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CONDITION AND FAULT MONITORING BY USING SENSOR NODES IN THE INTERNET OF ELEVATORS

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Abstract: The signal processing scheme of a smart sensor node for the Internet-of-Elevators is presented. The sensor node is a self-contained black box unit only requiring power to be supplied, which enables a cost efficient way to modernize existing elevator systems in terms of condition monitoring capabilities. The sensor node monitors the position of the elevator using an inertial navigation system in conjugation with a simultaneous localization and mapping framework. Features reflecting the elevator systems operation and health condition are calculated by evaluating the ride quality parameters defined by the ISO 18738-1 standards, the vibration versus frequency spectrum, and the vibration versus position spectrum. Abnormal stops are identified by detecting decelerations that deviate from the typical deceleration pattern of the elevator or when the stopping position of the elevator does not match the learned floor levels. Further, the condition of the door system is monitored by tracking the magnetic field variations that the motion of the doors creates; the number of door openings and the time required for the doors to close is estimated. The capability and performance of the signal processing scheme are illustrated through a series of experiments. The experiments show, inter alia, that using low-cost sensors similar to those in a smartphone, the position of the elevator car can with 99.9% probability be estimated with an error of less than 1 meter for travels up to 43 seconds long. Experiments also indicate that small degradations in the doors closing time can be detected from the magnetic field measurements.

