Stair Climb Power Measurements via Inertial Measurement Units
Towards an Unsupervised Assessment of Strength in Domestic Environments

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Abstract: In order to initiate interventions at an early stage of functional decline and thus, to extend independent living, the early detection of changes in functional ability is important. The Stair Climb Power Test (SCPT) is a standard test in geriatric assessments for strength as one of the essential components of functional ability. This test is also well suited for regular and frequent power measurements in daily life since the activity of climbing stairs is usually frequently performed.

We introduce an automated assessment of the SCPT based on inertial measurement units (IMU) in a study of 83 participants aged 70-87 years. For power evaluations of the lower extremities, the activity of climbing stairs was automatically classified via machine learning and the power was calculated based on the test duration and covered height. Climbing stairs was correctly classified in 93% of the cases. We also achieved a good correlation of the power calculations with the conventional stop watch measurements with a mean deviation of 2.35%. The system's sensitivity to detect the transition towards frailty has been confirmed. Furthermore, we discussed the general suitability of the automated stair climb power algorithm in unsupervised, standardized home-assessments.

1 INTRODUCTION

Functional ability is important for an independent living but with age functional decline is inevitable. The decline can be slowed down through timely preventive measures. For this purpose, early detection of performance changes is crucial. Usually, the functional status is evaluated via assessments, covering "strength", "mobility" and "balance" as essential parameters for the functional performance (Hellmers et al., 2017c). The power, which is related to the muscle strength, has shown to hold an important role in functional ability and seems to be a good indicator for functional decline (Reid and Fielding, 2012). For example, the power of the lower extremities is measured by the Nottingham power rig, cycle ergometry, rapid dynamic contractions on resistance training machines, maximal vertical jump (Hellmers et al., 2017b), stair climbing, stair sprinting, or sit-to-stand (STS) transfer (Zech et al., 2011). Bean et al. have shown that the muscular strength correlates with the determined stair climb power in the stair climb power test (SCPT) (Bean et al., 2007) and timed stair tests are considered as an objective measure of functional abilities (Nightingale et al., 2014). Especially the SCPT and the STS require less technique and physical demands. Therefore, they can be easily performed in all age groups and are often possible even with a beginning functional decline.

Figure 1 shows an assumed qualitative progress of the functional ability over age. While the ability remains stable until high age, at some point the ability suddenly declines. Thus, frequent assessments (e.g. monthly) would enable an early detection of functional decline and an initiation of preventive measures when they are needed most. It is important to detect performance changes Δa as soon as possible and to start interventions at an early stage because they can slow the functional decline and extend the time Δt of independent living. But since guided assessments require a lot of effort by health professionals (and thus, hold a significant financial burden to healthcare systems), they can only be conducted on an occasional basis.

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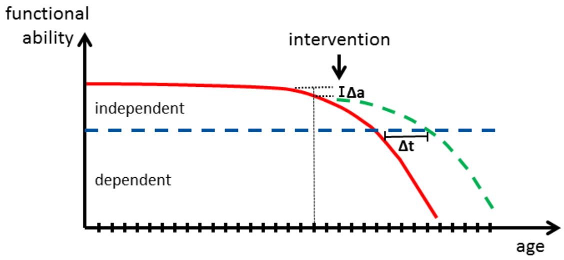

Figure 1: Qualitative progress of functional ability over time. Regularly performed assessments (lines on the horizontal axis) enable the possibility to detect early changes in the ability Δa to start interventions and slow the functional decline and extend the time Δt of independent living.

