Real-Time Sensor Data Integration in Vertical Transport Systems

Are conventional mobile devices capable of coping with industrial measurement?

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***Abstract*—In this project, mobile connectivity and an innovative approach to sensor data gathering and integration have been employed to automate maintenance inspection, performance monitoring and ride quality measurement in vertical transportation systems. An Inertial Navigation System (INS) has been proposed, implemented and tested to track lift car movement profile. The inherent characteristics of vertical motion have been used to minimize errors and obtain higher accuracy in the integration results. The measurement of a correlation between kinematic profiles constructed from lift-car tracking data compared to its nominal values provides key information on the lift condition at any time. A frequency analysis was applied to processing vibrations and noise data, effectively adding another dimension to the lift ride quality measurement. This approach enabled lift performance profiles to be compiled automatically and transmitted in real time, which significantly rationalized and improved the process of maintenance inspection and monitoring. An advanced prototype, AdInspect, has been produced, with the full set of described features. Industry partners are currently evaluating it.**

Keywords—inertial navigation systems; measurement standards; sensor applications; sensor data integration; sensor fusion.

I. Introduction

Sensor data applications are undergoing rapid development due to abundance of non-expensive micromechanical systems (MEMS), such as nano-scale beams used to measure acceleration, or vibrating petals measuring angular velocity in a gyroscope. They are being etched directly into silicon structures, next to the logical circuits, thus dramatically reducing production costs.

While these rather basic motion sensors, built into popular smartphones and tablets, are mainly used for gaming purposes, the question is could they be used for broader application domains, particularly in the industry-standard measurements context? This study aims to answer this question.

The proposed solution can be considered as an inertial navigation system (INS)—the one that uses sensor input (accelerometer, possibly gyroscope) to calculate, in real time, its motion parameters such as position, velocity, acceleration and second derivative of velocity (known as 'jerk'). The system was implemented in a vertical transportation vehicle, a lift car, to provide key information on its performance and condition. It is achieved through analysing the correlation between the kinematic profiles constructed from lift-car tracking data compared to its nominal values. The frequency analysis of the vibration signal is used to measure the ride quality. Combined with automatic light and noise measurements, as well as manually collected data, this makes a hand-held mobile device a powerful inspection tool with a capability of producing maintenance evaluation reports *in situ*, and with the aid of mobile connectivity, transmitting data immediately to the main storage and to the client. The prototype, 'AdInspect', built on an Android platform, is currently being tested by the industrial partner of this project, Movvéo Ltd, in a number of sites across Europe.

II. Related Work

Smartphone sensor technology is being successfully used in a range of applications, such as measuring sports performance [1], elderly assistance [2][3], determining user's activity [4][5] and controlling robots [6]. In gaming, spatial input provides invaluable means to control the game play through the user's activity and gestures; the latter are also more and more often used in non-gaming user interfaces [7].

Inertial navigation systems (INS) based on cheap sensors built into mobile devices inherently lack in accuracy—mostly due to low frequency and, less importantly, noise levels. They are often used just to aid other navigation solutions, such as

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GPS, wireless beacons or vision systems. However, in indoor environments GPS signal is also not very reliable, thus fuelling research in indoor INS. For example, Kourogi et al. in their classical work integrated self-contained dead-reckoning sensors with GPS and RFID tagged beacons to adjust for positioning errors [8]. A similar but more recent approach can be found in [9], and a good review of indoor INS solutions in [10]. Sometimes, with varied level of success, INS can provide navigation wherever other systems are not available or not applicable. R.Zhang with his team are using bio-mechanic model of human gait to constrain the kinematic model of the hand-held device by calculating length of each step [11]. Stockx, Hecht and Schöning provide reliable navigation data for underground railway networks. They detect trains stops and use geographical location of stations to constrain their model [12]. Markham with his team are also proposing underground navigation system, in this case for tracking burrowing animals behaviour, but their solution is based on magneto-inductive (MI) localization [13].