I. INTRODUCTTION

Today more than 54% of the world population lives in urban areas – a figure that is continuously growing. The transport logistics problems arising from this urbanization call for intelligent transportation systems with increased efficiency, capacity, and reliability for not only horizontal but also vertical transportation. To illustrate, 325 million passengers per day are estimated to be transported by elevators in the United States and Canada alone. To adapt the vertical transportation systems to the demands of the future, the elevator industry has identified a need to move from today's preventative and corrective maintenance strategies to predictive and pre-emptive maintenance strategies, and thereby maximize the uptime, prolong the lifetime, reduce repair costs, and improve the safety of the elevator systems. Accordingly, the latest generation of high-end elevator systems is frequently connected to the cloud, creating an Internet-of-Elevators, i.e., a subdivision of the emerging Internet-of-Things, where data from the elevator sensors and control systems is gathered, mined, and transformed into information about the elevator systems' performance and any current or potential problems. However, the majority of today's elevator systems are not equipped with sensors and control systems that support connection to the cloud for remote monitoring and fault diagnostics, and it will take decades before they are all renewed or upgraded with such systems. As an illustrative figure, there exist more than 4.3 million elevators in Europe alone, and it is not uncommon for an elevator to be in service for 25 years or longer before a major modernization is undertaken. In the interim, there will be a need for easy-to-install sensor nodes by which existing elevator systems can be upgraded and connected to the Internet-of-Elevators for condition and fault monitoring. Therefore, we will in this paper present the signal processing scheme of a smart sensor node characterized by non-intrusive sensing via accelerometers and magnetometers; embedded data processing and storage; and wireless connectivity; enabling the construction of a truly 'plug-and-play' node that can provide high-level elevator condition information. The envisioned sensor node and monitoring concept is illustrated .elevator car between different floor levels, and thereby change the potential energy of people and goods. The horizontal position of the elevators car is maintained through a set of guide rails against which the elevator car slides; see Fig. 1 for an illustration. Frequently, the elevator car is equipped with a motorized or semi-motorized door system, which provides protection for the passenger while traveling. If the elevator system is well tuned, the acceleration and deceleration of the elevator car is smooth, the vertical and horizontal vibrations negligible, and the doors open and close smoothly at each stop. However, as system components such as engine bearings and roller guide shoes experience wear and tear, guide rails becomes displaced, dust and gravel accumulate in the door systems, etc., the vibration level increases and the system's performance decreases. In general, the initial effect is a reduced ride quality, and the long term effect a malfunctioning elevator1. Hence, by monitoring the usage and vibration levels of the elevator system, information about its condition and potential future faults can be extracted. Maintenance strategies can then be designed to maximize the system's uptime, and services scheduled at time slots known to cause a minimum of interference in the usage of the elevator system. There exist a large number of publications on various techniques for condition monitoring, fault detection, and non-destructive testing in industrial process, machinery, and motors. See recent surveys and reviews on the topic. However, only a handful of publications exist about condition monitoring and fault detection techniques for elevator systems and elevator components such as the traction machine, the guide rails, the steel ropes (belts) and the door systems. Existing elevator condition monitoring techniques and systems can be broadly classified into two categories, those based on model-based and those based on data-driven condition monitoring methods. The benefit of model-based methods is that no training data is needed, but the drawback is that they require elevator system specific parameters to be known. Due to the large variety of elevator systems on the market, large scale deployment of after-market model-based condition monitoring systems is therefore considered infeasible. The benefit of the data drivenmethod is that they do not require prior knowledge about the elevator system. However, their drawback is that large amounts of training data from a representative set of elevator systems and faults are needed before reliable condition information can be extracted. Acquiring this training data is time consuming and costly due to the large variety of elevator systems that exist and the infrequent occurrence of faults. An important aspect of the development of a large-scale condition monitoring system is therefore to have a strategy for how to finance the collection of the training data, and how to monetize the collected data at an early stage. A second aspect to be considered in the development of a large-scale condition monitoring system is the ease and cost by which the sensor nodes can be deployed. Most, if not all, of the elevator condition monitoring systems described in the literature, as well as the ones currently on the market, are based upon information from the elevator's control and drive system, often in combination with additional sensors such as accelerometers. Therefore, the installation of these systems commonly takes 1-2 days and requires specially trained technicians with knowledge about the specific elevator control and drive system at hand. The deployment cost of existing systems is thus considerable and impedes the largescale deployment of these systems. A third aspect to consider is the amount of data which needs to be communicated and the cost associated with the data transfer. The result of a survey conducted by the authors with potential customers of an elevator monitoring system, such as building owners and elevator service companies, suggest that they are not willing to pay for more than 10-50 MB of data per month and per elevator at current cellular data fees. One way to approach these practical aspects of deploying a large-scale elevator monitoring system is via sensor nodes that use non-intrusive sensing and locally extract high-level condition information, a.k.a. smart sensor nodes. Therefore, a signal processing scheme for a smart sensor node that from accelerometer and magnetometer data can extract information about the travel pattern and usage statistics of an elevator, detect abnormal (emergency) stops, detect abnormal door behaviour and changes in the closing time of the doors, measure the ride quality according to the ISO 18738-1 standards, and calculate high-level condition information such as frequency and position vibration spectrums, is presented. Using non-intrusive sensing, the node can be made self-contained (only requiring power to be supplied) and thereby easy and cost efficient to install, as well as interoperable with elevators of all types and makes, irrespective of their sensor and control system. Further, by locally extracting high level condition information the communication requirements can be kept at a minimum. Moreover, as the proposed signal processing scheme without training data can provide basic condition information that customers may purchase, revenues for financing the data collection needed for training of datadriven condition monitoring methods can be obtained at an early stage.

II. SIGNAL PROCESSING SCHEME DESIGN OVERVIEW

An overview of the main building blocks and the information flow of the presented signal processing scheme is shown in Fig. 2. The specific force measured by the accelerometers is used as an input for a zero-speed aided inertial navigation system that estimates the motion dynamics of the elevator car, i.e., the travelled distance since last stop and the speed; see Section III-A. The estimated distances are used to drive a simultaneous localization and mapping (SLAM) framework that tracks the position of the elevator car and learns the floor levels; see Section III-B. The estimated motion dynamics and the measured specific force are also used to calculate the ride quality performance parameters defined in the ISO 18738-1, the vibration power versus frequency spectrum, and the vibration power versus position spectrum; see Section IV. Further, the measured deceleration pattern and the elevator car position together with the floor levels estimated by the SLAM framework are used to detect abnormal (emergency) stops; see Section V. The sensor node monitors the door openings and closings using a magnetometer that senses the changes in the local magnetic field caused by the doors' motion; see Section VI. The signal processing scheme extracted condition information can either be directly sent to the cloud for further analysis, or at the sensor node be compressed into daily or weekly condition statistics, depending on available communication resources and needed time resolution of the condition information.

