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Simulating the impact of noise on gait features extracted from smartphone sensor-data for the remote assessment of movement disorders*

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***Abstract*— Signs and symptoms of movement disorders can be remotely measured at home through sensor-based assessment of gait. However, sensor noise may impact the robustness of such assessments, in particular in a Bring-Your-Own-Device setting where the quality of sensors might vary. Here, we propose a framework to study the impact of inertial measurement unit noise on sensor-based gait features. This framework includes synthesizing realistic acceleration signals from the lower back during a gait cycle in OpenSim, estimating the magnitude of sensor noise from five smartphone models, perturbing the synthesized acceleration signal with the estimated noise in a Monte Carlo simulation, and computing gait features. In addition, we show that realistic levels of sensor noise have only a negligible impact on step power, a measure of gait.**

***Clinical Relevance*— Uncertainty propagation with synthesized yet realistic sensor data can be used to study the impact of sensor noise on calculated gait features.**

I. INTRODUCTION

Recent years have seen an increasing use of wearable sensors to assess functional ability, including gait [1–9]. Such assessments have the potential to provide a more objective and detailed picture of the disease state in people living with movement disorders than previously possible [9, 10]. A common approach for administering sensor-based assessments is to take advantage of the sensors embedded in consumer electronic devices such as smartphones [9].

In a Bring-Your-Own-Device (BYOD) setting, smartphone sensor-based assessments are administered directly on the patients' own smartphone device [11]. Such BYOD solutions allow for the assessments to be administered remotely at home outside of a clinical trial setting. However, they pose their own challenges. Different smartphone models

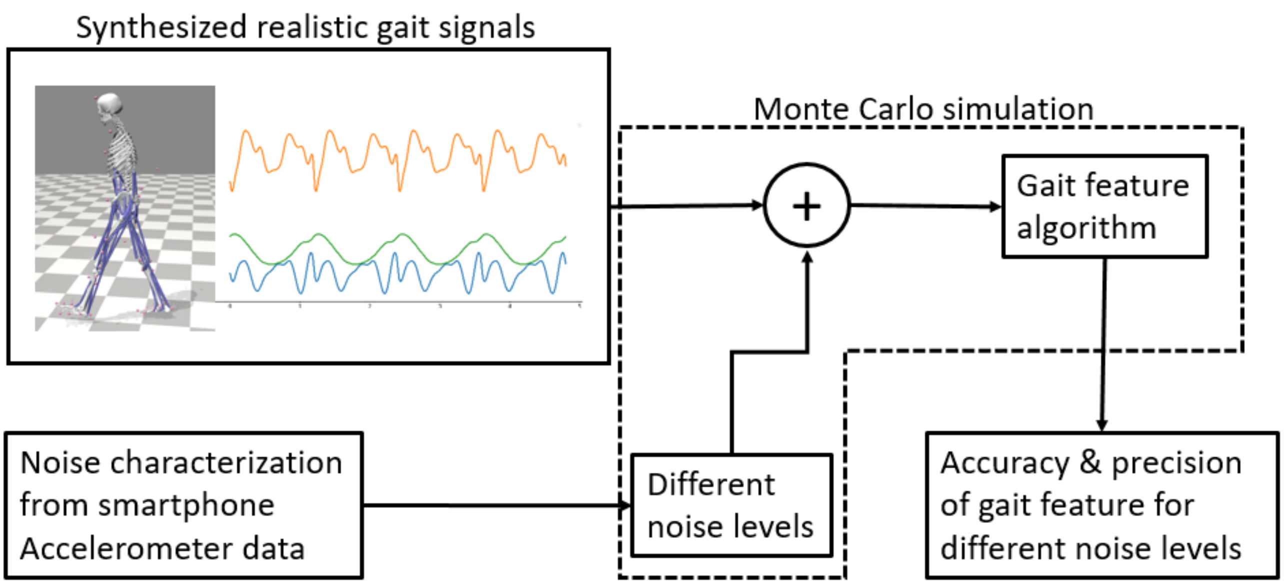

Figure 1: Diagram depicting our uncertainty propagation approach. Realistic noise-free gait signals were synthesized and corrupted by noise of different levels. Noise levels were informed by measurements obtained from smartphone accelerometer experiments and chosen such that they cover levels well above and below what is observed. A Monte Carlo simulation was used to obtain distributions of step power values for each noise level.

