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Do We Walk Differently at Home? A Context-Aware Gait Analysis System in Continuous Real-World Environments

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Abstract— **Driven by the advancements of wearable sensors and signal processing algorithms, studies on continuous real-world monitoring are of major interest in the field of clinical gait and motion analysis. While real-world studies enable a more detailed and realistic insight into various mobility parameters such as walking speed, confounding and environmental factors might skew those digital mobility outcomes (DMOs), making the interpretation of results challenging. To consider confounding factors, context information needs to be included in the analysis. In this work, we present a context-aware mobile gait analysis system that can distinguish between gait recorded *at home* and *not at home* based on Bluetooth proximity information. The system was evaluated on 9 healthy subjects and 6 Parkinsons disease (PD) patients. The classification of the *at home/not at home* context reached an average F1-score of 98.2 $\pm$ 3.2 %. A context-aware analysis of gait parameters revealed different walking bout length distributions between the two environmental conditions. Furthermore, a reduction of gait speed within the *at home* context compared to walking *not at home* of 8.9 $\pm$ 9.4 % and 8.7 $\pm$ 5.9 % on average for healthy and PD subjects was found, respectively. Our results indicate the influence of the recording environment on DMOs and, therefore, emphasize the importance of context in the analysis of continuous motion data. Hence, the presented work contributes to a better understanding of confounding factors for future real-world studies.**

I. Introduction

Wearable sensors with inertial measurement units (IMUs) are useful to objectively measure various mobility parameters and close the gap between specialized motion laboratories and continuous monitoring in real-world scenarios [1]. Due to their low cost and small size, they can unobtrusively assess several digital mobility outcomes (DMOs) in a person's everyday life. Those DMOs range from macro-level parameters, like walking bout (WB) distributions to spatio-temporal micro parameters, like stride length or gait speed [2]. Therefore, mobile sensor-based systems can help to quantify clinically relevant outcomes like mobility, gait performance, or fall risk as well as disease fluctuations or progression in neurological diseases like Parkinson's disease (PD) [2]. While wearable sensors already proved their feasibility to objectively measure gait parameters in standardized clinical settings [3], continuous real-world monitoring enables a more detailed and realistic insight into a patients health status which cannot be assessed during hospital checkups [1], [4]. However, in real-world studies, new challenges arise, such as various environmental factors that could potentially influence mobility behaviour and thus skew DMOs [2].

To control potential confounding factors, Wang et al. [5] proposed a wearable gait analysis system that used GPS location and IMU sensor data to successfully identify repeating paths to enable more comparable conditions in future studies. Patterson et al. [6] found significant differences in stride times of healthy subjects between simulated conditions like walking on a rough surface (gravel) or in a busy hallway while assessing context by a wearable camera. Lunardini et al. [7] showed that dual-tasking while walking in an outdoor scenario resulted in a reduced cadence in an elderly population. First real-world patient studies conducted by Del Din et al. [1], or Mc Ardle et al. [4] could indicate that WB length influences gait parameters and, therefore, could be interpreted as ”proxy measures of context” with varying clinical information gains. Even gait parameters assessed during standardized gait tests are influenced by changes of context, as reported by Gaßner et al. [8], where a reduced gait speed at home compared to in-clinic measurements of PD patients was found.

Evidently, there is a need for secondary data sources during real-world studies that can be considered along with the primary DMOs to enable comparable conditions or to consider confounding effects. Especially, the influence of frequent conditions like walking *at home* compared to walking *not at home* on gait parameters in unsupervised real-world studies has not been addressed in detail yet and systems which can assess such context information in an unobtrusive way are still missing.

In this work, we present a context-aware gait analysis system that can distinguish between gait recorded *at home* as well as gait *not at home* based on Bluetooth Low Energy (BLE) proximity information. The context detection mechanism was evaluated against diary annotations during a real-world gait monitoring study. Furthermore, we investigated the influence of the acquired context information on gait parameters of a cohort of 9 young and healthy and 6 PD patients. Our proposed system identified context-related differences in the WB length distribution and gait speed. The presented approach could be easily integrated into other monitoring systems which utilize BLE enabled sensors to better understand environmental and confounding factors in future real-world movement analysis studies.