III. POSITIONING AND MOTION DYNAMICS ESTIMATION

The position and motion dynamics of the elevator car are estimated using a two-stage filtering framework. In the first stage the travelled distances and motion dynamics of individual trips are estimated from the accelerometer measurements, and in the second stage the position of the elevator car, as well as the floor levels, are estimated using a SLAM algorithm measurement update equations can be formulated for the state-space model (2). However, the fact that the elevator car becomes stationary or moves at constant speed on a regular basis, and that these events can be detected from the accelerometer measurements can be used to overcome this problem. Assuming that the time instants when the elevator car is stationary or moves at constant speed are given, then the following pseudo measurements for the state space model can be formulated.

Here v(c) d (k) and v(z) d (k) denote the pseudo measurement errors for the cases when the elevator is moving at constant speed and is stationary, respectively.

These pseudo measurement errors are assumed to be white processes with variance σ2 c and σ2 z, respectively. Note that the constant speed observation model, i.e., (4), implies that the current speed is approximately equal to the one at the previous time instance. The auxiliary state s(k−1) was introduced in the state vector (1) to facilitate this type of pseudo observation. A large variety of algorithms has been proposed in the literature on how to detect uniform linear motion (stationarity being a special case) from accelerometer measurements. See e.g. [28] and the references therein. Since the elevator car is known to move only in the vertical direction and within a limited range, the mean of the vertical accelerometer measurements can be estimated by time averaging the measurements. The mean of the accelerometer measurements when the elevator car is in uniform linear motion can thus be considered known, and the detection of when the elevator car accelerates or decelerates can be formulated as a problem of detecting local changes (of unknown amplitude) in the mean of the accelerometer measurements. The generalized likelihood ratio test for this detection problem is derived in and is used as a uniform linear motion detector in the proposed signal processing scheme. Given the state-space model defined by (1)–(4), the Kalman filter based algorithm presented in Alg. 1, for estimation of the travelled distance δp(l) and the motion dynamics, can be constructed. The algorithm takes the measured vertical axis acceleration ˜ uz(k) as an input, and propagates the state vector.Since the uniform linear motion detector can only determine whether the elevator car is in uniform linear motion or not, the choice between the constant and zero speed observation model is made based on the magnitude of the normalized prediction error ξd obtained when fitting the zero speed hypothesis to the observed data. If the magnitude of the normalized prediction error is below the threshold γd, a zero speed measurement update is done, otherwise a constant speed update is applied (see line 14-27). Whenever the algorithm detects that the elevator car has become stationary and has traveled a distance longer than γδp, it outputs the traveled distance estimate δˆ p(l) and the estimated variance ˆ σ2 δp(l) of the distance estimation error. Thereafter, the distance state d(k), and the corresponding elements of the covariance matrix are set to zero by multiplication with natural basis vector e1; see line 31-40. The effect of such a reset on the propagation of the covariance estimate Pd(k) is analyzed in [30]. (8) One way to obtain a good initial state estimate is to have technician that install the monitoring system conduct a training trip, where the elevator car sequentially travels from the lowest to the highest floor. Other predefined travel patterns may also be used as long as they includes a stop at least every floor. A Kalgan filter based SLAM algorithm for the positioning of the elevator car and the estimation of the floor-level heights, that uses the suggested data association method, is presented in Alg. 2. The algorithm also includes an outlier detection step, which rejects the measurement update in the case that the normalized prediction error ξs exceeds the threshold γs. In case of rejection, a flag is set to indicate that the stop may have been an abnormal (emergency) stop; see Section V for details.