A promising approach to overcome conventional time-intensive and high-effort supervised assessments are technology-supported unsupervised and self-guided home-assessments, where the evaluation takes place during daily life activities. Frenken et al. (Frenken et al., 2012) pointed out that there is a clear need for technical support for implementing mobility assessments unsupervised in domestic environments in order to objectively measure capacity and performance of patients. Due to the regular and routinized manner of the SCPT execution, climbing stairs is a well suited activity to be considered for unsupervised assessments in daily living.
The SCPT is suitable for home-assessments, as long as elderlies climb stairs in their daily living. Whereby, wearable technologies offer a good approach for unobtrusive measurements.
Thus, we investigate an automated assessment of the (muscular) strength based on the common SCPT via 3D-accelerometers and 3D gyroscopes - so called inertial measurement units (IMUs)- integrated into belts. For an automated evaluation of the stair climbing performance two steps are necessary:

1. Classification of phases of stair climbing,
2. Calculation of the stair climb power.

The rest of the paper is structured as follows: We describe related work in Section 2 and the study design in Section 3. The method for the detection of stair climbing is presented in Section 4 and for power calculation in Section 5. The results and the evaluation are described in Section 6 and we discuss the suitability for home-assessments in Section 7. Finally, we describe our conclusions and future work in Section 8.

2 STATE OF THE ART

Regarding the suitability to classify climbing stairs, various combinations and placements of IMU-sensors have been shown to be practical. Table 1 shows a selection of studies and the applied sensors and positioning as well as the study size and the age of the participants. It is to mention that these studies do not only concentrate on as- or descending stairs but on the general recognition of several activities such as walking, sitting, standing, lying, running or cycling.
The first four examples show the influence of the sensor placements on the accuracy: Zheng et al. (Zheng et al., 2014) applied three IMUs positioned at one thigh, shank and foot and pressure sensors at the feet to achieve an accuracy of 99.03% with a linear discriminant analysis (LDA) classifier. Khan et al. (Khan et al., 2010) used one accelerometer at the chest and artificial neural nets (ANNs) as well as autoregressive (AR) modeling to get an accuracy of 99.0% in stair climbing recognition. Fida et al. (Fida et al., 2015) achieved an accuracy of 97.2% with a Support Vector Machine (SVM) as classifier and a 3D accelerometer and gyroscope attached to the shank of the dominant leg.
In the other studies mentioned in Table 1 the sensor was positioned at the waist and therefore have a similar sensor attachment as in our study. These studies show a lower precision, but the placement at the waist is less obtrusively and suitable for unsupervised attachments by the participants.
Shoaib et al. (Shoaib et al., 2014) applied an IMU and achieved an accuracy of >95% with a K Nearest Neighbor (kNN) classifier, whereas Fareed (Fareed, 2015) achieved 93.8% with a similar setting. A Support Vector Machine (SVM) as classification method was applied by Sun et al. (Sun et al., 2010) and the accuracy was 93.8 %. The selection shows that the used classification method also varies within different studies. It has been shown, that the type of classifier affects the accuracies, but the accuracies also vary within one method due to the influences of different data sets and their complexity. Besides the sensor placement and the applied classifier, the derived features and the specifications of the sliding window are important parameters. Therefore, we investigate and describe these parameters in Section 4.
It should be pointed out that the mentioned studies have been conducted with rather young participants, which clearly does not represent the intended primary user group to benefit from such systems. Thus, only a small variety of stair climbing patterns might be covered in the discussed works. For this reason, research for recognition of stair ascending in larger studies and

Table 1: Studies investigating classification of stair climbing via machine learning. The type of applied sensors (accelerometer (acc.), gyroscope (gyro.), magnetometer (magn), barometer (baro) and sensor positioning, as well as the sample size and the age of the study population are listed. The classification method with the best accuracy is written in bold. The abbreviations of the methods are: Linear Discriminant Analysis (LDA), Artificial Neural Nets (ANNs), Autoregressive (AR) Modeling, Decision Trees (DT), Bayesian Networks (BN), Naive Bayes (NB), Support Vector Machine (SVM), Multiclass-(Hardware Friendly)-SVM (MC-(HF-)SVM), K Nearest Neighbor (kNN), Rule-Based Classifiers (RBC), Logistic Regression (LR), Static Classifier (SC), Hidden Markov Model (HMM).

