Towards a Minimized Unsupervised Technical Assessment of Physical Performance in Domestic Environments

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ABSTRACT

Early detection of changes in mobility associated with functional decline can increase the therapeutic success by prolonging self-determined living. To get an unbiased and high frequently status of the physical performance of the persons at risk, unsupervised assessments of their functional abilities should ideally take place in their homes.

Thus, we have developed a minimized unsupervised technical assessment of physical performance in domestic environments. By conducting an exploratory factor analysis, based on the results of 79 study participants with a minimum age of 70 years, we could clarify that common assessment items mainly represent three key parameters of functional performance ”mobility and endurance”, ”strength” and ”balance”. Consequently, we identified a minimal set of assessment items that is suitable for home-assessments and that, since covering all three parameters, is able to generate clinical meaningful and relevant insights about the functional status.

Regarding the parameter mobility, we developed a technical assessment of physical performance for domestic environments, which utilizes short distance walk times assessed via ambient presence sensors as an indicator for potential functional decline. In a field trial over ten months with 20 participants with a mean age of 84.25 years, we could confirm the general feasibility of our approach and the proposed system.

Author Keywords

Ambient sensors; Domestic environment; Factor analysis; Functional decline; Home assessment; Home monitoring; Technical assessment; Walking speed

ACM Classification Keywords

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1. INTRODUCTION

Functional ability is essential for independent living, and facing the demographic change, healthy aging is a core societal and individual aim. But with aging, functional decline can occur. Thus, it is important to detect early changes of the functional status as soon as possible because interventions at an early stage can regain and maintain physical performance, reduce the rate of falls and consequently help the patients to maintain their independence [2]. The functional ability, physical health, cognition, mental health, and socioenvironmental circumstances [9, 3] are usually evaluated in clinical assessments. Since these supervised assessments require a lot of time, they can only be conducted on an occasional basis, but are not applicable on a regular (e.g. monthly) basis. However, such frequent assessments would enable an early detection of functional decline and an initiation of preventive measures when they are needed most.

Therefore, we want to identify a minimal set of assessment items for technology supported non-supervised functional assessments at elderlies' homes, which is able to generate clinical meaningful and relevant insights about the functional status.

- In a first step, we identify the essential components of functional mobility considered in a typical assessment. This is done by an exploratory factor analysis due to achieve a meaningful reduction while keeping the decrease of information as low as possible.
- For these identified components, we want to select a minimal subset of assessment items which covers all components and is suitable for unsupervised home-assessments. Therefore, we introduce a technology supported geriatric assessment, validate the measurement systems and discuss the suitability regarding a set of requirements.
- Finally, we exemplarily investigate the transferability of the assessment items' detection of one essential component into domestic environments and examine its medical meaningfulness in comparison to common gold-standard measurements.

2. RELATED WORK

The application of technology for clinical assessments has been discussed in several studies. Dasenbrock et al. [6] provided an overview of the current evidence for assessing frailty features using sensors. In regards to ambient sensors, electronic walkway systems, as well as cameras, force platforms, and foot switches are often used in laboratory environments

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for gait analysis [28]. Single tests of clinical assessments such as the Timed Up & Go (TUG) Test are also supported by technology. Sprint et al. [29] provided an overview of the TUG test and technologies utilized for TUG instrumentation. Another example is the measurement of sit-to-stand transitions via a pressure sensor platform in combination with inertial measurement units (IMUs) by Greene et al. [14].
However, recent studies already tried to transfer specific assessment items into domestic environments. Scanaill et al. provided a review of the architecture of smart home, wearable, and combination systems for the remote monitoring of the mobility of elderly persons while they are in their own living environment [27]. In [17] a 3D layer context model is described which uses three dimensions (clinical decision, frequency and context dependence) to determine the type of the data and further introduce a prototype personal health record system.
An approach to the assessment of mobility based on passive infrared detectors was examined by Pavel et al. [24]. This system was also extended by active radio frequency identification tags to enable measurements when multiple persons are in the home [23]. Especially for the assessment of the mobility status, some different approaches already exist. Examples are laser-scanner measurements for the precise and reliable computation of the self-selected gait velocity in domestic environments [11], or the use of an ambient TUG system (aTUG) for unsupervised mobility assessment tests in domestic environments [12]. Ejupi et al. [8] described the feasibility of a sensor-based self-assessment of fall risk at home via a Kinect-based system.
However, the results of such domestic assessments are usually not directly comparable to clinical assessment tests. In a systematic review, Liu et al. (2016) found no evidence that smart homes or home health technology can predict disability [21]. According to Isken et al. [18] three main problems can be found:

