Measurement of Accelerometry-based Gait Parameters in People with and without Dementia in the Field

A Technical Feasibility Study

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Keywords
Field study, dementia, accelerometer, gait parameters

1. Introduction

Gait can be seen as an expression of multiple intrinsic factors of a patient, e.g., medication, various diseases, or even the person’s mood, which can have an influence on the gait pattern. But also extrinsic factors like careful stepping on a slippery ground or a changed walking speed due to being accompanied by somebody can have an effect on the person’s gait.

Gait analyses, such as the Tinetti-Test [1], are used to measure the patient’s general fitness [2], the rehabilitation progress [3], or the risk of falling [4]. In practice, this is done by physicians or physical therapists. The examiner has to be very experienced in order to notice small deviations that distinguish between normal and pathological gait. To achieve objectiveness in gait analysis, sensor-based systems, such as accelerometers, gain in importance [3, 5]. Due to the progress in MEMS technology, accelerometers are getting smaller and cheaper. The advantages of such sensors are that they can measure gait in an unobtrusive manner and that they are suited to be deployed in field studies or in real-life applications. Smartphones are such real-life applications, which use accelerometers mainly for display orientation adjustment. Beyond, these accelerometer-equipped devices can also be used to measure the amount of physical activity or even for activity recognition [6]. Thereby, smartphones are unobtrusive devices, which can provide a suitable platform for accelerometer-based gait analyses in the future, but it is also imaginable that accelerometers get integrated into belt buckles or trouser buttons.

There are a lot of health-related conditions associated with dementia, including a higher risk of falling [7, 8], changes in behavior [9, 10], or gait patterns [11, 12]. From the perspective of demographic change, the number of patients suffering from dementia is expected to increase significantly. Currently, there are 35 million patients with dementia worldwide, which is predicted to nearly double every 20 years [13]. The worldwide costs in 2009 were es-
1.1 Related Work

Many recent studies used accelerometers in analyzing gait patterns in frail elderly and especially in patients with dementia [11, 15, 16]. All mentioned studies investigated subjects in a supervised clinical setting.

Ilmker et al. investigated a group of 15 patients with dementia wearing an accelerometer at the trunk during a three minute walk [11]. They computed gait parameters from the accelerometric data and compared these parameters with a group of 14 age-matched controls and another group of 12 younger adults. The dementia group showed decreased walking speed, longer stride time, higher stride time variability, lower magnitude of accelerations, and lower variance of the accelerometric signal compared with the other groups.

Trunk accelerations were also measured by Lamoth et al. [15]. The setup was a 40 m walkway and the subjects were asked to walk this distance for 3 minutes at a self-selected speed. They found no differences between the gait parameters of both groups (13 patients with dementia and 13 age-matched controls). Especially, walking speed differed not significantly. But they found differences in dual-tasking (walking and a verbal fluency test).

Gillain et al. obtained similar results [16]. They measured the gait of 6 patients with Alzheimer’s disease, 14 with a mild cognitive impairment and 14 healthy, age-matched controls. The subjects were asked to complete a 30 m walk at self-selected speed. The results showed differences between the three groups in gait speed, stride length (which was defined as speed divided by frequency), and stride length regularity in single as well as in dual-task performance tests. But they did not find differences in gait frequency and symmetry during single-tasking.

In addition to accelerometers, there is also a wide spectrum of other sensor systems used for quantitative gait analyses, e.g. Vicon motion capturing systems (Vicon Motion Systems, Los Angeles, CA, USA) [17], GAITRite walkway (CIR Systems, Sparta, NJ, USA) [18], Kinect (Microsoft, Redmond, WA, USA) [19] and Stride Analyzer (B&L Engineering, Tustin, CA, USA). An overview about such systems can be found in [17]. Most of these systems have the disadvantage that their field of coverage is limited. Accelerometers might be a cheap alternative to these systems.