Precision	Sensor	Position	Classification Method	size	age [years]	Reference
99.03%	3D acc & gyro & magn; pressure	thigh, foot, shank	**LDA**	5	24.8($\pm$1.3)	(Zheng et al., 2014)
99.0%	3D acc	chest	**ANN, AR**	6	27 (mean)	(Khan et al., 2010)
97.2%	3D acc & gyro	shank	**SVM**	9	29($\pm$ 5)	(Fida et al., 2015)
$>$ 95.0 %	3D acc & gyro	waist	SVM, **kNN**, RBC, LR, DT, BN, NB,	10	25-30	(Shoaib et al., 2014)
93.8 %	3D acc	waist	**SVM**	7	25-46	(Sun et al., 2010)
93.2 %	3D acc & gyro	waist	DT, NB, **kNN**, SVM	N/A	N/A	(Fareed, 2015)
87.2 %	3D acc	waist	**MC-SVM**, MC-HF-SVM	30	19-48	(Anguita et al., 2012)
84.6 %	acc, baro, ...	waist	**SC**, HMM	12	20-30	(Lester et al., 2006)

especially for older adults is important because their movements can deviate from movements of younger adults. For example, Stacoff et al. (Stacoff et al., 2005) found in their study that younger participants walked faster and produced larger vertical ground reaction force (GRF) maxima during level walking and on stair climb than the older age group. Considering this point, we carried out a larger study, which is described in the next section.
After concentrating on the stair climbing recognition, we now focus on the power-calculations. According to Bean et al. (Bean et al., 2002), power is a physiological attribute related to strength and reflects the ability to perform muscular work per unit of time. Power P can be calculated by the following equation

$$P = Fv = mgv = mg\frac{h}{t} \qquad \left[\frac{kg \cdot m^2}{s^3} = W\right], \quad (1)$$

where F is the force, v the velocity, m the participant's weight, g the gravity, h the covered height and t the test duration. Usually, the time for the SCPT is measured by medical professionals via stopwatches. While various studies concentrate on stair climb recognition, they have not yet conducted such IMU based power calculations. Regarding Equation 1 we need to determine the parameters "stair climbing duration" and "covered height" in the detected phases of stair climbing.

3 STUDY DESIGN

In order to develop an inertial-based system to measure the stair climb power test and to evaluate its sensitivity and specificity, we conducted the following laboratory study. IMUs integrated into belts were used due to their easy applicability, flexibility and suitability for measuring daily life activities. In this study, the SCPT was measured via conventional manner assessments with manual stopwatch measurements (assumed as gold standard) and IMU-based sensor belt recordings. Overall, 83 participants aged 70-87 years (75.64$\pm$4.17 years) performed the SCPT twice.
Initially, the examiner stands with each participant at the base of the stairway with eleven steps. The participants were instructed to safely climb the stair as fast as they could and to stop on the 10th step. In accordance with the proceedings introduced by Bean et al. (Bean et al., 2007), participants were allowed to use the handrail if necessary.

Figure 3 shows the used stairway with eleven steps. The yellow footprints mark the start positions, whereby the participants can choose their preferred side. The first yellow line is for safety issues and the reduction of the risk of stumbling. The participants should stop at the second line because the SCPT is usually performed on 10 steps. The red boxes mark the light barriers.
Besides the SCPT, other geriatric tests such as the Short Physical Performance Battery (SPPB), Frailty Criteria, de Mortan Mobility Index (DEMMI), 6 Minute Walk Test (6MWT), and Counter Move-