1. Applicability of only a subset of clinical assessments: Not all aspects of clinical assessment tests can be tested during every-day activities.
2. Contextual dependency on assessment results: While clinical assessment results are obtained under standardized conditions during a test, data of home-assessments may contain unclear influence factors.
3. Uncertainty of assessment results: Due to its unsupervised performance, an amount of uncertainty will remain whether sensor recordings and evaluations do really reflect the abilities of a patient.

3. REDUCTION OF ASSESSMENT ITEMS

With regard to the first problem, we want to identify the essential components of functional performance which are typically considered in common geriatric assessments. Therefore, we analyze the results of a laboratory study which consists of a comprehensive (two hours long) geriatric assessment-battery including tests for physical performance, muscle mass and independence. The medical aim of this observational study is the screening for functional decline and the identification of specific parameters which are sensitive to predict the future risk of functional decline. The test procedures were approved by the appropriate ethics committee (ethical vote: Hannover Medical School No. 6948) and conducted in accordance with the Declaration of Helsinki.
We considered the assessment results of 79 participants aged 70-84 years with a mean age of 75.7 years and a standard deviation of 3.3 years. 53% of the participants were female.

3.1 Exploratory Factor Analysis

The parameters measured in the specific assessment items correlate in a variety of ways and have more or less large parts of variance in common. The aim of a factor analysis is to reduce the information of the observed variables to a set of a few latent dimensions.
For the analysis we considered the following assessment items: Sex, weight, height, score of Instrumental Activities of Daily Living Scale (iADL) [19], Score of Frailty Criteria [3] and its single functional items, Timed Up & Go (TUG) Test [25], Short Physical Performance Battery (SPPB) [15], 6 minute walk test (6MWT) [31], Score of De Morton Mobility Index (DEMMI) [7] and its functional items (except the bed and chair transitions and the 50m walk test due to its low variance in our study population), Stair Climb Power Test (SCPT) [1] and 5 Time Chair Rising Test as part of the SPPB as well as the parameters power and height of the Counter Movement Jump (CMJ) [26]. In total, we take 20 variables into account. In contrast to medical investigations, we always analyze the second test if an item is measured twice (TUG, SCPT, SPPB Walk Test).
We used the principal components analysis as extraction method and Varimax as rotation method. The factor analysis is done with IBM SPSS Statistics (Version 23). The loadings of the rotated component matrix were sorted and cleaned (loadings < 0.1 are removed due to better clarity). The decision of the number of factors retained for rotation was done by a scree test. Therefore, the graph of eigenvalues was examined by looking for the breakpoint in the data where the curve flattens out [5].

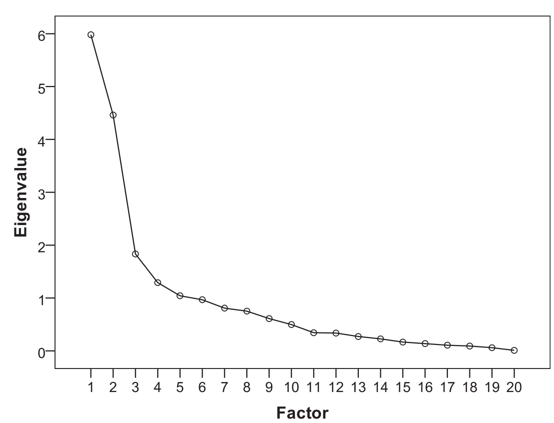


Figure 1: Screeplot: Eigenvalues associated with a factor in descending order versus the number of the factor.

