How Accurate Are Smartphone Accelerometers to Identify Intermittent Claudication?

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Abstract. Claudication is a cramping pain that is worsened by walking and relieved with rest. It is caused by inadequate blood flow to the leg muscles because of atherosclerosis. Recently, smartphones and their sensors have been proposed in the context of mobile health to monitor gait. However, their use remains disputed: objections concern the quality of the collected data. Therefore, the work presented in this paper proposes to study three main sources of noise observed in smartphone accelerometers and to objectively assess their impact on claudication detection. To do so, we first observe three noise sources in four different smartphones to get an idea of their ranges; we second compare the smartphones' signals to a ground truth from a vision-based system and third propose to detect claudication by estimating duty cycle from the vertical accelerometer signal and to evaluate the impact of the three noise sources on this basis.

Keywords: Intermittent claudication · Smartphone · Accelerometer Human motion · Gait analysis · Motion tracking

1 Introduction

Injury to a lower limb may disrupt natural walking. In intermittent claudication, significant differences can be observed in kinematic parameters as cadence, stance and swing times and step width when compared with healthy controls [1,2]. Hence, an accurate motion tracking system is needed to observe these differences. Several human motion tracking systems exist. The most famous are vision-based systems made popular from applications in sport analysis [3,4] and lead to the 3D localization of the patient's limbs by combining the data of several cameras. Markerless systems [5] follow the patient's contours while marker-based systems, such as VICON [6], follow either light-reflecting markers or light-emitting diodes attached to the patient. Such systems enable precise localization but they are expensive, cumbersome and therefore can not be used in outpatient care units or at home. Recently, smartphones and their sensors have been proposed to address theses problems [7]. In smartphone-based systems, the

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patient carries a smartphone and uses its sensors to capture his motion without interfering with his natural behavior [8,9] by integrating measurements of a GPS, accelerometer and/or gyroscope. Nevertheless, the use of smartphones and their low-cost sensors remains controversial in the medical community. Although the miniaturized and non-invasive aspect is attractive, objections concern the quality of the collected data as well as the reliability of the associated software technologies in a clinical context. In this context, our work addresses three issues. The first one aims to characterize three main sources of noise (sampling jitter, rate and quantification) observed in the accelerometers of smartphones to assess their ranges. The second one seeks to build a ground truth from a high frame rate video camera for comparison with the signals from the smartphones. Finally, the third one evaluates from the degraded signals (according to the characteristics identified in the first section) of the ground truth (built in the second section) the detection capacities for claudication.

2 Noise Study

Concerning the noise, we decided to study three characteristics: the quantification for which the information is readily available on the web, the sampling rate and jitter that can be easily obtained from simple acquisitions. Other sources of electronic noise (thermal noise, shot noise, flicker noise) have not been considered because they are much more difficult to estimate. In order to study the noise characteristics of the smartphone accelerometers, we had four different devices at our disposal: respectively a Samsung S6 (380 euros), a Samsung A5 (270 euros), a Samsung A3 (220 euros) and a LG Optimus F6 (130 euros).

Quantification. Most of the sensors in smartphones are MEMS (Microelectromechanical systems) based. The ADXL335 and ADXL345 are two of the most popular. According to their technical documentation [10], the output precision varies from 8 bits to 13 bits.

Sampling Rate. To estimate the sampling rate we performed experiments on the different devices. To do so, an Android program has been developed to consult, for each measurement, the system clock of the smartphone accelerometer and therefore to calculate a posteriori the delay between each measurement. On average, the sampling rates recorded for the different devices are respectively 15 Hz for the Samsung A5 and A3, 20 Hz for the LG Optimus F6 and adaptative sampling rate (maximum limit 50 Hz) for the Samsung S6.

Sampling Jitter. To estimate the sampling jitter we relied on the same experiments that for the sampling rate. For each device, time evolution, distribution and autocorrelation of the centered sampling jitter is illustrated in Fig. 1. The different devices behave differently regarding the sampling jitter. Galaxy A5, Galaxy A3 and LG Optimus F6 present a sampling jitter which is very closed to