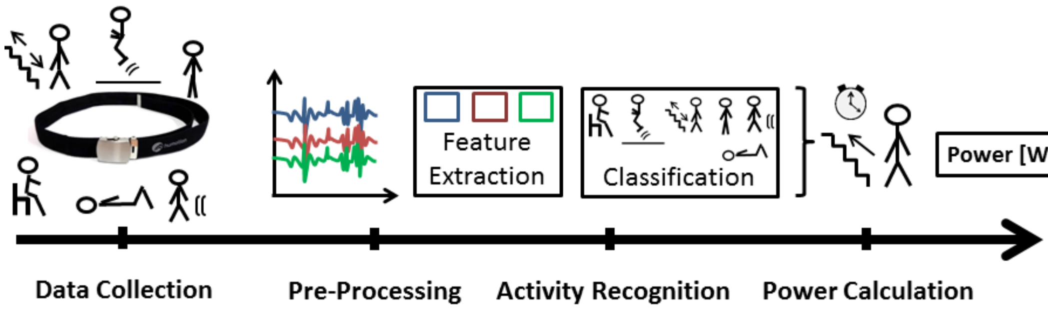

Figure 2: Process of activity recognition and stair climb power calculation. After data collection, data pre-processing follows. Before the classification of activities, feature sets must be selected. After classification of the activity of ascending stairs, the power can be calculated.

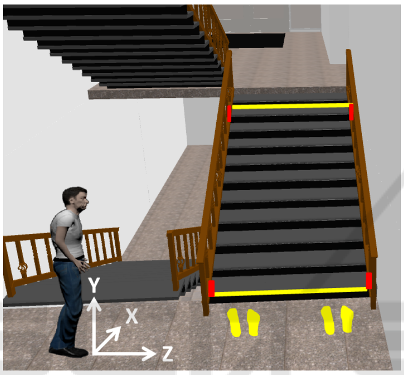

Figure 3: The stairway used in the study: The participants start at the yellow footprints and should stop before the second yellow line at the 10th step. The red boxes mark the light barriers. The coordinate orientation of the sensor belt is illustrated: x-direction is sidewards; y-direction is upwards; z-direction is straight forward.

ment Jumps (CMJ) were performed. After these assessments, the participants wear the sensor belts continuously for one week in their daily life. The study and the utilized technologies for each assessment item are summarized in (Hellmers et al., 2017a).

Sensor Belt

The measurement unit integrated into the belt includes four sensor types: A Bosch BMA180 triaxial accelerometer, which measures the acceleration force in $g \approx 9.81ms^{-2}$ applied to the device on all three physical axes (x, y, and z). The accelerometer has the following parameters: Sensitivity ranges from 1G up to 16G and the chip supports sampling rates up to 1200 Hz. The STMicroelectronics L3GD20H gyroscope measures the device's rate of rotation in $deg \cdot s^{-2}$ around each of the three physical axes (x, y, and z). A magnetometer measures the ambient geomagnetic field for all three physical axes (x, y, z) in μT and a barometer measures the air pressure in hPa. The coordinate orientation of the sensors is shown in Figure 3. A sampling rate of 100 Hz is used for all four sensors in this study, since the parameter settings have a significant influence on the recognition accuracies (Fudickar et al., 2012).

4 STAIR CLIMB DETECTION

Figure 2 shows the general processing work-flow of activity recognition via the intended machine learning approach and stair climb power calculation. After data collection during the different geriatric tests within the assessment (see section 3), steps of pre-processing follow, as well as the feature extraction for the classification. The stair climb power is calculated for the time spans, classified as stair ascending.
In order to describe our algorithm, we focus on the extracted features, the sliding window and the used classifiers in the following sections.