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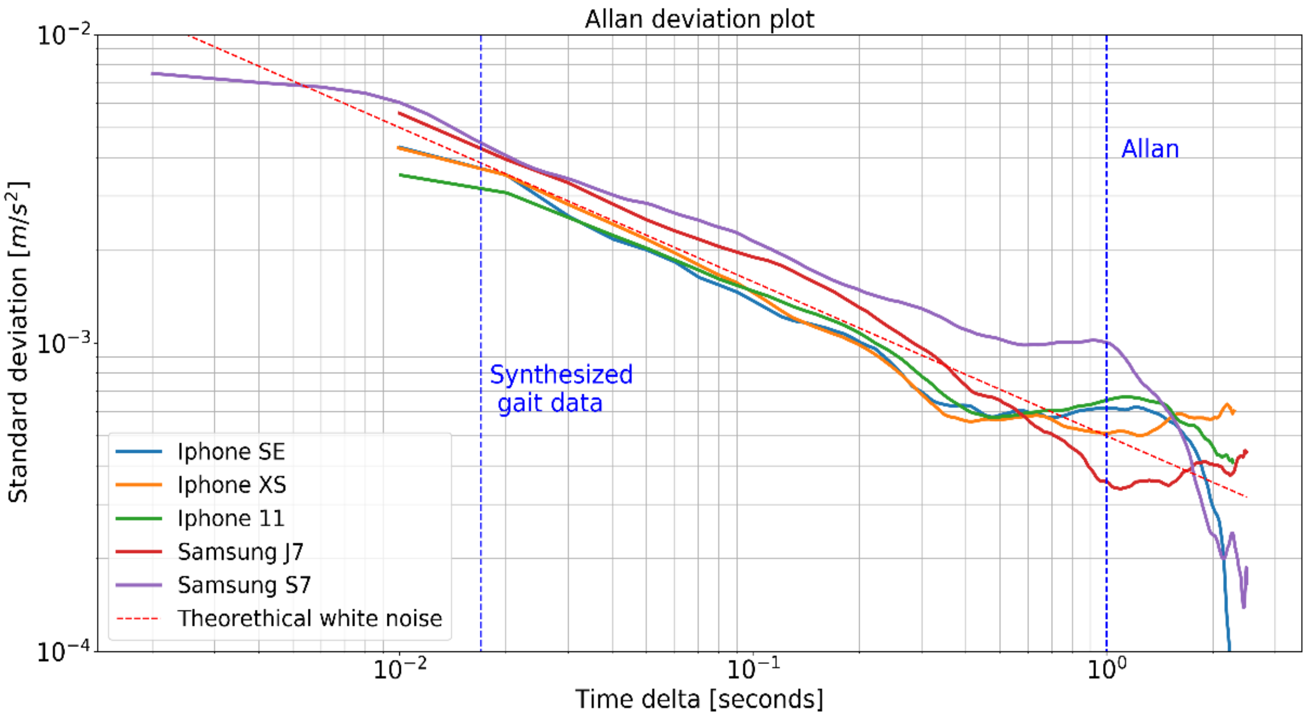

Figure 2. The Allan standard deviation plot for 5 seconds worth of acceleration data from 5 different phones. The slope of the lines are almost identical to the theoretical slope of -0.5 for white noise as indicated by the red dashed line. The vertical blue lines represent the 60 Hz (Synthesized gait data) and 1 Hz (Allan standard deviation) frequencies. Note that towards larger time deltas the slopes of the Allan deviation plots deviate from -0.5 due to increasingly less available data. This is taken into account when we fitted linear regression lines by using weighted least squares where weights were proportional to the number of data points per time delta.

use sensors with different specifications. Thus, the measurement noises originating from sensors such as accelerometers or gyroscopes may differ between models [12].

The influence of sensor noise on calculated gait features, i.e. step power, received limited attention in research. We aim to investigate the impact of acceleration sensor noise on calculated/estimated gait features using uncertainty propagation. First we obtained synthetic gait acceleration data using simulated inertial measurement unit (IMU) sensors [13]. The synthesized data was then corrupted with white noise of varying amplitude matching the noise characteristics obtained from commonly used smartphone models before calculating the gait features.

