security monitoring by independent third-party.

Researches have been done on analysis of elevator's movement. For instance, researchers have used the voltage on the dc bus to determine elevator's state [2], and accelerometer and barometer equipped in smart phones have been used for classifying elevator's movements [3] [4] [5]. However, both approaches are flawed.

Using data from the elevator's electrical system is invasive, which means it would unavoidably disrupt the integrity of the electrical system, posing threats to safety. Also, this approach is dependent on the operation of the electrical system, thus it would not be functional if the system is malfunctioning. As for the method that exploits sensors in smart phones, it is naturally not accurate, for the attitude, position and type of different phones would affect the result. Besides, the precision of sensors in phones are averagely inferior to those with specific purposes.

Inertial navigation relying on accelerometer has grown fast and proved to be of usefulness [6]. For instance, researches have been done relating to using MEMS sensors for indoor navigation [7] [8], for indoor maps are usually unaccessible because of privacy or inaccurate because of changes over time [9]. Through the process, precision and compatibility of MEMS sensor has greatly improved, and thus in this paper we propose a method for elevator's movement monitoring based on MEMS sensor.

The proposed method uses MEMS sensor containing high-precision accelerometer and other sensors to collect data. Application diagram of proposed method is shown in Figure 1. This paper is organized as follows. Section II formulates the determination of elevator's status, Section III discusses in detail the calculation of elevator's displacement using Kalman filter. In Section IV two application examples using the proposed method are provided, and finally in Section V we conclude this paper and offer directions for future work.

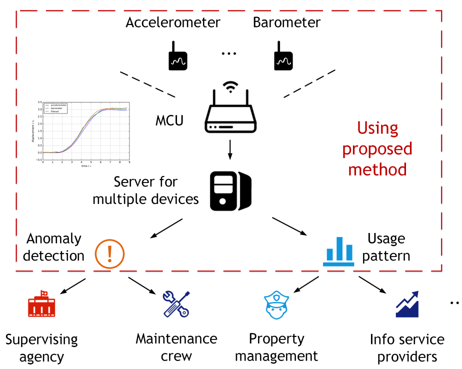


Fig. 1. Application diagram of the non-invasive method for elevator's movement monitoring based on MEMS sensor and Kalman filter

II. Determination of Elevator's Status

This section formulates the determination of elevator's status. The general idea of the method is to firstly find critical points, the points at which state transits, and secondly determine the state of a given point based on its relationship with critical points.

In summary, the approach is made up of two steps as follows:

1) Determine critical points at which states transit.
2) Determine states based on these critical points.

The determination of critical points and state is detailed below. Mathematical notations that are used in this section are summarized in Table I

TABLE I
NOTATIONS USED IN DETERMINATION OF ELEVATOR'S STATUS

Notation	Explanation
n	Time point
$\phi(n)$	Testing data at time n
$\phi_{test}(n)$	Template for testing at time n
D	Length of $\phi(n)$ and $\phi_{test}(n)$
$\alpha(n)$	Cosine of angle between $\mathbf{\Phi}$ and $\mathbf{\Phi}_{test}$
i	Time point at which state is to be determined
p	The critical point closest to i among all that are smaller than i
q	The critical point second closest to i among all that are smaller than i

A. Determination of critical points

Critical points mentioned above are listed below in the sequence of their appearances in a complete process of elevator's movement :

- Start of movement, i.e. the start of acceleration (deceleration) from stillness
- Start of steady movement, i.e. movement of constant velocity
- Start of deceleration (acceleration) in order to return to stillness
- The point at which elevator returns to stillness

In this passage, accelerations are differed into acceleration (that goes up) and deceleration (that goes down). The determination of these critical points is described below in detail.

1) Determination of start of acceleration and deceleration: The idea of finding the start of movement is using template matching. The reason why not simply use the point at which acceleration deviates from zero is the consideration for robustness, since some abnormal activities, like a child's jumping, could have output false results. As the start would be a period of acceleration or deceleration, the template could be selected as a parabola.