4.1 Derived Features

Deriving a minimal feature-set is an essential step for machine-learning based classification algorithms in order to assure efficient classification. In order to train the classifier, data sets of 80% (n=66) of all participants are considered. The activities of standing, walking, ascending and descending stairs were selected from the whole assessment and pooled. According to frequently used features in literature (see section 2), we derived the following features:

- Mean
- Root Mean Square
- Median
- Correlation Coefficient
- Variance
- Standard Deviation
- Entropy
- FFT Energy

These eight features are considered per axis of accelerometer and gyroscope, resulting in an overall set of 48 features. The data of the magnetometer was excluded due to its high influence to environmental noise. Including the magnetometer data would result in an over-fit for this specific stairway. Figure 4 shows, as an example, the standard deviation (SD) in comparison to the root mean square (RMS) in z-direction of the activities ascending and descending stairs, walking and standing. As expected, the SD for a static activity is quite small. Furthermore, while there is only a relatively low scattering of the walking activity, the values for ascending and descending stairs scatter significantly broader. Another example is shown in Figure 5: The distribution of the FFT Energy of the gyroscope in x-direction and Root Mean Square (RMS) of the accelerometer data in y-direction. While the FFT energy for standing is about zero (static activity), the FFT energy for ascending stair lies in a higher range than walking and descending stairs. The RMS is also lower than for the other both dynamic activities.

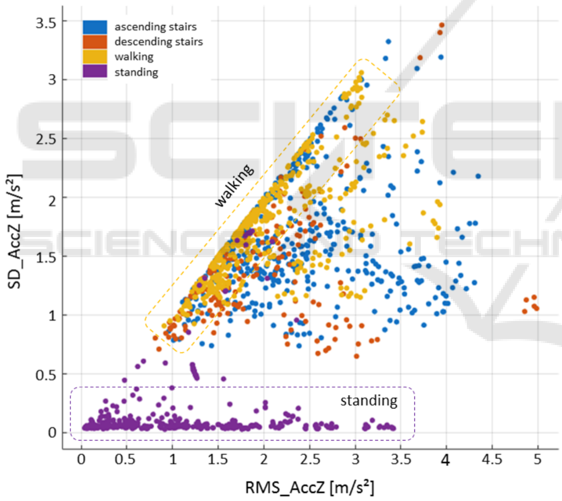

Figure 4: Scatterplot of Standard Deviation (SD) and Root Mean Square (RMS) of the accelerometer data in z-direction (straight forward). The activities of walking and standing show low scatterings, while ascending and descending stair scatter significantly broader.

4.2 Sliding Window and Classifier

Besides the features, the sliding window and the used classifier are also crucial factors. Since Shoaib et al. (Shoaib et al., 2014) have shown that an overlap of 50% of the sliding windows produces reasonable results, we considered a sliding window approach with a 50% overlap.

In accordance with the related work, we used the following classifiers, due to their high sensitivity. All of them are available in Mathworks' MATLAB (version R2015a):

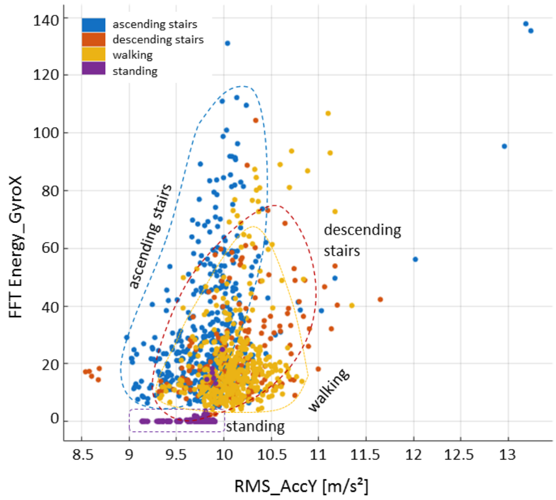

Figure 5: Scatterplot of FFT Energy of the gyroscope in x-direction (sidewards) and Root Mean Square (RMS) of the accelerometer data in y-direction (upwards). The mean ranges of values for each activity are marked in the graph.

- Decision tree (complex, medium, simple),
- Support vector machine (linear, quadratic, cubic, fine Gaussian, medium Gaussian, coarse Gaussian),
- K-Nearest-Neighbor (fine, medium, coarse, cosine, cubic, weighted).