Inertial dead-reckoning, which is principally a motion analysis technique, is naturally applicable for research in various aspects of transportation systems. Pfriem and Gauterin successfully used smartphones as multi-sensor platform in large vehicle field operational tests (FOT)—claiming that the solution proved not only to be cost-effective, but also robust and accurate [14]. A research has been carried on to automatically detect user's mode of transport [15][16] or to apply pattern recognition based on dynamic time warping and data fusion to automatically detect driving style [17].

Particularly interesting for this work were results achieved by Douangphachanh and Oneyama who used Android smartphone sensor data for road maintenance management and continuous monitoring. They utilised 3-axial acceleration data in a frequency domain, combined with velocity data, to provide a measurement of the road surface roughness (with a linear relationship) [18].

INS systems are not particularly frequently used in construction or lift industries. De Dominicis and his colleagues were using mobile devices as a multi-purpose and multi-sensor management tool for construction site management (mostly asset management), and they used INS indoors, where GPS signal was too weak to be usable [19]. Work presented here took inspiration from study on the lift ride quality published by Lorsbach in one of the industrial specialist magazines more than 10 years ago [20]. His work was based on using EVA-625, an industry level accelerometer system [21]. This comes with 4.5 kg weight, high price tag and technical specification which is quite comparable to sensors built into modern mobile devices.

III. Principles for the Proposed INS

Ideally , accelerometer output should provide a reliable 3D acceleration vector, which might be integrated to get the velocity vector, or doubly integrated to find the position. Due to integration, results are of course relational, and initial conditions need to be taken into account. In practical solutions the accelerometer measurement comes bundled with the gravitational acceleration vector that must first be extracted from any calculations. This is often achieved by applying a high-pass filter, but this approach generates a lag and in effect it is rarely working really well—particularly if the gravity vector changes rapidly, for example when the device is quickly rotated or shaken. Much more effective approach has been presented by David Sachs at Google Tech Talks [22]: combined information from gyroscope and compass is used to determine which way is down; this is used to effectively compensate for the gravitational acceleration and achieve more precise smooth acceleration with no lag.

A major challenge, inevitably present in accelerometer measurements, is noise. Throughout the process of integration, this noise tends to convert into drift, which in case of doubly integration is quadratic. Combined with even minor error margin in gravity estimation, it may lead to huge discrepancy. According to Sachs, noise generated by a conventional chip in a mid-range Android device, combined with the error margin in gravity reading, can generate a drift in position calculation of over 8 meters per second! [22] INS solutions proved to work well wherever velocities were low and measurement time short. In order to obtain more precise results fusion of all three sensory inputs may be required; or calibration from channels other than inertial, for example GPS; or compensation based on motion constraints, such as physical fundamentals of motion.

Lift car motion is inherently constrained and these constraints can be demonstrated to be sufficient to achieve precise and reasonably accurate results. These constraints are that: lift cars are only moving in vertical direction (lateral oscillations may be interesting when measuring vibrations, but not for the kinematic profile); and that measurement always starts and stops while the car is motionless.

IV. System Implementation

Raw accelerometer sensor measurement is a 3D vector and comes bundled with gravity, is in this solution reduced to one-dimensional vector by projecting it onto direction of the gravity force. The latter is determined using the output from the gravity sensor, one of Android *synthetic sensors*—heavily processed in software [23]. Only a normalised gravity vector is used—this eliminates numerical error on its magnitude, which might otherwise generate a strong drift after integration.

The magnitude of the gravity force may be better eliminated by integrating the acceleration signal over the whole measurement period. Considering that the car is motionless at both start and end time, the overall gain in velocity is zero, thus the gravity can be found as:

$$g = \int_{t_0}^{t_1} \frac{\alpha(t) \cdot \frac{\gamma(t)}{|\gamma(t)|}}{t_1 - t_0} dt$$

where $\alpha(t)$ and $\gamma(t)$ are, respectively, accelerometer and gravity sensors output signals. The acceleration value is:

$$a(t) = \alpha(t) \cdot \frac{\gamma(t)}{|\gamma(t)|} - g$$

We found this simple sensor fusion much more practical than using the raw gyroscope readings—results were coherent and drift-free even when the device was held in hand.