In all the mentioned studies, accelerometers and other sensor systems have been successfully used in supervised gait analyses. Supervision can influence behavior especially the gait of a subject as long as the subject is aware of the supervisor. This effect, named as Hawthorne effect, can cause a bias in the measured data [20, 21]. The use of unobtrusive sensors in unsupervised settings will cause the subject to be unaware of the measurement after a while and to obtain its normal behavior. In unsupervised settings, measuring during the subject’s everyday life, the amount of data in terms of walking episodes is expected to be higher compared to an once or more often performed test in a supervised setting [4, 11, 22]. To the author’s knowledge there has been no trial to measure gait parameters using accelerometers in a group of patients with dementia during their everyday life.

2. Objective

Aim of our research was to evaluate gait parameters in a field study using a single waist-mounted accelerometer. Due to the lack of a ground truth in unsupervised settings, we decided to choose two groups: A group of patients with dementia (DEM) and a group of active older people (ACT). This was done because of the expected difference between the two groups. We intended to investigate if this difference is quantifiable using accelerometry-based gait parameters. It was explicitly not intended to construct a diagnostic tool for dementia in this technical feasibility study. Our hypothesis was that DEM shows a lower walking speed compared to ACT [23], a less harmonic gait [23], and a lower variance of the accelerometric signal [11].

3. Methods

3.1 Hard- and Software

The used sensor node was a Shimmer sensor Rev. 1.3 [24] with an integrated triaxial analog accelerometer MMA7260Q [25] (see figure 1). The sensor node was configured at a resolution of 12 bit and a sensitivity of ± 4 g. The data was stored on a microSD card and analyzed after the measurements took place.

The sample rate of 51.2 Hz was chosen due to a human’s gait being associated with frequencies between 0.25 and 20 Hz [26]. Thus, the chosen sample rate is sufficiently high according to the sampling theorem.

3.2 Gait Parameters

Walking was detected using an improved version of the auto-correlation method described in [27]. This version has been modified from a step detector to a more robust walking episode detection algorithm, so that the detection will not be affected by missing or slower/faster steps. It remains to be shown how well the system does detect irregular gait. In a first step, the algorithm was evaluated with an additional data set in young healthy adults. The results can be found in section 4.2.
Only continuous and uninterrupted walking episodes of at least 20 seconds were considered for the gait analysis, as gait parameters computed from shorter walking episodes were empirically identified as being unstable in preliminary studies of the authors. Scanaill et al. reported that a 6 m walkway is too short to gather reliable gait parameters using accelerometry [22].

Because some gait parameters, specified in the following, refer to a certain axis of the human body, Figure 2 shows the definition of all axes. The alignment of the axes of the sensor node to the human body was done using a previously developed algorithm [28].

The following prospectively chosen parameters were identified by interviews with professionals in the field of geriatrics to characterize gait and can also be found in the literature, e.g. [11, 15, 16, 29–31]:

1. Gait speed \( v \): computed from the subject's anterior-posterior acceleration \( a_{ap} \) using

\[
v(t) = \int_0^T a_{ap}(t) \, dt,
\]

whereas \( T \) is the duration of the walking episode. The Simpson rule was used for numerical integration in all cases.

2. Average kinetic energy \( \overline{E}_{\text{avg}} \): the kinetic energy of gait should consider the acceleration measured in all three axes denoted as norm: \( ||a(t)|| \). Since the accelerometer signal also contains the gravitational force of the earth of 1 g, the norm was corrected by this static influence:

\[
\overline{E}_{\text{avg}} = \frac{1}{2} \cdot m \overline{v}^2 = \frac{1}{2} \cdot m \cdot \left( \int_0^T ||a(t)|| - 1 \, dt \right)^2.
\]

3. Compensation motions \( \text{comp} \) in all three axes and the norm of the measured acceleration vector \( a \):

\[
\text{comp}_{\text{axis}} = \int_0^T |a_{\text{axis}}(t) - \overline{a}_{\text{axis}}| \, dt,
\]

whereas axis can be one of ap, lr, si, or norm. \( \overline{a}_{\text{axis}} \) denotes the mean acceleration value of axis.