The F1-Score was used for the evaluation to consider both precision and recall. Figure 6 shows the F1-Scores for the recognition of the activity "climbing stairs" for each classifier of the three used methods with the best result for different window sizes. Table 2 summarizes the results.

Table 2: Best results of F1-Scores by optimized window sizes and an overlap of 50% of the sliding windows for the three used classifiers.

Classifier	Window Size [s]	F1 Score
Decision Tree	1.9	81.50
SVM	1.7	93.00
k-NN	1.6	93.99

While decision trees show the worst performance with an F1-Score of 81.5, k-NN (93.99) and SVM (93.0) achieve similar results. The best window size for the k-NN classifier is 1.6s and for the SVM classifier about 1.7s. At the basis of this result, in the following, we concentrate on the k-NN classifier.

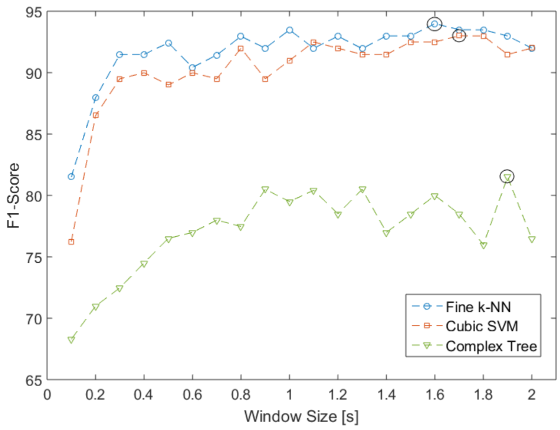

Figure 6: F1-Score for three different classifiers complex tree, Cubic SVW and Fine k-NN in correlation to the window size.

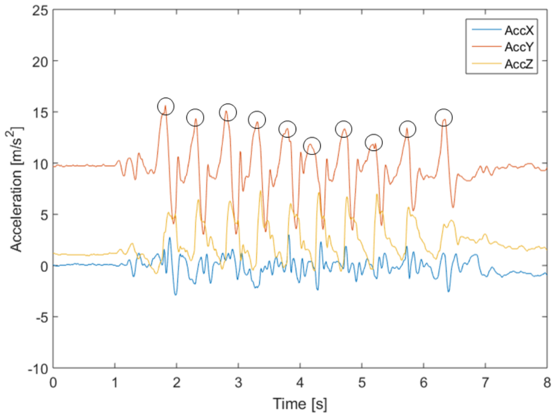

Figure 7: Acceleration in x-,y-, and z-direction during a phase of ascending stairs in a laboratory setting. The single steps can be recognized by characteristic peaks.

4.3 Post-Filtering

To remove incorrectly detected stair climbing activities, a minimum duration of 3s for this activity was defined and shorter durations declared as ascending stair were ignored in a post-filtering step. This threshold value is based on stopwatch measurements over all participants, whose needed duration was always $> 3s$. The majority of studies use a stairway of 10 to 12 stairs for testing, which is likely to be the average flight length available in buildings and therefore a practical length for testing (Nightingale et al., 2014). But in those studies, which are looking at medical conditions involving the heart and lungs, longer stairways are used to elicit a more cardiovascular response. Therefore, stair ascending activities with less stairs than 10 are less meaningful for the SCPT.

5 CALCULATION OF STAIR CLIMB POWER

In order to calculate the power and in accordance with Equation 1, the covered height and the duration for the SCPT are measured. While the duration is determined by the sequence of the recognized activity, the height was evaluated by counting the steps within this sequence of ascending stairs. Figure 7 shows, as an example, the acceleration of a sequence of climbing 10 steps. The activity of climbing stairs or other rhythmic activities usually show repetitive patterns. In cases of walking or ascending stairs, the impact of the foot on the floor causes a peak in acceleration data. These peaks were counted and assumed as steps. On the basis of the step number n the covered height h can be calculated by $h = n * 16.5$, where 16.5 is the height of one step in cm. In most European countries the height of steps is standardized by building regulations. Barometers can also be used for elevation measurements. But due to the low accuracy of the barometer in our study ($\pm 10\,cm$), we decided to use the peak detection algorithm based on the acceleration data for height estimations.