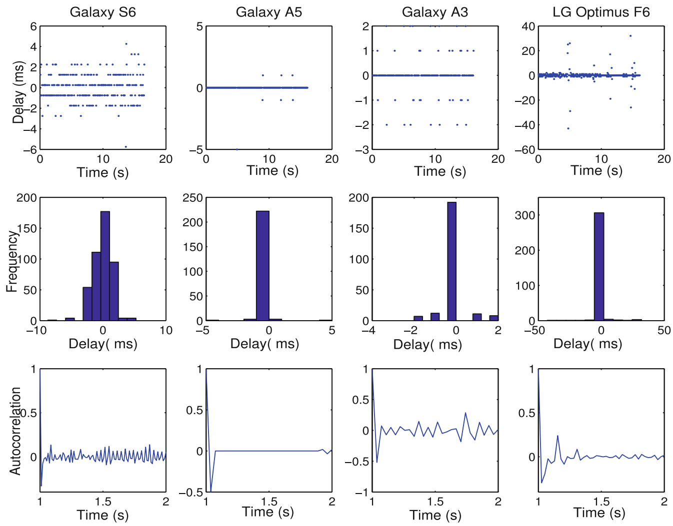

Fig. 1. Each column is for a different device. First line: time evolution; second line: distribution; third line: autocorrelation of the sampling jitter. Data were previously centered.

a Dirac distribution, where Samsung S6 presents the largest dispersion around the Dirac. The jitter of these three devices can be modeled by a white noise in accordance with their autocorrelation. Surprisingly, the Samsung S6 which has an adaptive sampling rate does not have the same shape of distribution for the jitter: its distribution is more like a generalized Gaussian and its autocorrelation indicates a deterministic and cyclic jitter which may come from a timer in the adaptation process.

3 Ground Truth from Vision-Based System

Subjects. Four healthy volunteers without any known gait pathology participated in the walking experiments. During the tests, they were asked to walk on a treadmill for 2 min: the first minute at 1.2 km/h and the second minute at 2.4 km/h. Then the subject realized exactly the same session with a knee splint.

Reference System. Validation of the accelerometer signals and extracted features was performed against a high frame rate video camera (Gige Vision). The motion tracking is based on markers that were placed on the different segments of the leg (respectively hip, thigh, ankle and foot) as illustrated on Fig. 2. On these same segments, the four different devices presented in Sect. 2 have been

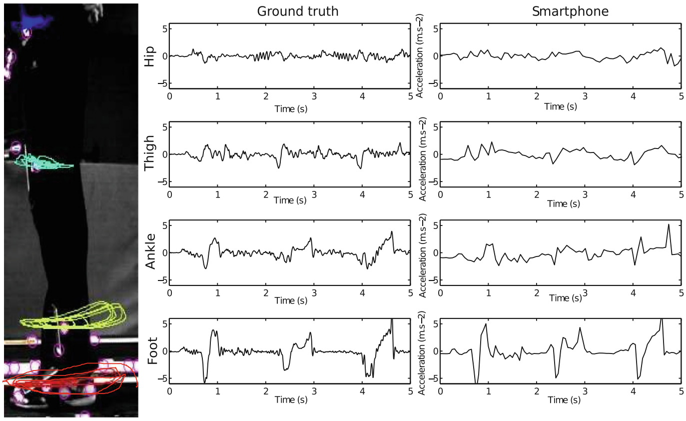

Fig. 2. Left: a frame of the video camera with in different colors the trajectories of the segments as estimated from the entire video sequence. Middle: vertical acceleration signals derived from the video sequence (double derivation from the positions). Right: vertical acceleration signals from the smartphones. Note that only the three first gait cycles of the 2 min test are displayed.

fastened (hip = Samsung A3; thigh = Samsung A5; ankle = LG Optimus; foot = Samsung S6). The video camera was placed close to the treadmill such that the pointing direction is approximately perpendicular to the sagittal plan to avoid distorsions. During each gait test, we collected simultaneous video at 300 Hz and acceleration signals in 3D at sampling rate indicated in Sect. 2 for hip, thigh, ankle and foot. The motion tracking from the video sequence was performed using an open-source tracking software [11]. Markers that were placed an the leg segments were automatically detected using local features detector (Laplacian of Gaussian): it requires to calibrate in size the frames of the video sequence and give an estimate of the size of the markers to be searched.

4 Claudication Detection

A number of spatio-temporal parameters of gait have been proposed over the years to detect claudication [1,2]: step length, step duration, stance phase, load response, single support, pre-swing, and swing phase (%). In this work, we propose to resume these in one indicator: the duty cycle (DC) of the periodic walking function. As illustrated on Fig. 3, the acceleration signal has to be binarized: from the vertical acceleration signal, the algorithm detects time intervals during which accelerometer is at rest (0) and vice versa (1). More precisely, the binarization was based on z-score: if a new acceleration is below a fixed signed number of standard deviations (3 in our case) from the mean (estimated over three gait cycles) then it is considered as at rest. DC is expressed as the ratio of the duration of the swing phase (1) over the total duration of the step.