To quantify the resemblance between the testing data and template, they are viewed as two vectors, and their angle could be the indicator of their resemblance.

To formalize the theory, let $\alpha(n)$ denotes the cosine of their angle at time n, D denotes the length of these two vectors, $\phi(n)$ denotes the testing data that is a D-point long segment of acceleration data and $\phi_{test}(n)$ denotes the template at time n.

When checking for the beginning of acceleration, $\phi_{test}(n)$ should have the following form:

$$\phi_{test}(n) = -n(n-D) \tag{1}$$

Similarly, when checking for deceleration, $\phi_{test}(n)$ should have the following form:

$$\phi_{test}(n) = n(n-D) \tag{2}$$

Then α is calculated in (3). As the angle is limited within 0 to π, α is negatively correlated with the angle and thus positively correlated with the resemblance between ϕ and ϕ_{test}.

$$\alpha(n) = \frac{\mathbf{\Phi} \cdot \mathbf{\Phi}_{test}}{|\mathbf{\Phi}| \cdot |\mathbf{\Phi}_{test}|} \tag{3}$$

The n at which $\alpha(n)$ reaches maximum value (or local maximum in case of multiple accelerations) should be the start of acceleration (deceleration). In practice, the calculation of $\alpha(n)$ through the whole period of interest is computation consuming, and thus setting proper threshold for $\phi(n)$ to trigger calculation of $\alpha(n)$ could reduce the demand for computational resources while maintaining agreeable precision.

Besides, as deceleration (acceleration) towards stillness has identical features to acceleration data, the determination of this type of critical point is the same.

2) Determination of other critical points:

1) Start of steady movement
   The start of steady movement follows the start of movement. To find the start of steady movement, the following two criteria should be met:
   - The start of steady movement should be at least D later than the start of movement.
   - At the start of steady movement n_s, $\phi(n_s)$ should be steady, i.e. $|\phi(n_s)|$ should be below a certain threshold.

   The first point after the start of acceleration (deceleration) that meets these two criteria is decided to be the start of steady movement.
2) Return to stillness
   The point at which elevator returns to stillness is similar to the start of steady movement in that they are both points at which the state transits from acceleration (deceleration) to others. Consequently, this point should also meet the two criteria described above. The distinction is that at this point the elevator stops acceleration (deceleration) and start to remain still, rather than move with constant velocity. To separate this point and the start of steady movement, the state before acceleration (deceleration) should be taken into consideration. Specifically, the start of steady movement is determined if the previous state is stillness, and the return to stillness is determined if otherwise.

B. Determination of states based on critical points

The movement of elevator could be divided into seven states as shown below:

- Accelerating
- Decelerating
- Steadily moving up
- Steadily moving down
- Accelerating towards stillness
- Decelerating towards stillness
- Stillness

As critical points are defined as the points that states transit, state of any given point is naturally determined if all critical points are determined. However, when faced with a huge volume of data, an efficient and precise algorithm to determine state is essential. An algorithm that involves loops as few as possible and minimizes computation consumption is proposed.

The fact exploited is that the state of a given point i is always relevant to the critical point which is the closest one to i among all that are smaller than i. In mathematical terms, i is always relevant to the critical point p that ensures

1) $i > p$
2) $i - p$ is smallest among all ps that meet the first requirement

In some cases, the state of i is also relevant to q that ensures

1) $i > q$
2) $i - q$ is the second smallest among all qs that meet the first requirement

To summarize, the state of i depends on the type of p and q. As a result, if p and q are determined, which involves simple numerical calculation and is hence computational efficient, the state of any given point could be determined. The detailed algorithm is shown in Table II.

TABLE II
ALGORITHM FOR DETERMINATION OF ELEVATOR'S STATE

Type of p	Type of q	State
Start of acceleration	–	Accelerating
Start of deceleration	–	Decelerating
Steady movement	Accelerating	Steadily moving up
Steady movement	Decelerating	Steadily moving down
Acceleration towards stillness	–	Accelerating towards stillness
Deceleration towards stillness	–	Decelerating towards stillness
Return to stillness	–	Stillness

III. CALCULATION OF ELEVATOR'S DISPLACEMENT

A. General introduction

This part focuses on the algorithm that estimates the displacement, or relative height, of elevator accurately.