The participant's weight was measured via a stadiometer (seca 285) and the gravity is assumed to be $g = 9.81 ms^{-2}$.

6 EVALUATION

6.1 Recognition of Stair Ascent

Since the data sets of 80% (n=66) are considered for model training, the other 20% (n=17) of data sets are used for testing. Figure 8 shows the confusion matrix of our Fine k-NN classifier, with a window size of 1.6s and an overlap of 50%. The recognition of standing and walking show very good results with a rate up to $> 98\%$. Climbing stairs is correctly recognized in 93% of the cases'. Descending stairs was incorrectly assigned as climbing stairs in 6% and as walking in 10%.

6.2 Calculation of Stair Climb Power

Table 3 shows the mean deviations of power, test duration and covered height of the sensor-based measurements with the already presented k-NN classifier to stop watch measurements. The weight and the gravity values are same in both calculations and therefore not further considered.

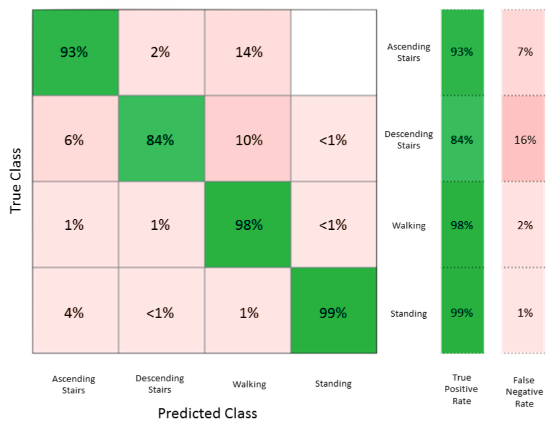

Figure 8: Confusion matrix of activity recognition with a k-NN classifier.

Table 3: Mean deviations of sensor-based power measurements to stopwatch measurements.

	Mean Deviation [%]	Median [%]
Power	2.35	4.71
Duration	14.49	6.46
Height	15.00	15.00

While the k-NN classifier achieves quite good power values with a mean deviation of 2.35 % to the gold standard, the deviation of the estimated height and durations are with respectively $\leq$15% very high. As already described in Section 3 the duration of climbing ten stairs will be measured by the stop watch in the SCPT and is assumed as gold standard. But the technically detected number of stairs is not exactly 10 in all cases. In our assessments, the number of passed steps varied among users between 10 and 11 stair due to the following reasons: The setting consists of an 11 step stair flight, but some participants forget to stop at the 10th step, as instructed. In addition, a step might be not recognized due to the transition from standing to climbing stairs. However, this isn't a problem due to the fact that according to Equation 1 the ratio of height and duration influences the power ($v = h/t$). Thus, the difference in the power of the gold standard measurement (ten stairs) is small, due to the low effect on the participants' fatigue or the fluency of the test sequence (acceleration and deceleration) of climbing one additional or less stair. But of course, the accurate detection of the beginning and end of the activity is a major task and needs further investigations.

6.3 Medical Sensitivity

In order to clarify the medical sensitivity of our system, we compared its error to the medical required sensitivity to detect the transition to functional decline (as covered by frail state). Table 4 summarizes the power values of our participants at baseline (t0) and after 6 month (t1). They were categorized in groups of frail and non-frail according to the classification of the Frailty Criteria. The mean deviation in power between these groups is about 14% and therefore, significantly higher than our system's deviation from the gold standard measurements of about 2%. Thus, we conclude that our system's sensitivity is sufficient for medical meaningful detection of transitions towards the frail state under controlled conditions.