4. Variance \( \text{var}_{\text{axis}} \) in all three axes and the norm of the accelerometric signal.

5. Main frequency: the frequency of the weighted maximum value in the frequency spectrum (determined by a spectral analysis using the discrete Fourier transformation (DFT)). The weighting was done using a normal distribution with an expectation value of 2 Hz and a standard deviation of 1 Hz. This may fit to the gait of frail elderly people as well as to a runner.

6. "Gait harmony": composite parameter between 0 and 1 of the dominant frequencies. \( f \) to treat the multiples of \( f \) (harmonics of the DFT) in an appropriate way, we employed a sawtooth function \( \mu(f) \) with range \( [0, 1] \) in a preliminary step. After that, \( \sigma(f) \) was computed as the value DFT(\( f \)). Finally, a fusion of the tupels (\( \mu, \sigma \)) was obtained by a simple Kalman filter [32]. The "gait harmony" is the maximum value with respect to the result of the fusion.

### 3.3 Subjects

Two groups of elderly subjects were investigated. The first group comprised 10 patients with dementia (group DEM), which were investigated 2011, April 14 – August 22. They were recruited from three nursing homes in the region of Braunschweig, Germany.

The second group, the control group, comprised 10 active elderly people (group ACT) who do exercise regularly (at least once a week). This group was investigated 2011, February 21 – May 14 and was recruited from a patient empowerment event at Hannover Medical School, Germany.

The subjects wore the sensor nodes in a case that was attached at the right hip. The hip was chosen, because this position is near the center of mass and therefore the occurrence of movement artifacts would be reduced. The second reason is that the cases can be attached to a belt, which simplifies the procedure of applying the case and increases the acceptance of subjects and nurses. The right side of the hip was chosen, for reasons of reproducibility. The subjects were asked to wear the sensor node for one week, but only during the day, because the subjects may feel uncomfortable to wear the sensor case in the night or during sleep. Both groups were measured while they performed their normal daily activities during the study. This study was approved by the local ethics committee. All subjects respectively their legal guardians (in case of patients with dementia who have a legal guardian) have given their written informed consent to participate.

### 3.4 Data Analysis

In a first step, we computed the AUC values ("Area Under the Curve" also called ROC area) for each gait parameter. This value ranges from 0.5 to 1, whereby AUC(parameter) = 0.5 means no discriminating ability between the groups and AUC(parameter) = 1 means perfect discrimination.
After that, the computed gait parameters were analyzed using the machine learning software WEKA version 3.7.4 [33]. We used three different classification algorithms to distinguish between the groups DEM and ACT. Since the relationship of the parameters regarding the target variable (group member ACT or DEM) was assumed to be hierarchical, the decision tree induction algorithm J48 (a WEKA implementation of the C4.5 algorithm [34]) was used. The hierarchical relation can be seen especially in the casual relationship between gait velocity and step frequency. Gait of patients with dementia may change to small steps with a higher frequency [11]. On the other hand, long and slow strides associated with a low step frequency can lead to gait instability [26].

The second method used was the logistic regression method, because of the binary response of the target variable. ZeroR was used as the reference algorithm, which always predicts the most common value (the mode) of the target variable. For evaluation purposes a 10-fold cross-validation method was used.

4. Results

4.1 Subject and Data

The DEM group (7 female/3 male) was aged 83.5 ± 5.14 years (average ± standard deviation) and had a MMSE [35] score below 24 points (out of 30). The subjects of the ACT group (5 female/5 male) were aged 68.3 ± 6.16 years. The algorithm to detect walking episodes was able to identify 1,187 episodes of at least 20 s in the DEM group during the week of wearing the sensor node. The ACT group produced 1,809 episodes of at least 20 s in average. Due to the circumstance that subjects wore the sensor node only in daytime, the DEM group had a measured wearing time per day of 9.56 ± 1.0 h and the ACT group of 10.16 ± 0.76 h.

4.2 Walking Episode Detector

We evaluated the walking episode detector with 4 young and healthy subjects walking 60 m at self-selected speed. The algorithm detected all of the walking episodes, but showed a delay at the beginning of walking of 2.7 s in average. This results in approx. 5 steps, because the minimum of steps to start to detect walking was defined by 3. At the end of walking the delay is 1.1 s.