There are two sensors whose data could be used to calculate displacement, which are accelerometer and barometer. As both sensors are not perfectly accurate, an algorithm that yields estimation based on acceleration and height is needed, which is extremely important when dealing with short range displacements. There was precedence to use Kalman filter to estimate elevator's location using infrared interrupter and MEMS accelerometer [10], and similarly barometer and accelerometer could serve as Kalman filter's two inputs. Kalman filter is a classic estimation algorithm introduced by Kalman [11]. The implementation and tuning of Kalman filter is detailed below. Notations used in this section are summarized in Table III.

B. Implementation and tuning of Kalman filter

The state estimation vector is given in (4). In the state estimation vector, $h_{est}(n)$ denotes the estimation of elevator's height and $v_{est}(n)$ represents the estimation of elevator's velocity.

$$X(n) = \begin{bmatrix} h_{est}(n) \\ v_{est}(n) \end{bmatrix} \tag{4}$$

Let

$$A = \begin{bmatrix} 1 & dt \\ 0 & 1 \end{bmatrix} \tag{5}$$

TABLE III
NOTATIONS USED IN CALCULATION OF ELEVATOR'S DISPLACEMENT

Notation	Explanation
n	Time point
$h_{est}(n)$	Estimated relative height at time n
$v_{test}(n)$	Estimated velocity at time n
$X(n)$	State estimation vector at time n
dt	Time interval between n and $n-1$
$X'(n)$	Projected state estimation vector at time n
$Z(n)$	Estimated relative height at time n, as matrix
ϵ_z	Measurement noise matrix
ϵ_x	Calculation noise matrix
$P(n)$	Estimation error covariance at time n
$P'(n)$	Projected estimation error covariance at time n
$K(n)$	Kalman gain at time n
n_s	Standard deviation of acceleration estimation
n_m	Standard deviation of measurement

and

$$B = \begin{bmatrix} \frac{dt^2}{2} \\ dt \end{bmatrix} \tag{6}$$

Then, the projected state estimation vector, denoted as $X'(n)$, has the relationship with $X(n-1)$ and previous acceleration $a(n-1)$ that is shown in (7).

$$X'(n) = A \cdot X(n-1) + B \cdot a(n-1) \tag{7}$$

Similarly, measurement of height, denoted as $Z(n)$ in (8), has the relationship with $X(n)$ that is shown in (9).

$$Z(n) = [h_{est}(n)] \tag{8}$$

$$Z(n) = C \cdot X'(n) + \epsilon_z \tag{9}$$

where

$$C = \begin{bmatrix} 1 \\ 0 \end{bmatrix} \tag{10}$$

The projected estimation error covariance could be written as

$$P'(n) = A \cdot P(n-1) \cdot A^T + \epsilon_x \tag{11}$$

and in each iteration the Kalman gain, $K(n)$, is updated using (12).

$$K(n) = P'(n) \cdot C^T \cdot (C \cdot P'(n) \cdot C^T + \epsilon_z)^{-1} \tag{12}$$

Then $X(n)$ could be obtained by modifying $X'(n)$ using (13).

$$X(n) = X'(n) + K(n) \cdot (Z(n) - C \cdot X'(n)) \tag{13}$$

After calculation of $X(n)$, $P(n)$ needs to be updated for next iteration.

$$P(n) = (I - K(n) \cdot C) \cdot P'(n) \tag{14}$$

Initial value of estimation error covariance, $P(0)$, equals ϵ_x. Tunning factors, ϵ_x and ϵ_z, are related to standard deviation