II. METHODS

A. *Synthesized realistic gait signals*

Fig. 1 summarizes our proposed framework to study the influence of sensor noise on calculated gait features. We built on the recently introduced method of synthesizing acceleration sensor data from biomechanical human models and accurate motion simulation [13]. More specifically, OpenSim version 4.1 (Simbios, Simbios/ SimTK, CA, USA) [14] was used to simulate biomechanical models during walking. Synthesized accelerometer data was obtained from a 23 degree-of-freedom, lower-body-torso-head musculo-skeletal human model (Gait2354) [15]. This model includes motion capture data from a subject performing one gait cycle on a treadmill as well as configuration files to perform scaling and inverse kinematics. Scaling refers to adapting the dimensions of the model to match the subject whose motion was captured, and inverse kinematics refers to the estimation of joint angles at each time point by matching the model marker positions to the measured marker positions.

B. *Simulated sensor*

Next, the simulated sensor was defined as an OpenSim marker attached to the lower back to simulate a smartphone worn in a running pouch. Three additional markers were defined that together make up a three-dimensional axis system with the simulated sensor on the lower back at the origin. This allowed us to track the orientation of the simulated sensor and synthesize three-dimensional acceleration signals similar to a real three-axial rotating accelerometer.

C. *Derivation of acceleration from position time series*

A position time series was derived from the position trajectory of the simulated sensor at each point in time during the gait cycle and exported from OpenSim. The acceleration signal could in principle be obtained by computing the second derivative of this position time series. However, any uncertainty in the position of the simulated sensor would be amplified by the double differentiation, resulting in a noisy acceleration signal. To synthesize smooth signals, we thus applied a Kalman smoother to each of the three axes separately [16].

The state of the simulated sensor at each time point is described by a position, velocity and acceleration and can be written in vector notation:

$$x = [x \ \dot{x} \ \ddot{x} \ ]^T \tag{1}$$

State transitions from one point in time to the next are described by the transition matrix A:

$$A = [1\ \Delta t\ 0.5\Delta t^2;\ 0\ 1\ \Delta t;\ 0\ 0\ 1\ ] \qquad (2)$$

In this analysis, the sensor has constant acceleration, including random variations that result in the transition covariance vector:

$$q = \begin{bmatrix} \frac{\Delta t^3}{6} & \frac{\Delta t^2}{2} & \Delta t \end{bmatrix}^T \qquad (3)$$

Hence, transitions are described by:

$$x_{t=1} = Ax_{t=0} + q\sigma q^T \qquad (4)$$

With σ the standard deviation of the model noise. The observation covariance is estimated using Expectation Maximization (EM). For σ we can take a fixed value because the amount of smoothing that is applied only depends on the ratio between observation and model noise which is assumed to be constant. The EM estimation and subsequent calculation of smoothed state vectors (including acceleration) was implemented using the Python package pykalman (https://github.com/pykalman/pykalman). A gravity constant of 9.81 m/s^2 was added to the vertical axis before projecting the signals onto the axes of the local reference frame spanned by the three additional markers. Finally, the accelerometer signal was concatenated to obtain two minutes of data to resemble the accelerometer signal obtained from a smartphone-based Two-Minute Walk Test. To ensure smooth transitions between consecutive gait cycles, we first concatenated three cycles, applied the Kalman smoother, and subsequently used the middle one to create the two-minute long signal.

D. Noise characterization from smartphone accelerometer data

We collected acceleration data from five different stationary smartphones for a duration of five seconds. The data were collected as part of a study investigating sensor precision and accuracy for various controlled acceleration levels.

Sensor measurements such as those obtained from accelerometers embedded in smartphones are perturbed by noise that can be modelled as a Gaussian white noise process [17]. To compare the noise levels of different smartphone models with different sampling frequencies, the estimated noise levels were scaled to the frequency used in the OpenSim simulation. This was achieved with the Allan standard deviation, which is a log-log plot of the sampling interval versus the measurement standard deviation as shown in Fig. 2 [18]. More specifically: $\sigma = \frac{1}{\sqrt{\Delta t}}\sigma_{Allan}$ with σ_{Allan} the standard deviation at 1 Hz, and σ and Δt the standard deviation and sampling interval used in the simulation, respectively. σ_{Allan} was derived by fitting a linear regression model with fixed slope of -0.5 through the Allan standard deviation plot. As can be seen in Fig. 2, the slope of the lines are around -0.5 which indicates the noise can indeed be modeled as a Gaussian white noise process.

E. Uncertainty propagation

We used a Monte Carlo approach to evaluate the effect of different noise levels on step power, a characteristic defined as the integral of the squared and gravity-corrected acceleration magnitude signal per step, with unit m/s^3. Step power was computed for each step detected by the algorithm of [19] and averaged across all steps. Other gait features could be investigated as well but in this paper we limited the illustration of our method to step power.