4.3 Parameters and Classification Results

To evaluate the discriminating ability of each parameter, the AUC values were computed. The results are summarized in Table 1.

The gait parameters were computed for all identified walking episodes, so that each walking episode represents an instance to classify. The J48 algorithm induced a tree with 27 nodes, which is shown in Figure 3. Table 2 shows the rate of correctly classified instances, Cohen’s κ [36] and the AUC for the generated models.

Due to the disparity of the groups DEM and ACT, the duration of the uninterrupted walking sections is different. The average duration in group DEM was 36.3 ± 21.5 s (95%-confidence interval of the average using a percentile bootstrap method with R = 10,000 repetitions: [35.12, 37.56]) and in group ACT 82.0 ± 147.3 s (95%-confidence interval of the average: [75.67, 89.11]). The duration of the walking episodes could have affected the computed gait parameters. Hence, we studied the influence of the duration on the gait parameters using the sample correlation coefficient. The results are shown in Table 3. Histograms of the distributions of the detected walking durations are shown in Figure 4.

5. Discussion

The subjects of both groups had a good compliance in wearing the sensor node. This is reflected by the average wearing time. The results showed that in field studies the amount of analyzable data (in terms of walking episodes) is very high compared to a supervised study in a clinical context, where usually only one or a few walks (e.g. for reliability reasons) per subject are measured, which is directly related to the study costs due to the need for a supervisor.

The ACT group was more active and had longer walking episodes compared to DEM. At a maximum, an episode of 3,572 seconds of continuous and uninterrupted walking was detected during a Nordic walking workout. The maximum duration in the DEM group was 241 seconds. Against this background the influence of the duration of walking episodes with respect to the gait parameters was studied. Although the gait parameters seemed to be positively correlated with the duration, the correlation is negligibly small. The distribution of the duration in Figure 4 shows the difference between the groups. This difference might have also been affected by age.

The analysis of the AUC values of the gait parameters showed that most of the parameters performed well in distinguishing between the groups ACT and DEM. Especially, the compensation and variance parameters have the highest AUC values (between 0.88 and 0.92). The difference in variance of the accelerometric signal was already reported from a supervised setting [11]. To the authors’ best knowledge, the compensation parameters of this study were not investigated in similar settings by now.

An unexpected result was the low AUC values for the velocity (gait speed) and the
main gait frequency. These two parameters are often stated to be associated with the change of gait in people with dementia [23, 37]. But there are also contrary studies [15, 16]. Scherder et al. found in a literature review indications that only some types of dementia might be associated with a decreased gait speed [38]. There are too few studies, which investigated gait and different types of dementia or preclinical stages of dementia so that a definite answer cannot be given, yet.

It was possible to train classification models, which showed a similar rate of correctly classified instances of nearly 90%. Although this is not a perfect classification result, it seems to be possible to distinguish between the groups ACT and DEM merely on the basis of objectively and unsupervised measured gait parameters. However, misclassified instances emerged from walking episodes of less than 25 seconds. ZeroR was used as reference algorithm to simply classify all instances as ACT to show the minimum expectable result. Due to the number of available walking episodes in both groups (1,809 in ACT vs. 1,178 in DEM) this model reached a result of 60%.

The time of investigation differed for both groups. DEM was recruited in spring and summer, ACT in winter and spring. This might have an influence on the measurements, because activities could change in different seasons. It is likely that walking episodes in DEM group were longer, especially if they were measured outdoor. But in winter this group might stay more often indoors, because of slippery weather conditions. It can also be assumed that the ACT group was less active in winter.

The intra-individual analysis of the gait parameters also showed that the variability of these parameters may have a high potential regarding the informative value and needs further investigation. Due to the prospective choice of the classification and analyzing methods, we did not include the variability in our instance-based analysis, yet. A next step is to use classification algorithms that consider the change of the parameters over time in addition to the instance-based analysis.