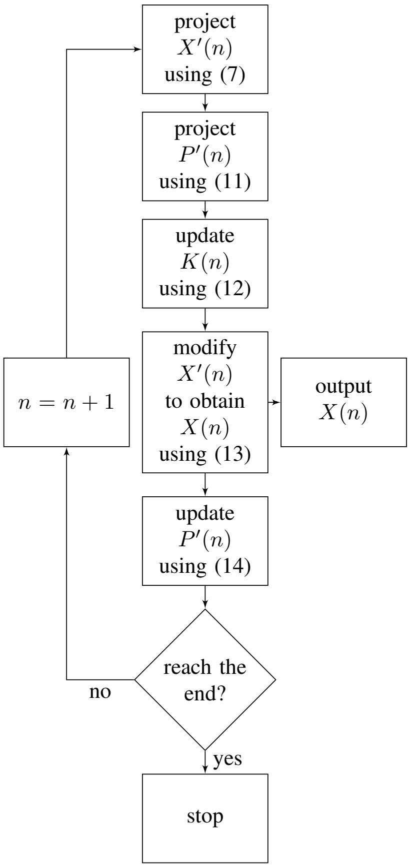


Fig. 2. Flow chart of Kalman filter algorithm

of acceleration estimation n_s and standard deviation of measurement n_m as shown in 15 and 16. n_s and n_m, are related to the specific MEMS sensor used.

$$\epsilon_x = {n_s}^2 \begin{bmatrix} \frac{dt^4}{4} & \frac{dt^3}{2} \\ \frac{dt^3}{2} & dt^2 \end{bmatrix} \tag{15}$$

$$\epsilon_z = {n_m}^2 \tag{16}$$

The flow chart of the complete Kalman filter algorithm is depicted in Figure 2.

IV. Applications

This section introduces two examples of applications using the method proposed above. The first example is using the Kalman filter to accurately estimate elevator's short range displacement, and the second one is the analysis of elevator usage pattern based on the analysis of its state . The acquisition of data in both examples is also described. Notations used in this section are summarized in Table IV.

A. Experiments

In the experiments, the MEMS sensor is connected via Blue-tooth to the MCU(booted Android OS), and both the sensor and MCU are powered by power banks. Sensor, MCU and power banks are fastened and remain relatively still with respect to the container. The device is shown in Figure 3. The device was installed on the roof of an elevator car with the assistance of maintenance staff.

TABLE IV
Notations used in introducing applications of proposed method

Notation	Explanation
N_{total}	Total times of usage
$\min(A, B)$	A function that yields the minimum among A and B
N_A	Times of 'Acceleration' state
N_{DTS}	Times of 'Deceleration towards stillness' state
N_D	Times of 'Deceleration' state
N_{ATS}	Times of 'Acceleration towards stillness' state

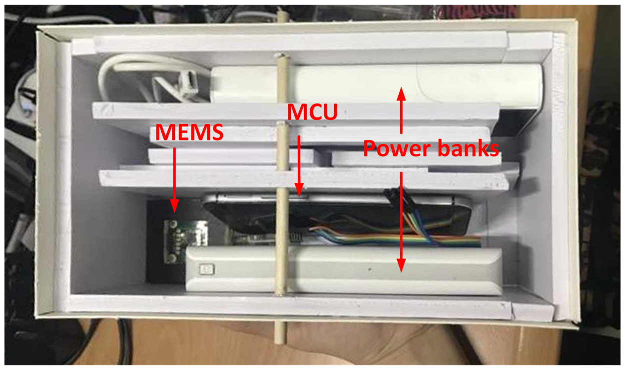


Fig. 3. Device used for obtaining data in experiments

B. Estimation of elevator's short range displacement

The Kalman filter algorithm developed in Subsection III-B is tested with data from the device. For this device, tuning factors n_s and n_m are 0.98 and 1, respectively. The device was installed on a elevator that went through a short range movement, going up one floor, which is three meter high. Both acceleration data from accelerometer and height data from barometer were used for Kalman filtering. Displacement calculated using these data and the result of filtering are shown in Figure 4.