In each repetition of the Monte Carlo simulation, Gaussian white noise was added to the concatenated and synthesized accelerometer signal. The resulting noisy accelerometer signal was then used to compute step power. One hundred repetitions were used for each of the seven noise levels (range: 0.001 to 1 m/s^2).

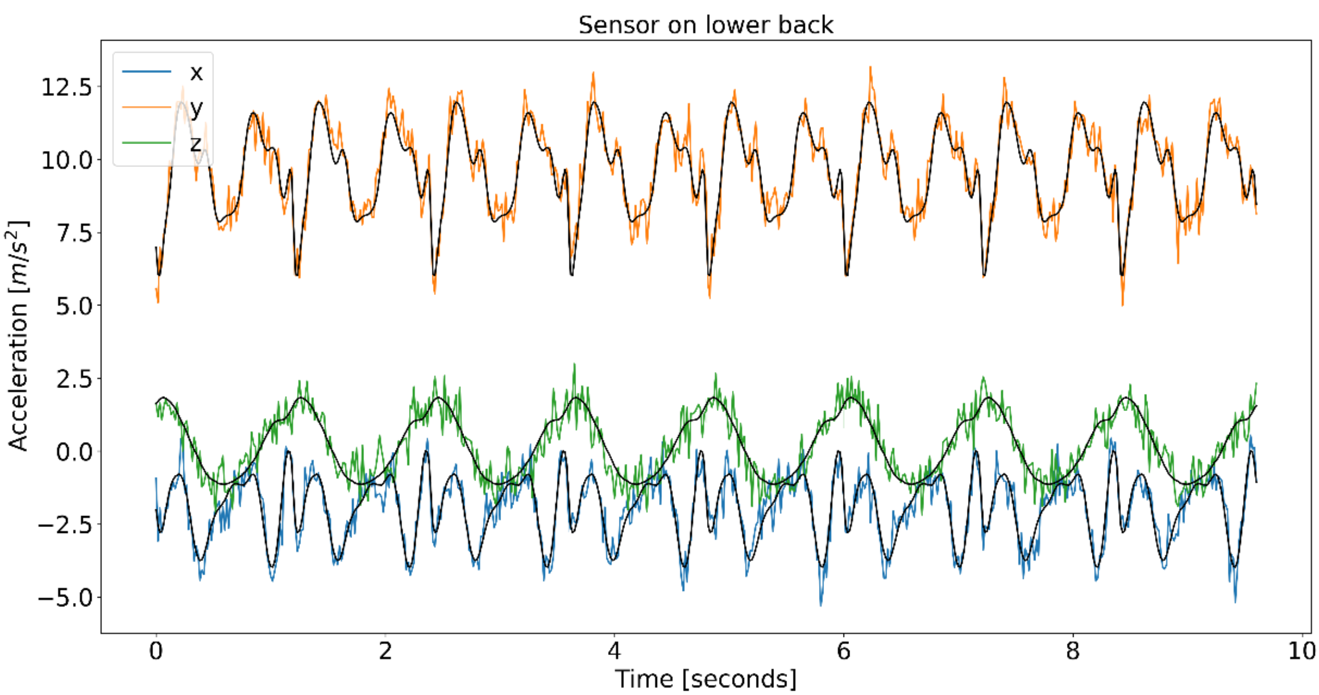

Figure 3. Synthesized three-axial acceleration data without noise is shown in black. The colored data shows an example of noise with an amplitude of 0.5 m/s^2 added to the synthesized data. This example consists of eight concatenated gait cycles.