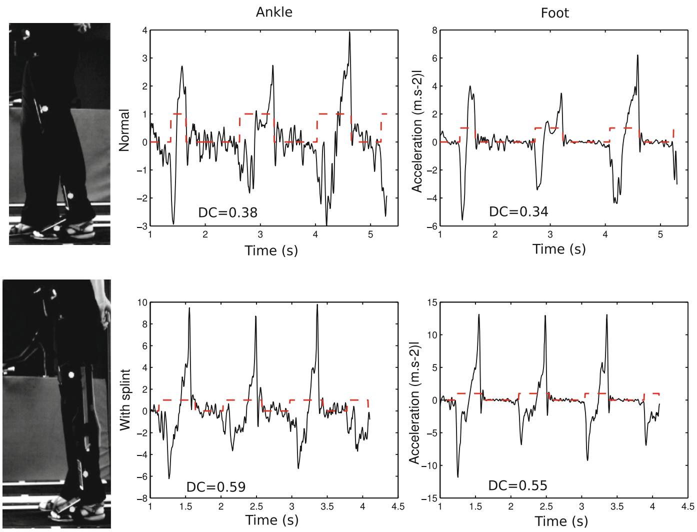

Fig. 3. First row: normal walk. Second row: walk with knee splint. Middle column: ground truth acceleration signals from the ankle segment. Right column: ground truth acceleration signals from the foot segment. Averaged DC for the 2 min test is given for each condition in the lower left angle of the graph. Note that only the three first gait cycles are displayed.

Table 1. Averaged DC and standard deviation computed for the 2 min test regarding the different sources of noise for the foot. For each line, the other sources of noise are fixed: quantification, sampling rate and jitter studies are carried out with respectively 50 Hz and no jitter, 13 bits and no jitter and 13 bits and 50 Hz.

# Bits	13	12	11	10	9	8
Normal	0.338 ± 0.002	0.338 ± 0.002	0.338 ± 0.002	0.337 ± 0.003	0.328 ± 0.005	0.321 ± 0.011
With splint	0.523 ± 0.002	0.523 ± 0.002	0.523 ± 0.003	0.521 ± 0.003	0.510 ± 0.012	0.505 ± 0.023
Rate	50	40	30	20	10	
Normal	0.338 ± 0.002	0.328 ± 0.005	0.327 ± 0.015	0.315 ± 0.022	0.303 ± 0.030	
With splint	0.523 ± 0.002	0.519 ± 0.009	0.517 ± 0.025	0.506 ± 0.031	0.483 ± 0.039	
Jitter	S6	A5	A3	F6		
Normal	0.3204 ± 0.021	0.3294 ± 0.004	0.3305 ± 0.003	0.3232 ± 0.023		
With splint	0.5010 ± 0.033	0.5150 ± 0.064	0.5152 ± 0.071	0.5061 ± 0.037		

In order to measure the impact of the three noise sources on DC, we simulated degraded signals from the ground-truth accelerometer signals for observed ranges in Sect. 2. In other words, ground truth signals were sampled by the appropriate factor, quantified on the adequate number of bits and jittered by the four distributions given in Fig. 1 to aim the observed ranges. The analysis of DC regarding the different noise sources (see Table 1) has to be done in comparison with DC observed in ground truth (see Fig. 3).

5 Discussion and Conclusion

DC is able to distinguish normal free walk from constrained walk (miming claudication with a knee splint) on ground truth data at the levels of ankle and foot: the Welch's t-test respectively reported a p-value of 1.18e−4 and 3.16e−05. DC has not been applied to thigh and hip signals because it was not significative to distinguish normal walk from claudication: these signals have smaller amplitudes and hence flat and non-flat phases less marked. DC proved to be robust when confronted with realistic quantification, sampling rate and jitter variability observed on smartphones's accelerometers: the Welch's t-test reported a p-value below 0.05 for all cases reported in Table 1. Noise tend to under evaluate the swing phase whatever the source of noise leading to a smaller DC. The most critical noise source appears to be the sampling rate and its impacts seems to be greater with splint: if the sampling is too coarse, peaks of acceleration constituting the non-flat phase can be missed.

We presented an original noise analysis of smartphone accelerometers from devices of varying prices for a specific informational task: claudication detection. Claudication was detected by estimating duty cycle from the vertical accelerometer signal. Three noise sources were investigated: sampling jitter, sampling rate and quantification. Validation of this study was based on ground-truth from high frame rate video camera. Our results demonstrate for the first time that smartphones' sensors are sufficiently accurate to detect claudication. This pilot study opens interesting perspectives: state-of-the-art methods for claudication detection could be compared to determine which one is the most robust to the typical noises identified in this study; and smartphones' sensors could be tested to detect other walking irregularities.

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