The acceleration signal is furthermore smoothened by either low-pass or median filter (the best experimental results have been delivered for the latter, with median window of 0.5

seconds). Consequently, numerical integration is applied for the velocity, and double integration for the position function. Euler, Verlet and Beeman integration methods have been tested but eventually the trapezoidal rule has been selected for the final implementation—due to simplicity and sufficiently good quality of results. Jerk requires calculation of the acceleration derivative. This process is easily affected by noise; however satisfactory results have been achieved with linear regression (least squares method) .

V. Kinematic Profile of a Lift Car Ride: Analysis

Typical output of the measurement process—a kinematic profile of a single lift ride—is shown in fig. 1. The accelerometer signal before any filtering is shown together with the final, smoothened acceleration.

To evaluate the accuracy and quality of the profiles obtained in the process, they have been compared with the theoretical, ideal dynamic profile of a lift based on the nominal velocity, acceleration and jerk values for the given type and model of the lift. These are typical catalogue parameters widely used in vertical transportation industry. An example of such comparison is shown in fig. 2 (this is for the same lift ride as depicted in fig. 1). There is a good level of correlation between the ideal and measured profiles. Coefficient of such correlation may provide a valuable tool for a lift consultant conducting an inspection or maintenance monitoring; its interpretation, for example critical alarming values, need further investigation but remain out of the scope of this study. Particularly interesting are the results of the distance travelled by the car, calculated through double integration of the acceleration function. Unlike other measurements, distance can be easily verified directly on site, with a tape measure. Results of distance measurement for 24 separate lift rides (4 different lifts, up and down, two different devices and two orientations) are presented in table I. The drift error obtained is typically below 2% and never exceeds 3% in case of one of the analysed devices, and is slightly higher in case of another one—still below 10% in all cases.

VI. Frequency Analysis and Lift Ride Quality

The kinematic profile of a lift car ride may be adequate in terms of its correlation with the rated values, and still overall quality of the ride may be poor. This is because the main factor affecting human perception of transport quality is the level of vibration [20]. Goldman [24] in his classical study of human response to vibration identified three levels: perception, discomfort and tolerance. However, the exact threshold of *discomfort* is difficult to determine. Earl Abraham, in another early study, stated that quality of ride, and perception of comfort, is in case of vertical transportation related to the vibrations between 1 and 10 Hz [25]. This looks promising in regard to mobile devices sensors, for which sampling frequency is often limited to 100 Hz. However, Abraham's study was released in 1984, and more recent analysis indicates that a broader range of frequencies needs to be considered. British and international standards specify the minimum sampling rate for measurement instrumentation as 160 Hz [26][27]. Technically, this excludes any use of lower band measurement; but—does it? The goal of this study is to demonstrate that 100 Hz mobile sensors may be sufficient for a wide class of industry standard measurement.

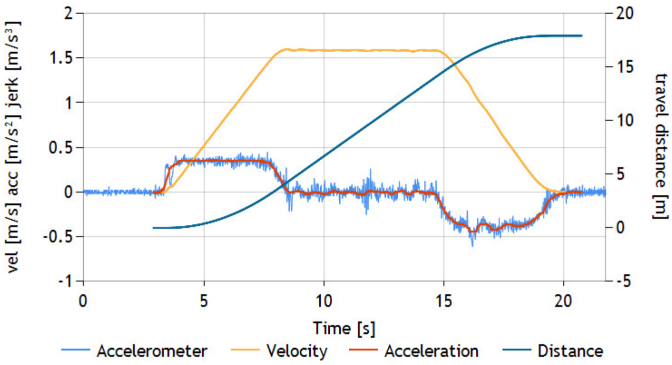

Fig. 1. Measured kinematic profile of a single lift ride: raw accelerometer signal is shown together with smoothened acceleration, velocity and distance profiles. Lift PL29, JG Building, Kingston University campus.