Table 1: Rotated component matrix of the manually measured assessment. The assessment items (variables) represent three factors, interpreted as strength (1), mobility (2) and balance (3). The main loadings are written in bold.

Variable	**Factor**		
	1	2	3
Muscle Mass	**,909**		,195
Sex	**,877**		
Frailty - Hand Strength	**,876**	-,140	
Max. Jump Power	**,872**	-,209	
Body Height	**,831**		
Body Weight	**,707**	,317	,106
iADL Score	**-,550**		,218
Max. Jump Height	**,502**	-,433	
TUG		**,873**	
SPPB - Walk Test		**,860**	-,126
Frailty - Walk Test		**,818**	-,158
Stair Climb Power Test		**,799**	-,291
6 Min Walk Test	,209	**-,788**	,190
Chair Rise Test	,121	**,773**	
Frailty Score	-,159	**,376**	,341
Frailty Activity Questionnaire		**-,286**	
DEMMI Score	,151	-,316	**,874**
DEMMI - Static Balance	,195	-,342	**,847**
DEMMI - Dynamic Balance	-,259	,178	**,451**
SPPB - Static Balance		-,222	**,443**

3.2 Identification of Essential Components of Functional Ability

For the reduction of assessment items, we categorized the 20 assessment items (variables) into a few latent dimensions (factors) based on an exploratory factor analysis. According to the scree test, three factors were retained for rotation (Figure 1) because the curve flattens out below these eigenvalues. The resulting rotated component matrix with the factor loadings of each item is shown in Table 1.

Factor 1 : Strength

Due to the variables included in Factor 1, this factor correlates clearly with the physical parameter "strength". This factor consists of eight variables. Five variables of these have strong loadings (absolute value > 0.8) and three moderate loadings (absolute value > 0.4). The muscle mass has the highest loading on this factor. The jump parameters height and power load on this factor as well. There are some cross loadings. Especially the weight has a cross-loading to Factor 2 as well as the maximum jump height. The sex and the body height are also included in this factor and represent the strength because men are on average stronger and have a greater body height than women. For this analysis, the nominal variable sex is scaled as follows: female=1, male=2. The inverse correlation (negative value in component matrix) of the iADL with the other factors lies in the fact that men sometimes did not get the full score in this test, since wives often do the bulk of the housework for their husbands due to gender construction theories [20].

Factor 2 : Mobility

Factor 2 includes eight variables. Three variables have strong and three moderate loadings. Due to the variables included in this factor and the strong loadings for the TUG and walking tests, this factor seems to represent the physical parameters "mobility and endurance". The score of the Frailty Criteria and the activity questionnaire have only weak loadings (absolute value < 0.4). This might be due to the fact that the questionnaire documents the subjective assessment of activity and is not measured physically. One reason for the weak loading for the Frailty Criteria could be that this test is not sensitive for our healthy study sample. The 6 Minute Walk Test (6MWT) and the activity questionnaire correlate negatively to this factor because of its scope. For the TUG test, the walking tests, the 5 Time Chair Rise test, and the Stair Climb Power Test the durations of the tests are measured. A shorter duration means a better result, while the other tests in this factor have an inverse score. For example, a longer distance in the 6MWT achieves better results.

Factor 3 : Balance

Factor 3 has four variables with two strong loadings and two weak loadings. Thus, Factor 3 is the weakest factor and might not be solid. Due to the variables included, the factor represents the parameter balance. The DEMMI Score, which is a test for mobility, is also included in this category. This might be due to the fact that the variance of the results in our healthy study sample might be attributed to the differences in the dynamic and static balance measurements. The transitions and the 50m walk test (also part of the DEMMI) were passed by nearly all participants without the deduction of points.
The reduction of the assessment items to three essential factors of the functional performance and the interpretation of these as "**mobility** and endurance", "**strength**" and "**balance**" correspondents to the findings of Cooper et al. [4], who specified that strength, balance and walking are key components of physical performance.