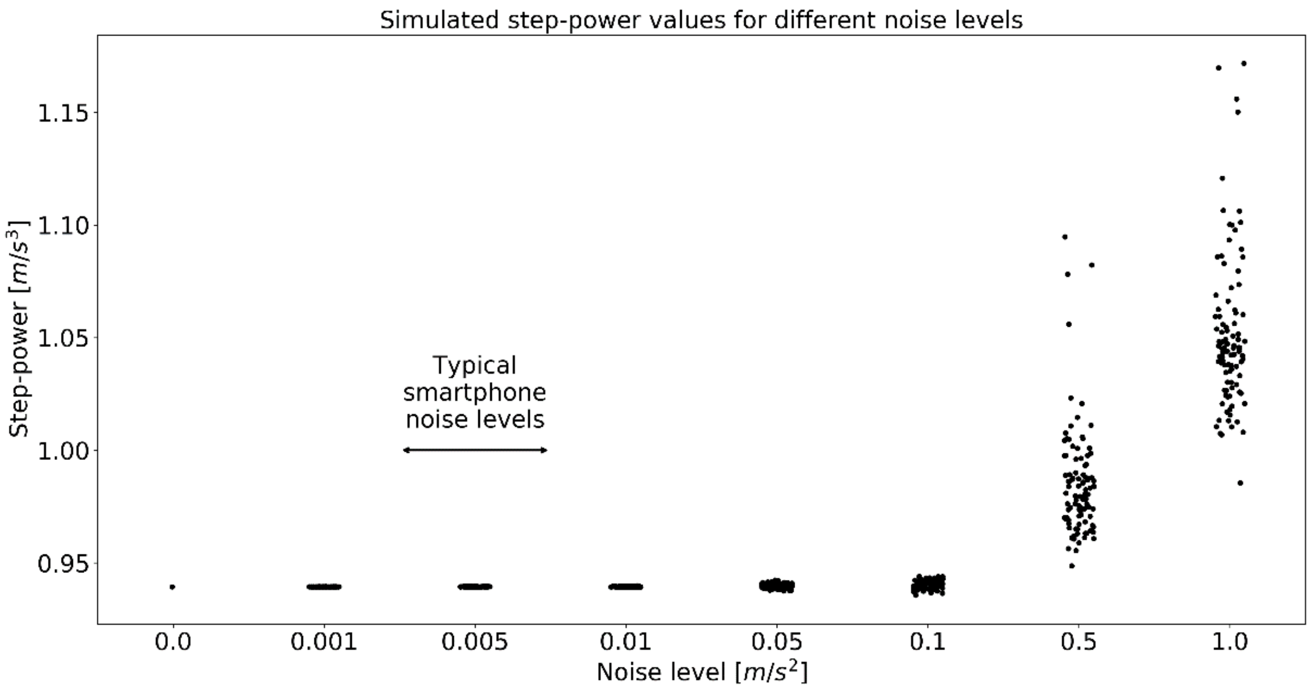

Figure 4. Monte Carlo simulation of step power using different noise levels. Samsung and Apple phones have noise ranging between 0.0031 and 0.0086 m/s^2.

III. RESULTS

A. Synthesized realistic gait signals

Fig. 3 shows the synthesized acceleration signal obtained using OpenSim and the Kalman smoother approach for each of the three axes. The noisy signal obtained after applying Gaussian white noise is superimposed in blue, orange and green, respectively.

B. Noise levels

Table 1 shows the scaled sensor noise levels obtained with the Allan standard deviation approach. Both the Samsung J7 and S7 had noise levels that were approximately twice as large as those measured for the tested iPhone models (iPhone SE, iPhone XS, iPhone 11).

C. Noise simulation results

Fig. 4 shows the step power results obtained from the simulation. The true, noiseless, value of step power is 0.94 m/s^3. It can be seen that noise affects the variance of step power and can also introduce a bias. The variance of step power is affected proportionally to the noise level as shown in Fig. 5A. However, up to a noise level of 0.1 m/s^2 the bias is negligible (Fig. 5B). This bias can be explained by steps not being detected resulting in some detected step being twice as long as a single step and thus higher step power.

IV. DISCUSSION

In this work we illustrated how OpenSim and motion capture data can be used to study uncertainty propagation from sensor noise to gait features. Our proposed uncertainty propagation method, which is versatile and agnostic to data synthesis approaches, could be applied to different sensor modalities, i.e. gyroscopes. It can also be applied to movement domains other than gait.

Uncertainty propagation is a viable method to investigate data quality of sensors that are embedded in smartphones. Previously we reported that patients living with Parkinson's disease have significantly reduced step power compared with healthy controls, suggesting that this measure captures gait impairment [20]. Our analysis revealed that sensor noise is negligible when calculating step power with data derived from a smartphone during a Two-Minute Walk for normal gait. Whether step power for abnormal gait patterns in people with a movement disorder is impacted differently, and to what extent, would require further research.

Acceleration data could also be exported from OpenSim directly. However, in contrast to velocity, which is derived from position by differentiation, acceleration in OpenSim is derived from calculated forces, moments and constraints, which are additional steps to be performed after inverse kinematic calculation. Since this OpenSim-derived acceleration signal is prone to artefacts, we computed the

TABLE I. THE ALLAN STANDARD DEVIATION IS DEFINED AS THE STANDARD DEVIATION OF THE NOISE AT 1 HZ. TO COMPARE NOISE LEVELS FROM THE PHONES WITH THOSE USED IN THE NOISE SIMULATION WE HAD TO TRANSLATE THEM TO THE SAME SAMPLING FREQUENCY AS USED IN THE SYNTHESIZED DATA.