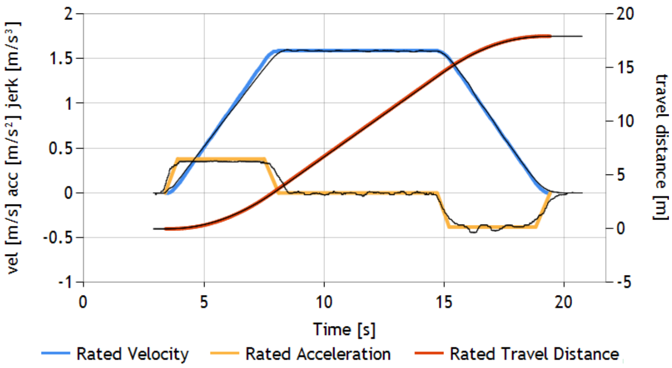

Fig. 2. Comparision of measured and rated profiles for a single lift ride. Lift PL29, JG Building, Kingston University campus.

TABLE I
Measured Distance Travelled by Lift Cars and Error

Rated Distance [m]: 18.00							
Device: HTC Nexus 9 in vertical orientation							
Lift	Dir	Distance	Error	Lift	Dir	Distance	Error
PL29	↑	17.92	0.44%	PL30	↑	17.85	0.83%
	↓	17.63	2.06%		↓	17.65	1.94%
PL31	↑	17.89	0.61%	PL32	↑	17.96	0.22%
	↓	17.60	2.22%		↓	17.71	1.61%
Device: HTC Nexus 9 in horizontal orientation							
Lift	Dir	Distance	Error	Lift	Dir	Distance	Error
PL29	↑	18.03	0.17%	PL30	↑	17.86	0.78%
	↓	18.07	0.39%		↓	17.82	1.00%
PL31	↑	17.36	3.56%	PL32	↑	18.18	1.00%
	↓	18.12	0.67%		↓	17.96	0.22%
Device: Samsung Galaxy S3 in vertical orientation							
Lift	Dir	Distance	Error	Lift	Dir	Distance	Error
PL29	↑	17.55	2.50%	PL30	↑	16.22	9.89%
	↓	16.21	9.94%		↓	16.95	5.83%
PL31	↑	16.95	5.83%	PL32	↑	17.11	4.94%
	↓	16.94	5.89%		↓	17.30	3.89%

To achieve the goal, procedures defined by appropriate standards must be followed as closely as possible. Lift ride quality measurement procedure is defined by BS ISO 18738-1 [26], which refers to BS ISO 8041 for measuring instrumentation [27], and most importantly to BS ISO 2631-1 for evaluation of human exposure to whole-body vibration [28] (all cited British standards are based on their international ISO equivalents).

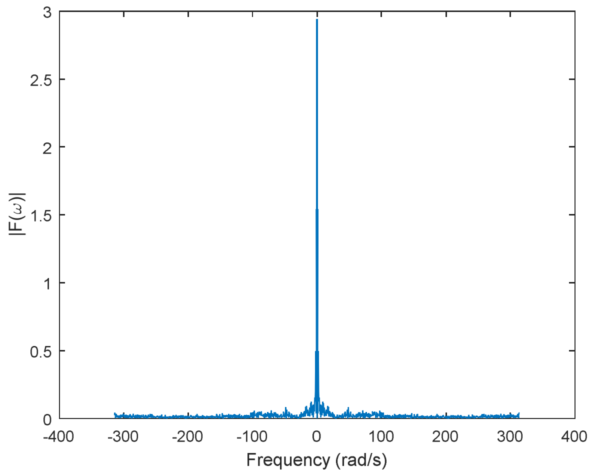

Fig. 3. Frequency analysis of acceleration ouput obtained from a mobile sensor during a lift car ride.