The choice of the groups ACT and DEM was made intentionally, because of the expected difference between these groups. Primarily, we wanted to evaluate

![Figure 3](image-url)  
*Figure 3* The result of the J48 decision tree induction

<table>
<thead>
<tr>
<th>Classification algorithm</th>
<th>Correctly classified instances</th>
<th>Cohen’s kappa [25]</th>
<th>AUC</th>
</tr>
</thead>
<tbody>
<tr>
<td>J48</td>
<td>88.9%</td>
<td>0.77</td>
<td>0.926</td>
</tr>
<tr>
<td>Logistic regression</td>
<td>87.4%</td>
<td>0.74</td>
<td>0.914</td>
</tr>
<tr>
<td>ZeroR</td>
<td>60.4%</td>
<td>0*</td>
<td>0.5</td>
</tr>
</tbody>
</table>

*Table 2* Results of the used classifiers. *Cohen’s kappa is zero, because all instances were classified as ACT and therefore, the AUC equals 0.5.*
the technical feasibility to measure gait parameters in an unsupervised setting. The expected differences between these groups are reflected by the measurements.

This paper presented results of a pilot study in the context of a larger prospective study, which targets to distinguish between fallers and non-fallers in a cohort of patients with dementia using a similar study setting. If the measured gait parameters had failed to detect the expected difference between DEM and ACT, it would hardly be possible to distinguish between fallers and non-fallers using this setup. So, it was a necessary condition to proceed with the larger study, to extend the study population, and to continue with the more challenging question.

### 6. Conclusion

This technical feasibility study showed that it is possible to compute well interpretable, relatively duration-independent and objectively measured gait parameters in unsupervised settings from accelerometric data using a single waist-mounted sensor. It was possible to distinguish between patients suffering from dementia and active elderly people using these parameters.

#### 6.1 Limitations

There are a number of limitations to discuss. First, the choice of the groups was intended to reach a high variability between both groups. We intended to evaluate gait parameters in an unsupervised setting with the use of this variability. The groups did not only differ in the diagnose dementia, but also in age, which could also have an influence on gait. Thus, a structural equivalence of both groups is not given. That is why we did not intend to diagnose dementia based on the measured gait parameters. Second, the generalizability of the results should be proven with a larger cohort. In fact, we continue the measurements and enlarge our sample of subjects in the context of a larger study to assess the risk of falling in people with dementia using the gait parameters presented in this paper. Third, the duration of the walking episodes and the time of wearing the sensor node differed in both groups. It cannot be definitely excluded that this might had an influence on the results. Forth, no ground truth data were collected in this study, e.g.

<table>
<thead>
<tr>
<th>Gait parameter</th>
<th>Correlation in ACT group</th>
<th>Correlation in DEM group</th>
</tr>
</thead>
<tbody>
<tr>
<td>Velocity</td>
<td>0.11</td>
<td>0.06</td>
</tr>
<tr>
<td>Kinetic energy</td>
<td>0.04</td>
<td>0.01</td>
</tr>
<tr>
<td>Compensation norm</td>
<td>0.09</td>
<td>0.04</td>
</tr>
<tr>
<td>Compensation ap</td>
<td>0.05</td>
<td>0.01</td>
</tr>
<tr>
<td>Compensation lr</td>
<td>0.22</td>
<td>0.20</td>
</tr>
<tr>
<td>Compensation si</td>
<td>0.18</td>
<td>0.16</td>
</tr>
<tr>
<td>Variance norm</td>
<td>0.20</td>
<td>0.29</td>
</tr>
<tr>
<td>Variance ap</td>
<td>0.19</td>
<td>0.27</td>
</tr>
<tr>
<td>Variance lr</td>
<td>0.16</td>
<td>0.15</td>
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<tr>
<td>Variance si</td>
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<td>0.15</td>
</tr>
<tr>
<td>Main frequency</td>
<td>-0.02</td>
<td>-0.05</td>
</tr>
<tr>
<td>Gait harmony</td>
<td>0.17</td>
<td>0.08</td>
</tr>
</tbody>
</table>

Table 3  
Correlation of the gait parameters with the duration of the detected walking episodes in ACT and DEM group.

Figure 4  
Histograms of the distributions of the detected walking durations in seconds (logarithmic scale). The DEM group (left) shows shorter walking durations than the ACT group (right).
References