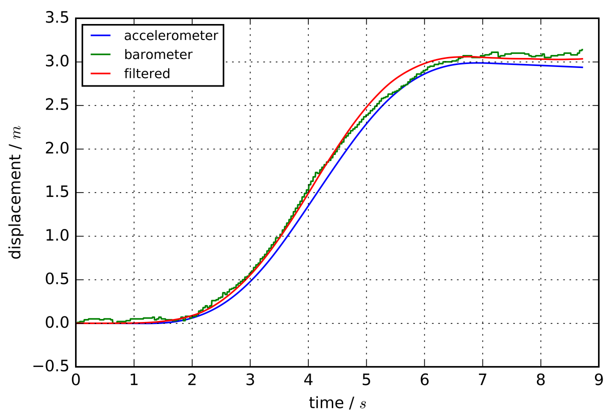


Fig. 4. Comparison of short range displacement calculation using Kalman filter with original data from accelerometer and barometer. Actual total displacement is 3.0 meters.

Clearly, Kalman filter yielded a result better than both barometer and accelerometer did. Measured data from barometer is not smooth and has obvious error in estimating the total displacement. The calculated result using accelerometer is not satisfactory either, for even though it is smooth enough, it still has error in estimating the total displacement.

In contrast, Kalman filter takes advantage of both sensors, making its result smooth and closer to the actual value than the other two results.

Furthermore, such experiment has been repeated 20 times, with the elevator going up and down 10 times respectively. Total displacements calculated in all experiments are shown in Figure 5. Means and variances of results are displayed in Table V.

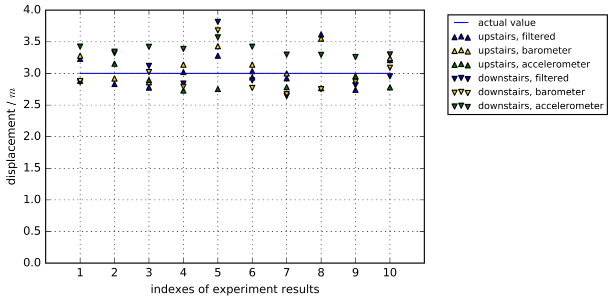


Fig. 5. Total displacements calculated in elevator short range displacement estimation experiments

TABLE V
MEANS AND VARIANCES OF EXPERIMENTS' RESULT IN FIGURE 5

Experiment type	Mean (m)	Variance (m^2)
Upstairs, filter	3.067	0.067
Upstairs, accelerometer	2.864	0.015
Upstairs, barometer	3.144	0.050
Downstairs, filter	3.001	0.107
Downstairs, accelerometer	3.372	0.008
Downstairs, barometer	2.984	0.087

The statistics shows that Kalman filter outputs better estimation than both accelerometer and barometer, proving that the usage of Kalman filter for estimating elevator's short range displacement is effective.

C. Analysis of elevator usage pattern

Apart from estimating individual displacement, proposed method could also be used in revealing elevator's statistical usage pattern.

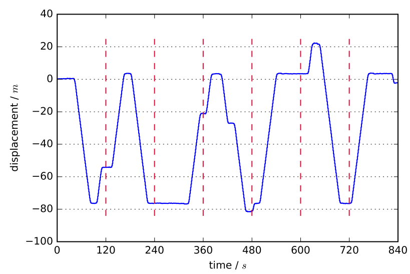
Specifically, elevator has only two types of movement: move up and move down. Every moving up process begins with the state shift from Stillness to Accelerating and ends with the state shift from Decelerating towards stillness to Stillness. Similarly, every moving down process begins with the state shift from Stillness to Decelerating and ends with the state shift from Accelerating towards stillness to Stillness. Therefore, the total times of movement N_{total} should be obtained as in (17).

$$N_{total} = \min(N_A, N_{DTS}) + \min(N_D, N_{ATS}) \tag{17}$$

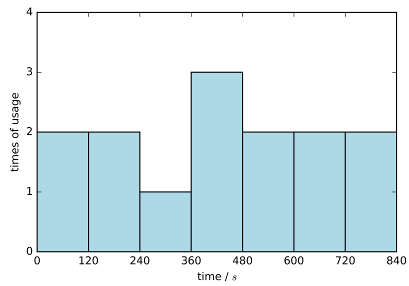
where N_A is the times of Acceleration, N_{DTS} is the times of Deceleration towards stillness, N_D is the times of Deceleration and N_{ATS} is the times of Acceleration towards stillness.