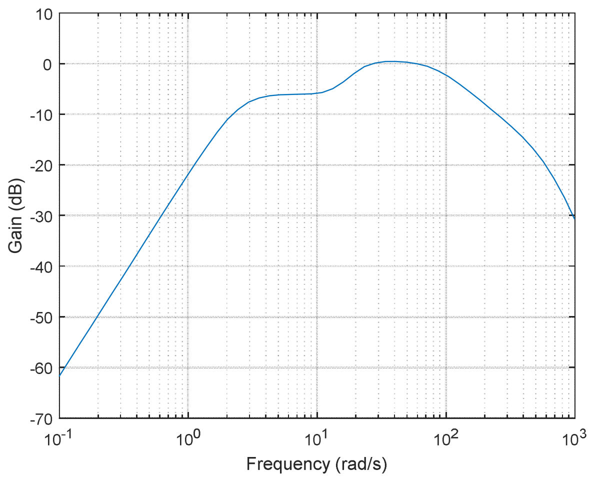

Fig. 4. Transfer function H used to filter the acceleration (vibration) signal using weightings defined in frequency domain—in accordance with BS ISO 2631-1. The diagram shows absolute values—corresponding to the signal magnitude gain.

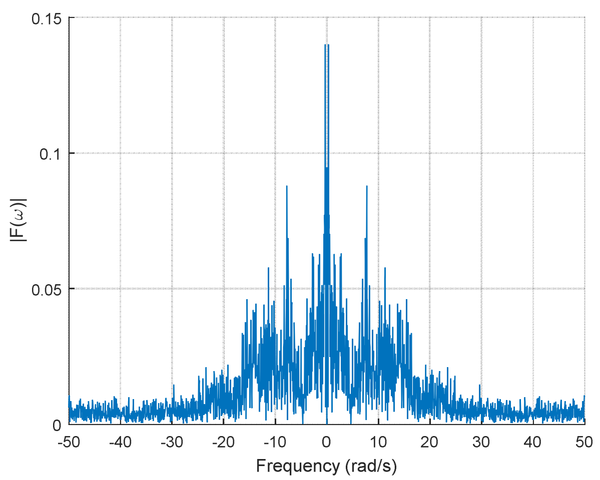

Fig. 5. Vibration frequency spectrum after ISO 2631-1 compliant filtering.

In accordance with BS ISO 2631-1, the accelerometer output signal has been analysed using Fast Fourier Transform (FFT, fig. 3). The profile is dominated by very high amplitudes corresponding to frequencies below 1 Hz—mostly corresponding to the lift acceleration and deceleration. The standard defines a filtering operation based on weightings determined in frequency domain. It is provided as a combination of four component transfer functions, defined in the analogue, Laplace s-domain [29]. The resulting function describes the magnitude and phase in the form of a complex function of the imaginary angular frequency $s = j2\pi f$ (fig. 4):

$$H(s) = H_h(s) + H_l(s) + H_t(s) + H_s(s)$$

$H_h(s)$ and $H_l(s)$ are conventional high and low pass filters are used to create a band-limited Butterworth characteristics. More interestingly, $H_t(s)$ and $H_s(s)$, which are, respectively, acceleration-velocity transition and upward step filters, represents the actual weightings, with regard to a certain application:

$$H_t(s) = \frac{\frac{\omega_4^2}{\omega_3} s + \omega_4^2}{s^2 + \frac{\omega_4}{Q_4} s + \omega_4^2}$$

$$H_s(s) = \frac{s^2 + \frac{\omega_5}{Q_5} s + \omega_5^2}{s^2 + \frac{\omega_6}{Q_6} s + \omega_6^2}$$

The standard specifies six different application areas; for the purpose of this study one of them has been selected, which is applicable for full-body vibrations along z-axis (vertical), standing or seating—marked in the standard as the W_k *curve*.

The results of application of the filter are shown in fig. 5, in frequency domain, and in fig. 6, in time domain. The latter is obtained by using inverse Fourier transform (iFFT). Additionally, a simple rectangle filter was applied to cut-off frequencies lower than 1 Hz.

VII. System Evaluation

Tests have been performed on a variety of Android devices. Comparison of their basic parameters is shown in table II. An industry-level standard-compliant EVA-625 device [21] has been used as reference.