3.3 Validation of Technology-Supported Laboratory Assessment

In order to validate the study's technical measurement systems and to make an intermediate step towards a home-assessment, we performed the clinical assessments on the one hand in a conventional way, and on the other hand simultaneously supported by technology. Within the clinical assessment, we used light barriers to measure the SCPT and the different walking tests such as the 6MWT, the walk test in the Frailty Criteria and the SPPB. The Timed Up & Go Test and the 5 Time Chair Rising Test (5TCRT) part of the SPPB were performed with the ambient TUG-system (aTUG) [12] which includes light barriers, force sensors and a laser rangefinder. The system can make detailed gait analysis and detect the sit to stand cycle. Further devices such as a force plate for balance measurements and the Counter Movement Jumps, a handgrip dynamometer for measurements of the hand strength, or a bio-impedance analysis device are also used in this study.
In a previous study, we already confirmed that light barrier measurements achieve a high sensitivity and a good

Table 2: Rotated component matrix of the technically measured assessment items (marked as bold). The factors are interpreted as strength (S), mobility (M) and balance (B). The main loadings are written in bold. LB marks the light barrier measurements and FS the force sensor measurements of the aTUG system.

Variable	**Factor**		
	S	M	B
Muscle Mass	**,908**		,201
Sex	**,877**		
Frailty - Hand Strength	**,876**	-,134	
Max. Jump Power	**,871**	-,218	
Body Height	**,836**	,137	
Body Weight	**,708**	,360	,103
iADL Score	**-,544**		,214
Max. Jump Height	**,503**	-,458	
FS_TUG		**,840**	-,166
Chair Rise Test	,123	**,794**	
LB_6 Minute Walk Test	,244	**-,792**	,225
LB_Stair Climb Power Test		**,624**	
LB_Frailty - Walk Test		**,581**	-,172
Frailty Score	-,156	**,417**	,320
Frailty Activity Questionnaire		**-,362**	
LB_SBBP - Walk Test		**,248**	
DEMMI Score	,148	-,286	**,888**
DEMMI - Static Balance	,192	-,308	**,863**
SPPB - Static Balance		-,230	**,456**
DEMMI - Dynamic Balance	-,263	,184	**,433**

correlation to the manual measurements and examined the inter-tester variability and its influence on the measured results [16]. The examination shows that there was no influence given in most tests with time measurements except the $4.00m$ walking test as part of the SPPB.

The aTUG has been validated to measure reliably and precisely the total duration of TUG and durations of the single components of this sequence- like standing up, walking there, turning, walking back and sitting down - with a mean error of 0.05 seconds and a mean standard deviation of 0.59 seconds using force and range measurements [10].

In order to confirm the classification of the variables in three essential factors and to validate our technical measurements in another way, we made an exploratory factor analysis with the light barriers and aTUG-measurements (Table 2). For the aTUG-measurements, we used the test duration collected by the force sensors.

This analysis indicates that the results measured with technology correspond to the same factors as the manual measurements. Therefore, these measurements are valid. Among the technologically measured items, only the walk test of the SPPB has a weak loading. One reason for this difference to the manual measurement could be the inter-tester variability, but it does not completely explain the significant weaker loading. In general, we have weaker loadings of the sensor measurements. This may be due to the fact that the reaction time within this test is not measured by the light barriers, but has an influence on the overall (manual) results.

3.4 Identification of a minimal subset of assessment items

Since the general applicability of technical measurements was confirmed, we aimed to reduce the amount of time and efforts required for such an assessment by trying to identify a sufficient subset of assessment items based on our results of the factor analysis, while keeping the decrease of information as low as possible. Due to the reduction of assessment items, a better applicability of assessments in domestic environments might be achieved.