The reason why take the minimum in each pair is the same as why not directly use the number of Steadily moving up plus the number of Steadily moving down, which is the consideration that data may not end in Stillness state. In that case, the last movement process is not complete and should not be counted. This is particularly important especially when dealing with huge amount of data, e.g. data of over 24 hours, for it would be not practical to read in the whole data and analyze. Therefore, the original data needs to be segmented, read in and analyzed one piece at a time and finally put it together. In that case, dealing with edges between segments becomes essential.

Figure 6 shows the result of the implementation of the method. Figure 6(a) shows elevator's displacement in 840 seconds, and Figure 6(b) shows the times of usage in seven time sections which are equally divided from the whole 840 seconds. Data in Figure 6(a) is obtained directly from the barometer that outputs relative height of the elevator. It could be seen that the result in Figure 6(b) corresponds well to data in Figure 6(a).



(a) Displacement of elevator, obtained from barometer in MEMS sensor. A total of 840 seconds are equally divided into 7 sections, and times of usage in all section are calculated



(b) Times of usage in seven time sections, each covering 120 seconds, calculated using the proposed method

Fig. 6. Implementation of elevator's usage pattern calculation

The method proposed above is also tested with acceleration data acquired from a MEMS sensor that has been installed on an elevator in a newly-built residential building which has 34 floors for over 24 hours. Data is generated by residents' normal usage on a normal work day.

The result of the test is presented in Figure 7. The horizontal axis displays the range of time from 15 p.m. (previous day) to 15 p.m., and the vertical axis displays how many times the elevator has been used in the corresponding hour.

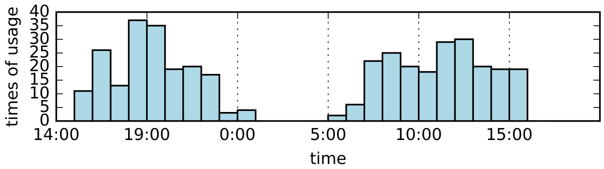


Fig. 7. Usage pattern of an elevator in a residential building covering over 24 hours

The result shows that the usage in a day has interesting features.

One feature is that the intensity of usage reaches its peak during 18 p.m. to 19 p.m. at over 35 times of usage in an hour. This peak corresponds to the fact that people normally get off from work at about 17 p.m. and get home at about 18 p.m..

Another feature is that the drop from 18 p.m. to 23 p.m. has a flat stage at 20 p.m. to 21 p.m.. This is relevant to urban residents' habit to stroll after dinner.

Besides, there is a rapid growth in usage at around 7 a.m., indicating the start of morning rush hour, which reaches its peak at around 8 a.m.. This is related to the fact that people generally get to work before 9 a.m..

Analysis above testify that the usage pattern extracted from acceleration data using the method proposed corresponds closely to the actual situation, which shows that the method is effective and accurate, and that it has great potential for extraction of useful information. Furthermore, it is also possible to determine the pattern of the floor at which elevator stops accurately with the assistance of Kalman filter, i.e. calculate elevator's height and map it to corresponding floor.

V. Conclusion

The work in this paper puts forward a method for elevator's movement monitoring using MEMS sensor. Specifically, the method could determine elevator's status and estimate accurately elevator's displacement. Firstly theoretical development of the method is presented, and then two application examples using it are illustrated. Several conclusions could be drawn:

1) Using Kalman filter based on accelerometer and barometer could improve the precision in estimating elevator's displacement without interfering with its operation, as demonstrated in IV-B.
2) Proposed method is also useful in extracting other meaningful statistical information, such as elevator's daily usage pattern, as demonstrated in IV-C.

In summary, the method proposed is non-invasive, independent of elevator system and compatible with any type of elevator. It has been tested with actual scenarios and has proved to live up to expectations, being able to analyze elevator's movement in various aspects without interfering with elevator's normal operation. Besides, it displays the potential for extraction of other information for more practical uses.

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