C. Example: Position and motion dynamics estimation

To illustrate the positioning and motion dynamics estimation capability, the algorithms Alg. 1 and Alg. 2 were used to process data recorded in an elevator within a seven-floor building. The data was recorded using an inertial sensor array consisting of 32 Invensense MPU-9150 sensor modules (see [34] for details of the array), which was attached to one of the sides of the elevator car. The position estimates calculatedfrom the 32 sensor modules (accelerometer triads) can be seen in Fig. 3, together with the mean of the position estimates and the three standard deviations (3σ) confidence interval calculated from the filter's covariance estimate. From Fig. 3 it can be seen that all the estimated positions are within the confidence interval, which indicates that the filter is reasonably tuned and provides consistent estimates. Further, it can be seen that after the initial training sequence, the SLAM framework efficiently limits the position error growth; the floor levels to which the elevator travels can readily be determined from the filtered data. Moreover, when the SLAM framework detects that the elevator car has stopped in between two floor levels, it signals that an abnormal stop has occurred; see Section V for further details. In Fig. 4 the speed estimates for a single journey, together with the mean of the speed estimates and the 3σ confidence interval, are shown. Also shown are the time instances when the detector has decided that the elevator car is moving at constant speed or is stationary. From the figure it can be seen that once the elevator have reached a steady-state speed, after some time the uniform linear motion detector detects this and constant speed pseudo measurements are applied. The result is that the speed uncertainty ceases to grow and the position error growth becomes linear in time instead of quadratic. At the end of the trip, when the elevator car has become stationary, it can be seen how the zero speed pseudo measurements correct the speed estimates. The importance of the constant speed updates is best seen in the case of high-rise buildings where the travel time of the red square.

Elevator car can be long. For the SLAM algorithm to be able to associate the position of the elevator car after a travel with the correct floor, the error in the estimated travelled distance should be much smaller than the distances between the floors. The elevator systems for which the proposed positioning method can be used are thus determined by the maximum travel time, the distances between the floors, and the quality of the accelerometer sensor. Fig. 5a shows the theoretical root mean square error in the distance estimates as a function of the travel time. The theoretical values were calculated from the discrete-time algebraic Riccati equations used in the distance estimation filter. A speed profile was assumed where the acceleration and deceleration of the elevator car takes four seconds in total and the remaining time the car keeps a constant speed. The process noise and measurement noise were set to Fig. 5a also shows the empirically calculated root mean square error of the distance estimates, obtained using the inertial sensor array together with Alg. 1. As can be seen there is a good agreement between the theoretical and empirical results. Assuming the distance estimation error to be Gaussian distributed, then the probability of the distance estimation error being larger than a certain value as a function of the travel time can be calculated. In Fig. 5b the probability of the error exceeding 0.5, 1.0, 1.5, and 2.0 meters are shown. Consider for example a building in which the distance between sequential floors is three meters. Then Fig. 5b shows that if the probability of the distance estimation error exceeding 1.5 meters should be less than 10−3, the travel time of the elevator car should not exceed 43 seconds; a modern elevator system in a high-rise building travels around 25 floors in 40 seconds.

IV. VIBRATION AND RIDE QUALITY MONITORING

To encourage industry-wide uniformity in evaluation of elevator ride quality, the standards ISO 18738-1 – measurement of ride quality – has been developed. The standards defines a set of vibration and noise parameters that describe the elevator ride quality, and methods to measure and calculate these parameters. Despite the fact that the standards specifies that the vibration monitoring sensor should be placed on the car floor and no more than two persons (assumed to remain still) should be in the elevator car during the performance evaluation, indicative ride quality vibration values may be calculated using a sensor node mounted on e.g.,.the car roof. Vibration values that can be used by elevator service companies and building owners to objectively evaluate the performance of a group of elevators within a property portfolio. An example of peak-to-peak (P2P max) sideways vibration values calculated according to the ISO 18738-1 standards from an elevator in a high-rise building is shown in Fig. 6. Of note is the correlation between the maximum speed and the vibration magnitude; the elevator car travels at a higher speed during longer trips. The elevator speed must thus also be considered if the ISO 18738-1 standard vibration parameters should be used for condition monitoring. Although the ride quality parameters defined in the ISO 18738-1 standards provide information about the health condition of the elevator system and can be used as data features in a predictive maintenance system [8], it is difficult to directly map these measures to certain faults. However, by monitoring the vibration power versus frequency and vibration power versus position spectrums of the elevator car, a more direct insight into the health condition of the elevator system can be obtained.