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II. Methods

A. System Overview

The proposed system consisted of two major parts: first, the wearable sensor units (Portabiles GmbH, Germany) for gait data recording, and second, a gateway device responsible for aggregating sensor data and assessing context information (Fig. 1). The sensor units feature BLE 5.0 connectivity and incorporate an IMU with a 3D accelerometer and a 3D gyroscope. The sensors are able to record more than 40 h of continuous 6-axis IMU data and can be recharged wirelessly based on the Qi-standard. The gateway device, developed for this study, was based on a Raspberry Pi 3B+ to receive data from the IMU sensor units and continuously scan for BLE advertising packets. Respective Received Signal Strength Indicator (RSSI) data was recorded to derive the context information. Therefore, the wearable sensors additionally served as BLE beacons sending advertisement packets with an interval of 500 ms. The sensors started logging raw IMU data to their internal storage as soon as they were removed from their charging station and terminated the recording when put back onto the charger at the end of a day. Subsequently, the gateway automatically downloaded the recorded data via a BLE connection overnight, re-synced the sensor internal clock, and triggered a flash erase.

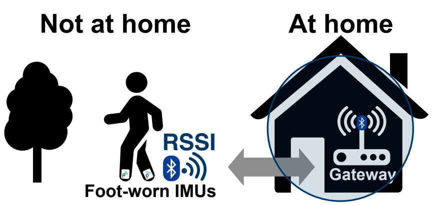

Fig. 1. Concept of the context detection mechanism: Foot-worn IMU sensors serve as BLE beacons, resulting in a binary context classification.

B. Study Design

In the first part of the study (prior to the COVID-19 pandemic), the system was evaluated on 9 healthy subjects (Tab. I), who used the system for 7 consecutive days. Participants wore the sensors on their shoes' lateral side (or socks, if preferred) using 3D printed clips. To evaluate the RSSI-based context detection, the subjects were asked to log the time whenever they left the house or came back home using a timestamp smartphone application ("TimeStamp" from Google Play Store). Additionally, we also performed a pilot study (during the COVID-19 pandemic) with 6 PD patients (Table I) and an updated version of the system. Patients received a set of orthopaedic shoes with the sensor attached to the shoes instep position to wear the system continuously for 14 consecutive days. PD patients did not perform manual time stamp annotations.

The study was approved by the local ethics committee Re-No. 165_18B (Friedrich-Alexander-University Erlangen-Nuremberg, Germany). All participants gave written, informed consent, prior to the data collection.

TABLE I
Demographics of study population.

	Healthy	Parkinson's Disease
Demographics		
Age [years]	26.6 ± 1.8	64.8 ± 8.8
Sex (f/m)	2/7	2/4
Height [cm]	177.0 ± 9.5	171.3 ± 13.5
Weight [kg]	75.7 ± 11.9	68.2 ± 12.6
UPDRS-III	-	13.8 ± 5.6
H & Y	-	2.2 ± 0.4
Recording Setup		
Sampling rate [Hz]	204.8	102.4
Duration [days]	7	14
Sensor position	lateral	instep

C. Context Detection Pipeline

For this work, a binary context detection was considered. The system differentiates if a person is *at home* or *not at home*, comparable to a geofencing approach. Therefore, the acquired RSSI data were re-sampled to a fixed time period of 10 s for easier handling. Second, the generated RSSI data streams of the left- and right-sensor were fused by calculating their mean over each time point (as illustrated in Fig. 2). As long as any advertisement packets were received, the sensors had to be still within the range of the gateway and, therefore, the context information was set to *at home*. In case no advertisement packets were received, the sensors were considered out of range and thus *not at home*. However, as obstacles or moving around at home could influence an all-time stable reception of BLE packets, context changes with a window size of less than 10 min were rejected.

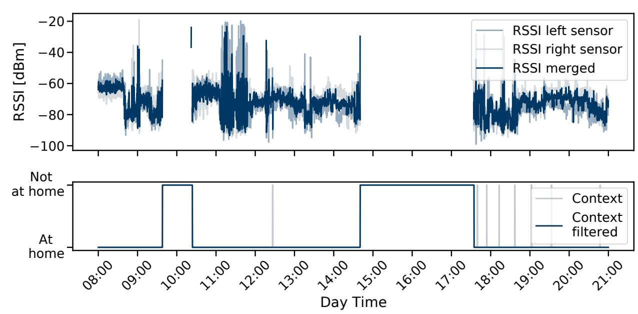

Fig. 2. Example of a re-sampled and merged RSSI data stream over one day as well as derived context information.

D. Context-Aware Gait Analysis Pipeline

All sensors were calibrated, according to Ferraris et al. [9] prior to the recordings. To extract gait parameters from the IMU data, the following pipeline was applied: Gait sequences were extracted using harmonic frequencies [10] to identify potential WB candidates. The sensor-coordinate-frame was aligned to gravity based on static acceleration windows for each WB to ensure the sensor's constant alignment to the body-frame. Next, stride candidates were segmented using a template matching method, based on dynamic time warping [11]. Temporal stride parameters were derived from detected gait events and spatial stride parameters were calculated using a zero-velocity-based double integration approach [12].