Table 4: Stair climb power (P) of participants in our study at baseline (t0) and after 6 month (t1) categorized in groups of frail and non-frail according to the classification of the Frailty Criteria.

	number	P_{t0} [W]	P_{t1} [W]
non-frail	56	2302	2298.0
frail	27	1979.5	1968.1
Δ		322.5 (14.0%)	329.9 (14.0%)

7 SUITABILITY FOR HOME-ASSESSMENTS

We have introduced a first approach to measure the stair climb power via a single inertial sensor worn at the waist. Due to the easy applicability, elderlies can wear the sensor belt correctly without further assistance. The participants of our study have worn the sensor belt continuously without supervision during their daily living for one week following their assessments and written an activity diary for the week. Investigating these data sets, we want to study the applicability of our SCPT system to an unsupervised use by detecting the correctness of detected stairs.
Figure 9 shows the acceleration data during climbing stairs of one participant at home. This sequence was classified as stair ascent by our algorithm. To validate this classification we compared our results with the participants diary (ground truth). The diary and the classified activity match in this case.
In comparison to Figure 7 the pattern and amplitudes are significantly different from the acceleration data measured during the assessment (test situation) although it shows the activity of the same participant. Thus, we could confirm, that phases of climbing stairs could also be recognized during these home-assessments.
Furthermore, to clarify the degree of variations in stair-climbing patterns for different environments by investigating it in the participant's daily life. Therefore, the one-week measurements of the sensors will be analyzed concerning the frequency, the covered

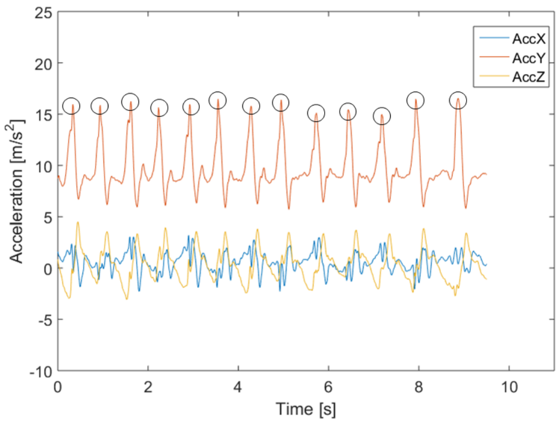

Figure 9: Acceleration in x-,y-, and z-direction during a phase of climbing stairs in daily life.

steps and the estimated stair climb power of the activity stair climbing. Regarding the medical meaningfulness of unsupervised power measurements at home, a comparison of the results in the laboratory setting with results at home will follow. Within, especially the influence of diverging conditions such as step number or the absence of a test situation will be examined. For further validation of our stair climbing detection in domestic environments, it is planned to install ambient sensors at the stairways in the homes of a subgroup of our participants.

8 CONCLUSION

Due to the importance of strength analysis to detect functional decline in an early stage, we introduce stair climb power measurements based on IMUs in a laboratory setting. Therefore, we recognized the activity of climbing stairs automatically via machine learning and calculated the power based on the needed time and covered height. Climbing stairs is correctly classified in 93% of the cases. For power calculations, we achieved good results in comparison to conventional measurements with a mean deviation of 2.35%. The system's sensitivity to detect the transition towards frailty has been confirmed.

Additionally, we showed the general suitability of sensor belt measurements at home and confirmed, that phases of climbing stairs could also be recognized during home-assessments However, further investigations of the stair usage behavior of our participants and the recognition of stair ascending in domestic environments are planned based on one-week measurements at home following the assessments. The use of ambient sensors such as RFID technologies or light barriers in the homes of a subgroup of our participants is intended for further validations of the activity detection and the determined duration of the stair climbing activity. Especially regarding the medical relevance of unsupervised home-assessments, further investigations and comparisons between laboratory and home results are needed.

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