A. Vibration power versus position

Guide rail misalignment and displacement may cause the elevator car to vibrate abnormally at certain locations. A vibration power versus position spectrum can therefore provide valuable information about the condition of the guide rails and potential faults for discussions on various guide rail faults. With the elevator car positioning estimation framework presented in Sec. III it is straightforward to calculate such a spectrum. Fig. 7 shows an example of a vibration power versus position spectrum from an elevator system where there is a misalignment between two guide rail sections. Every time the elevator car passes the intersection between the two misaligned guide-rail sections, the roller guide momentarily becomes stuck and causes the car to vibrate excessively. These vibrations are seen as a peak in the spectrum at a height of 3.8 meters. Leaving the guide rails in this condition will cause an increased wear on the roller guide shoes and shorten their lifetime. Of note is the fact that the displayed spectrum is calculated using only those accelerometer measurements that correspond to time instants when the elevator car is moving at constant speed. The vibration levels close to the lowest and highest floor can therefore not be estimated using this method.

B. Vibration power versus frequency

Valuable information about the condition of the elevator system can also be gained via a traditional vibration power versus frequency spectrum. The frequency spectrum of the vertical vibration levels in the elevator car can, when evaluated while the car is traveling at constant speed, be related to the condition of the traction system. In Fig. 8 the vibration power versus frequency spectrum form a gearless traction elevator system, is shown. There are two peaks in the spectrum, corresponding to the first and third harmonic of the speed of the engine. The magnitude of the third harmonic being stronger than the first one due to the frequency response of the rope. Changes in the magnitude of these frequency peaks can be related to the condition of the engine, gears system, bearings etc., in the traction system.

V. ABNORMAL STOP DETECTION

Due to faults in the elevator system, or in the case when a passenger presses the emergency stop button, the elevator car may come to an abnormal halt. In either case it is important to immediately notify the person responsible for the elevator system about the situation. The signal processing scheme therefore constantly monitors the motion of the elevator car to detect if it stops at a position other than that of the floor levels, or decelerates abnormally. The monitoring of the stop position is done within the SLAM algorithm, i.e., Alg. 2, where an abnormal stop is declared if the normalized prediction error of the Kalman filter exceeds a predefined threshold. To monitor for abnormal decelerations of the elevator car, the sensor node learns (assuming that abnormal stops are rare) the typical deceleration pattern and checks for deviations from this pattern. This is achieved using Alg. 3, where first the maximum deceleration within each trip is calculated (lines 4-5). These values are then fed into two Kalman filters (lines 10-12), which tracks the mean of the decelerations peaks while going up and down, respectively. If the normalized prediction error of an observed deceleration peak is larger than a predefined outlier threshold4, an abnormal stop is declared (line 17). In Fig. 9 the measured vertical accelerations from two elevator systems are shown. Also shown are the tracked deceleration peak values while going up and down, respectively. Elevator #1 is an old elevator system with deceleration peaks whose magnitude varies with the travel direction. Elevator #2 is a modern elevator system with deceleration peaks of uniform magnitude. As can be seen from the figures, the magnitude of the deceleration peaks varies significantly among different elevator systems, and direct thresholding of the deceleration signal cannot be used to detect abnormal stops. Instead the peak tracking filter in Alg. 3 checks if the deceleration signal deviates from the learned mean deceleration value. In the data set associated with the elevator system #2 there is a large deceleration peak at t = 164 seconds caused by a forced emergency stop. This abnormal deceleration is detected by the algorithm (indicated by a black star in Fig. 9) as it falls outside the 3σ uncertainty regions of the deceleration peak tracking filter. The same emergency stop, but detected by the SLAM algorithm, is also indicated in the position trajectory plotted.

VI. DOOR CONDITION MONITORING

Malfunctioning doors is one of the most frequent faults of an elevator system [8], and there exist several studies on elevator door condition monitoring. The methods proposed in these studies all rely on measurements from door mounted sensors or signals from the door control system, which makes them unsuitable for a non-intrusive conditioning monitoring systems. However, as most elevator doors contain some ferromagnetic material, the motion of the doors will cause a change in the local magnetic field and a magnetic field sensor, a.k.a. magnetometer, can be used to remotely monitor the motion. Fig. 10 illustrates how the magnetic field (along one sensitivity axis) changes at the opening and closing of the doors in an elevator with an automatic door system;