Stride parameters were divided based on their start timestamp and respective RSSI-based context information into strides *at home* and strides *not at home*. Next, individual strides were filtered to keep only straight strides (sensor heading angle $\pm 45°$) and finally combined to WBs (minimum number of strides = 5, maximum resting period between WBs = 3 s) for further analysis.

1) Walking Bout Length Distribution: The resulting WBs were divided by their recording context and grouped by their number of strides into bins. To account for absolute differences in the number of WBs between subjects, WB counts were normalized by the total number of WBs within the recording period for each subject individually. Due to the constrained space and finite walking path available in the *at home* environment, an upper limit for the *at home* WB length distribution was expected. This limit was defined as the 95$^{\text{th}}$ percentile ($N_{P95home}$) of the WB length distribution *at home* and calculated per subject. The definition was chosen to exclude potential outliers (long WBs) in the *at home* context which might be misclassified during the transition between *at home/not at home*, or during short context changes which could not be detected by our system.

2) Gait Speed: To analyze the effect of the *at home* vs the *not at home* context on a primary DMO, the gait speed was considered. To consider potential differences caused by varying WB length (as previously reported in [1]), an additional condition was introduced, namely *not at home*$_{N_{P95}}$. Here, only *not at home* WBs that contain a smaller or equal number of strides than the before defined limit $N_{P95home}$ were included, to only compare WBs of equal length. This should result in a matching condition for the *at home* group where differences can be solely attributed to the change in context rather than influences due to WB length. Finally, the mean gait speed of all strides within each condition was calculated per subject and compared between the different conditions. Therefore, gait speed was normalized per subject to their gait speed *not at home*.

III. Results

A. Context Detection Evaluation

In total, 164 context changes (leaving the house or coming home) were annotated by the healthy subject cohort; 149 of these events could be captured by our proposed system with a timing error of 0.59 ± 4.30 min. Overall, 15 of the annotated events were missed (no matching event available in a 30 min time window). These events could be identified as very short labelled time windows, for example if a subject labelled leaving the house for less than 10 min. Also, some subjects reported that they occasionally forgot to label leaving the house or coming back home using the smartphone app, which is a common problem with subjective diary annotations. The binary context classification, reached an average F1-score of 98.2 ± 3.2 % (precision: 98.2 ± 2.2 %, recall: 98.2 ± 4.3 %) in terms of correctly classified 10 s *not at home* time windows. In total 531 h of recording time in the *not at home* and 307 h in the *at home* context were available.

B. Context-Aware Gait Parameters

1) Walking Bout Length Distribution: Subjects of the healthy cohort walked most of their WBs *not at home*, with a high proportion of short WBs (Fig. 3). For the PD cohort, the frequency of WBs *at home* and *not at home* was similar for the shorter WB groups with a slightly higher proportion of short WBs *at home*. The limit for the WB length *at home* ($N_{P95home}$) was found to be 16.8 ± 6.2 strides for the healthy subjects and 44.2 ± 8.6 strides for the PD patients, respectively. Longer WBs with more than 50 strides were almost exclusively available within the *not at home* context.

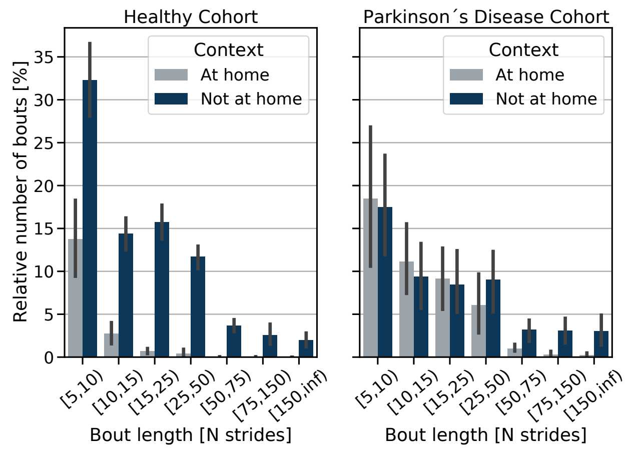

Fig. 3. Normalized WB length distributions grouped by their recording context. Bars represent mean values; error bars correspond to the 95 % confidence interval using bootstrapping.