Sampling frequency, according to the standard, should be at least 160 Hz, to allow reliable measurement of vibrations up to 80 Hz (500 rad/s). Most Android devices are slightly below this threshold, at 100 Hz (50 Hz or 314 rad/s vibrations). Some models provide accelerometer parameters exceeding the minimum. Even if the device is rated at 100 Hz, the filtering weighting for the maximum frequency of about 314 rad/s is -16 dB, or 0.15 ratio. Therefore, high frequency vibrations that get cut-off are of but marginal influence. Interestingly, the sampling frequency is intentionally limited in mobile devices in order to increase battery life.

Accelerometer resolution required by the standard is 0.005 m/s^2. Modern devices are usually two times less precise. In some cases the resolution is as low as 0.15 m/s^2, these are rather outdated or cheaper devices and do not have to be used. It is

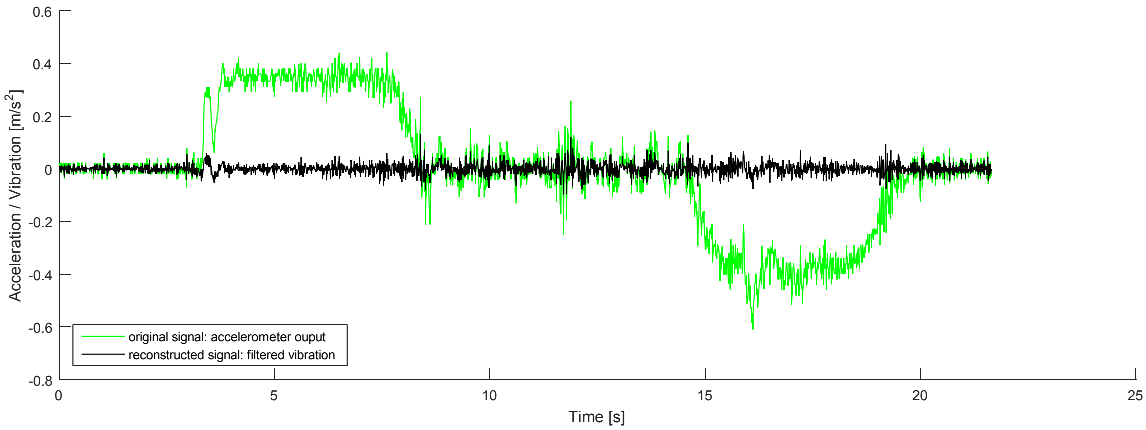

Fig. 6. Raw accelerometer output and the reconstructed vibration signal after ISO 2631-1 compliant filtering.

TABLE II
DEVICES USED FOR TESTING—COMPARISON OF PARAMETERS

DEVICE	RANGE [m/s^2]	RESOLUTION [m/s^2]	SAMPLING FREQUENCY [Hz]
BS ISO 8041 requirement		**0.005**	**160**
LG Nexus 5	39.2	0.0006**	200
HTC Nexus 9	39.2	0.01	100
Samsung Galaxy Tab 10.2	19.6	0.01	100
Samsung Galaxy S3	39.2	0.15	100
Sony Xperia	78.5	0.15	100
EVA-625*	15	0.006	256/512

* approved standard-compliant industry-level device [21]
** this rating is probably wrongly provided by the OS

important to notice that these rated values cannot be entirely trusted: they depend on the accelerometer range and the digital resolution of the internal A/D converter. The latter may be anything between 8 and 13 bits, but very rarely more. The actual accuracy of the accelerometer reading is greatly affected by the **internal sensor noise** and may be 10 or even more times worse.

This puts Android hand-held devices well away the range required by the BS ISO 8041 standard. But does it rule out any possibility of industrially valid measurement? The standard BS ISO 18738-1 relies on BS ISO 8041 in terms of instrumentation, but also specifies which measurements should be reported in regard to the lift ride quality.