The magnetometer (Invensense MPU-9150 sensor module) was mounted on the roof of the elevator car at a distance of approximately 30 cm from the door5. As can be seen, the door motion creates a distinct pattern in the measured magnetic field, and the door opening and closing is clearly observed. Although the magnetic field pattern displayed in Fig. 10 is typical for an elevator with an automatic door system, the absolute shape and amplitude depend not only on the door system and the sensor location, but they also vary between different floors in the same elevator system and with time. Predefined magnetic field levels can therefore not be used to determine when the doors are opened or closed. Instead, at every stop, the sensor node first determines the time instances when the magnetic field is constant by evaluating the variance of the measured field over a short time window. If the variance falls below a threshold, the magnetic field is classified as constant, and the doors considered stationary. In Fig. 10, the data points classified to correspond to a constant magnetic field are marked by green squares. To determine the magnetic field levels corresponding to open and closed doors, a twocomponent multivariate Gaussian mixture model is fitted to the constant field data points using an expectation-maximization (EM) algorithm [42]. In Fig. 10, the estimated mean and covariance values are indicated in blue, red, and gray colors. Once the magnetic field levels corresponding to the open and closed door conditions have been identified, the sensor node can calculate the number of door openings and closings. This information can be used to detect abnormal door behaviour, such as a sequence of repeated door openings and closings. In automatic door systems where the control system controls the torque rather than the speed of the door motors, the wear and tear of the door system will cause the doors to move more slowly. On the basis of this, the time required for the door system to open and close was used as an input for a logistic regression that predicted the time to failure. In their experiments, an increase of about 0.3 seconds (12% of the nominal closing time of the door) in the motion time of the doors was seen between the service intervals. To investigate if small changes like these can be detected using the magnetic field based door monitoring system, an experiment was conducted where magnetic field data was recorded at different door closing times. The door system used in the experiment was a high-end door system where the closing time could be adjusted with a resolution of approximately 0.15 seconds. The relative closing time motion of the doors was then estimated as the time it took for the signal to go between the 3σ uncertainty bounds estimated by the (EM) algorithm. The mean (each calculated over 350 closings) of the estimated relative closing times for the different true closing times are seen in Fig. 11. Also shown are the 3σ uncertainties of the mean estimates calculated from the variations in the closing time estimates. As can be seen, changes in order of 0.3 seconds (10% of the nominal closing time of the doors) of the closing time can be detected with high probability. Though the accuracy with which changes in the motion time of the doors can be estimated will vary depending on the door system, the sensor location, the sensor noise characteristics, etc., the experiment indicates the feasibility of monitoring degradations in the functionality of the door system.

VII. CONCLUSIONS AND OUTLOOK

Condition monitoring techniques, already widely used in other industries, have to date been largely neglected in elevators. Those condition systems that exist are generally tailored to elevator systems of certain makes or are costly and labour intensive to install. Therefore, their deployment has been limited to high-end and prestige elevator systems. To change this, a signal processing scheme for elevator condition monitoring using easy-to-install smart sensor nodes has been proposed. The proposed signal processing scheme can, using data from an accelerometer and a magnetometer, (i) track the position of the elevator car, (ii) determine the ride quality according to the ISO 18738-1 standards, (iii) calculate vibration spectrums that provide information about the condition of the engine system and the guide rails, (iv) detect abnormal stops, and (v) detect abnormal door operations. The functionality and performance of the proposed scheme have been illustrated through a set of experiments, where data was recorded from different elevator systems using ultra-low-cost accelerometers and magnetometers of the same kind as those found in current smartphones; the Invensense MPU-9150 sensor module was used in the experiments. The results show, inter alia, that the elevator car can, for travels up to 43 seconds long, be tracked with an error of less than 1.5 meters in 99.9% of the travels. Furthermore, the experiments illustrate how information about the condition of the traction and guide rail system can be monitored via vibration power versus frequency and vibration power versus position spectrums. Moreover, the experiments indicate that degradations and faults in the door system of the elevator can be detected by monitoring the variations in the magnetic field that the doors' motions cause. The described signal processing scheme has been integrated into a commercial elevator monitoring system and field tests of the system are currently being undertaken. Our future research will therefore focus on the development on high-level data driven condition monitoring methods. Furthermore, as the proposed signal processing scheme already makes use of data from both accelerometers and magnetometers, we will in our future research look at how magnetic-field SLAM strategies can be adapted to the positioning of the elevators. This would make the elevator positioning more robust and enable positioning of the elevator car for travel of unlimited duration.

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