2) Gait Speed: Subjects of both cohorts tended to walk slower in the *at home* context (Fig. 4). Compared to the *not at home* context, the gait speed was reduced by 27.2 ± 7.2 % for healthy subjects and 20.7 ± 9.4 % for the PD patients. After the exclusion of long WBs, resulting in the matched condition *not at home*$_{N_{P95}}$, the reduction in gait speed to the *at home* context was found to be 8.9 ± 9.4 % and 8.7 ± 5.9 % for the healthy and PD cohort, respectively.

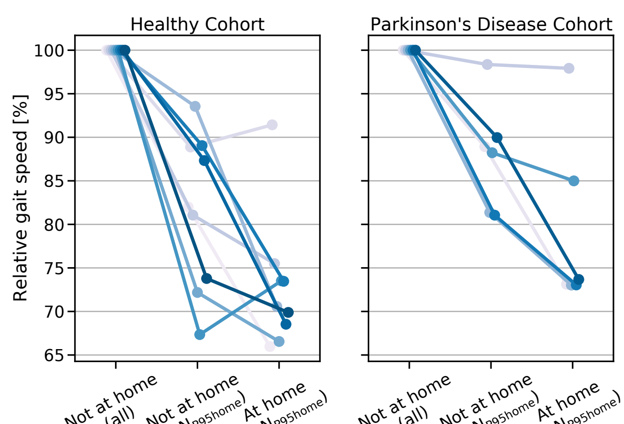

Fig. 4. Mean values of gait speed, normalized to the *not at home* context. Each line represents an individual subject.

IV. Discussion

Our proposed context-aware gait analysis system was able to accurately differentiate between *at home* as well as *not at home* WBs with a promising context classification F1-score of $98.2 \pm 3.2\,\%$ without the need for additional hardware (e.g., GPS loggers) carried by subjects or error-prone diary annotations. This additional context information could enable more comparable conditions as proposed by Wang et al. [5] or yield information about sedentary behaviour and community participation.

Furthermore, our context-aware analysis approach revealed differences in WB length distribution as well as gait speed related to the walking environment. The healthy subject cohort walked considerably more WBs *not at home*, with a low average limit ($N_{P95home}$) of 16.1 strides *at home*. This is most likely related to the fact that those subjects (mostly employees and students) had to leave their house to go to work or attend lectures during workdays and, therefore, spent most of their activities *not at home*. For the PD cohort, in contrast, the distribution of *at home* and *not at home* WBs was similar, with an higher average limit ($N_{P95home}$) of 44.2 strides *at home*. The increased proportion of *at home* strides and higher limit could be explained by more time and activities spent *at home*, which could be a first indication for reduced community participation (this might be even enhanced by the COVID-19 pandemic). The size or available space within individual homes might be an additional factor for longer and more *at home* WBs, but was not assessed during our study. WBs with more than 50 strides were almost exclusively found in the *not at home* context for both groups. These WBs could most likely be attributed to outdoor walking in an unconstrained environment.

Regarding gait speed, average differences of up to 27.2 % for healthy and 20.7 % for PD subjects were found, when comparing walking *not at home* with *at home*. To consider the effects of varying WB length as reported previously by Del Din et al. [1], the additional condition *not at home*$_{N_{P95}}$ was introduced by applying the defined *at home* WB length limit. Our results confirmed that parts of the difference in gait speed were related to long WBs, which were only present in the *not at home* context. However, after correcting the effect of WB length, an average difference of 8.9 % and 8.7 % in reduced gait speed was still present, for the healthy and PD cohort, respectively. These differences in gait speed could be attributed to the change in context, which might be related to less space and a more constrained walking environment *at home*, as already reported by Gaßner et al. [8]. Furthermore, social and psychological factors like walking more relaxed or less target-oriented *at home* might be reasons for the reduced gait speed. The larger differences for the healthy subjects could be explained by an increased functional capacity and overall higher maximum walking speed in the *not at home* context compared to the PD cohort. One PD subject showed only small variations between all conditions but also only few *not at home* WBs, compared to the others, which might be related to sedentary behaviour or low functional capacity.

V. Conclusion and Outlook

The presented context-aware gait analysis system accurately distinguished between WBs *at home* or *not at home*, using BLE-based proximity information. Our results revealed context-related differences in WB length distribution as well as in gait speed. The PD cohort showed an increased proportion of WBs *at home* compared to *not at home*, which could be a first indicator for sedentary behaviour or reduced community participation. Furthermore, a context-related reduction of gait speed, for almost all investigated subjects, was identified, which might alter the interpretation of such DMOs if not considered. Due to the rather low number of subjects, similar experiments need to be repeated in a larger patient cohort to enable also profound statistical analysis of context-related effects. Overall, our work contributes to a better understanding of the effects of confounding environmental factors on DMOs in sensor-based real-world gait analysis.

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