Model	**Allan SD**	**SD for noise simulation**	**SD measured accelero-meter data**	**Sampling frequency (Hz)**
iPhone SE	0.0005	0.0037	0.0045	100
iPhone XS	0.0004	0.0031	0.0046	100
iPhone 11	0.0005	0.0039	0.0040	100
Samsung J7	0.0011	0.0086	0.0056	100
Samsung S7	0.0008	0.0065	0.0098	500

SD, standard deviation.

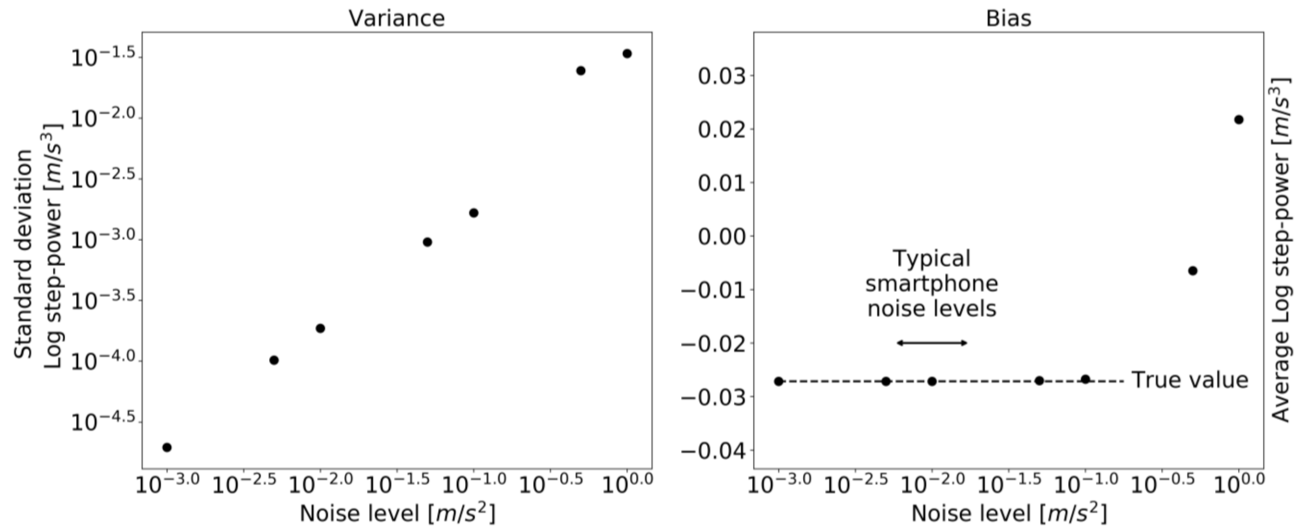

Figure 5. A: Standard deviation of step power over 100 Monte Carlo repetitions per noise level. Variance changes proportionally to the noise level. B: Average step power values over 100 Monte Carlo repetitions per noise level as an indicator of bias. The dashed line indicates the true step power value calculated on the synthesized signal without noise. Only noise levels above 0.5 m/s^2introduce a bias. For visualization purposes both axes in both graphs are logarithmic.

acceleration signal directly by differentiating the position time series twice.

One limitation is that we ignored centrifugal and Euler forces that are in reality also measured by the accelerometer. Because the virtual sensor is located at the lower back we assume that the contributions of these two forces can be neglected since there is hardly any rotation of the sensor. However, when considering body locations with a large range of motion, e.g. the lower arm or foot, the modelling and investigation of rotational forces needs to be addressed.

Another limitation is that we only estimated sensor noise from smartphones not undergoing motion. An area for further research would be to extend the present analysis to sensor noise estimated from acceleration data collected from smartphones worn during walking. This would also enable the comparison of the synthesized acceleration data generated in this study with real acceleration data. Finally, by collecting longer recordings than the five-second recordings used here, such future research would allow us to better estimate the noise properties of the sensors, including sensor drift.

V. CONCLUSIONS

We illustrated here a proof-of-concept framework for investigating the impact of sensor noise on calculated gait features such as step power and for addressing concerns regarding sensor quality in real-world settings. Using this framework, we show that sensor noise has only a negligible impact on the computation of step power.

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