Considering **measurement of vibrations** (which are lower values therefore more vulnerable to errors), the standard requires reporting the maximum peak-to-peak value, and A95 (typical) peak-to-peak level—this is the value for which 95% of the peak-to-peak levels, between defined boundaries, are equal to or less than the maximum. Typical values are unlikely to drop below 0.1 m/s^2, but alarming level of vibrations will be at least 10 times higher, therefore distinctly above typical noise signal. In many maintenance related scenarios the precise value of these critical vibrations is not that important: it means that a conventional Android device should be capable to at least detect the problem if one exists. Still, for a precise, standard-compliant measurement an industry-level instrument will be necessary.

Considering **measurement of acceleration**, the standard requires reporting the maximum acceleration and deceleration, and the A95 value defined as the acceleration derived from 5% to 95% of maximum velocity. Typically, these acceleration values are at least 1 m/s^2. It has been demonstrated that, even after doubly integrating acceleration values—to generate the profile for the distance travelled—the error rate measured for a state-of-the-art tablet did not exceed 3% (compare the table I). This is a good result, unless full compliance with the standard is required.

VIII. ADINSPECT ANDROID APPLICATION

Figure 7 shows a tablet being used by a consultant to record the ride data in a lift car. *AdInspect*, an application developed in collaboration between Kingston University and Movvéo Ltd on Android platform, is currently used by consultants to conduct *in-situ* inspections of vertical transportation systems (lifts, escalators and moving walks)—as a part of beta phase testing. Apart from the ride quality, the tool also collects other sensory information, such as noise and light level. As a complete inspection and maintenance application, *AdInspect* allows also for manual entry of a variety of records regarding various aspects of maintenance evaluation, surveying and safety issues. Once the inspection is complete, the entire data set can be submitted by a single click, wirelessly, over the Wi-Fi or 3G connection, to the central storage, typically located in the company headquarters. Subsequently, a comprehensive, multi-page maintenance evaluation report is automatically generated and e-

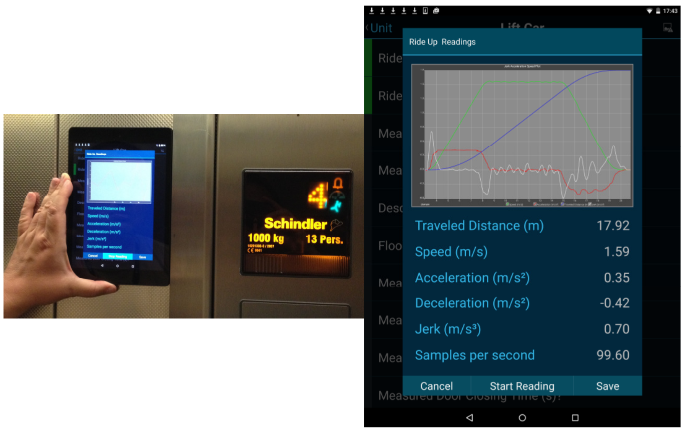

Fig. 7. AdInspect application: used by a consultant to measure lift ride quality (left) and a Ride Up screen shot (right).

mailed to the client. This creates a complete, 'all-in-one' inspection tool that can be installed on a small tablet and easily brought to the inspection site.

IX. Discussion and Conclusion

Until the advent of the AdInspect prototype, the industry standard device for measuring lift ride quality had been instruments such as EVA-625, weighing 4.5 kg. The standard [26] determines this minimum weight to ensure required conductivity of vibrations between the lift car floor and the measurement device. While EVA is still in use, it is considered not very practical by the maintenance inspectors and the industry was seeking an alternative system—easy to carry and use and providing connectivity at all times. It is against that background that AdInspect was conceived as a new concept and implemented with a view to complementing EVA-625.

As proposed, it is a low-cost, light-weight system, utilising off-the-shelf hand-held device with an innovative software solution, capable to measure ride quality *in situ* and in real-time—which promises to be a game-changer. Although Android hardware cannot yet be considered an industry standard, obtained measurement results are sufficiently reliable and accurate to be applicable in most scenarios involving lift maintenance inspection and evaluation.

Extrapolating the outcome of this case study, it should be envisaged that further development of applications that utilise hand-held device sensor technology can positively impact measurement processes in a variety of industrial contexts.

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