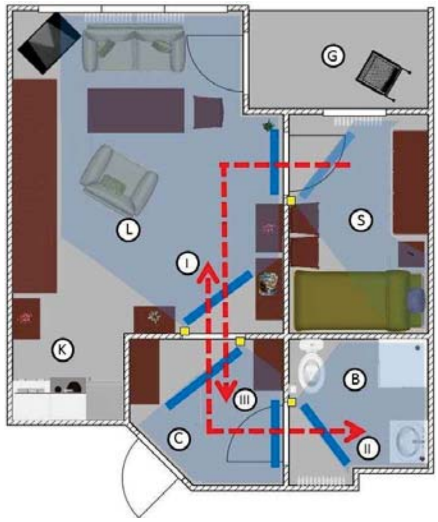
Based on the analysis, which indicated three essential factors interpreted as the physical parameters ”mobility and endurance”, ”strength” and ”balance”, we tried to find a minimal subset to cover these factors. Therefore, we examined each assessment item of the laboratory study except the questionnaires regarding for its suitability for self-guided home-assessments (Table 3) in terms of following requirements: The test of the desired subset should be safe, simple, frequently performed and self-guided. The utilized technology and the measuring method should be again safe and simple as well as unobtrusive, accurate, robust, cheap, low-maintenance and accepted by the users.

Table 3: Overview of the assessment items, their suitability for a home-assessment (+ to +++ increasing suitability, - low suitability), and the physical parameter strength (S), mobility (M) and balance (B) belonging to this item (see Table 1).

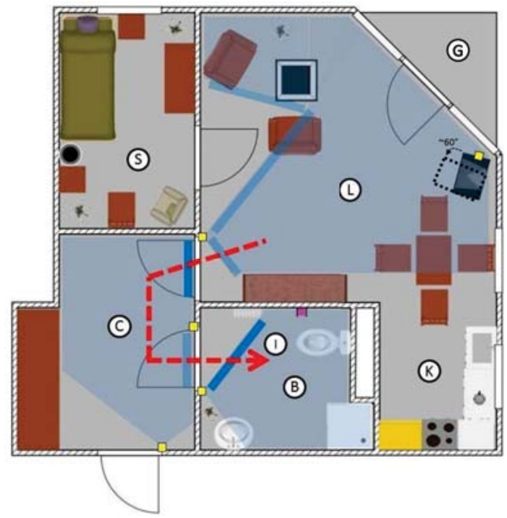
Variable	**Suitability**	**S**	**M**	**B**
Body Weight	+	X		
Muscle Mass	+	X		
Body Height	+	X		
Frailty - hand strength	+	X		
Counter Movement Jump	-	X		
SPPB - Walk Test	+++		X	
Frailty -Walk Test	+++		X	
TUG	++		X	
Stair Climb Power Test	+		X	
6 Min Walk Test	-		X	
SPPB - Chair Rise Test	-		X	
DEMMI - Static Balance	-			X
DEMMI - Dynamic Balance	-			X
SPPB - Static Balance	-			X

However, the Counter Movement Jump as the established test for **strength** is not suitable for unsupervised home-assessments due to safety criteria (high fall risk) and the fact that persons at risk of functional decline rarely jump in the daily life. The other items representing the strength can be measured via medical devices such as stadiometers, body composition monitors or handgrip dynamometers.

For the measurement of **mobility**, walking tests with a short distance (SPPB $(4.00\,m)$ or the Frailty Criteria $(4.57\,m)$) have a good suitability and can be measured by light barriers as in the laboratory study or by other ambient sensors in an unobtrusive way in domestic environments. The TUG test is also suitable for home-assessments. The complete phases of the tests can be measured by the aTUG system. Concentrating only on the walking phases, the TUG test can be measured by light barriers as well. Due to the necessity of stairs,



(a) Illustration of the apartment of participant A.



(b) Illustration of the apartment of participant B.

Figure 2: Illustration of the apartments of the participants A (a) and B (b). The rooms are marked as following: living room (L), corridor (C), bathroom (B), bedroom (S), kitchen (K) and balcony (G). The motion sensors are marked with yellow boxes and cover the blue triangular areas. The red arrows mark the trajectory of frequently used transitions.The dark blue boxes illustrate the initial entering of regions considered as suitable signals for the calculation of region-transition-durations.

the Stair Climb Power Test is not generally transferable into every domestic environment. But for homes with stairs, this item is suitable as a test for the mobility and can be measured by light barriers. The 6MWT has a low suitability because the measurement inside a home is quite difficult and will not be usually performed in daily life. The 5TCRT can be measured by the aTUG system, but normally it is not usual to stand up from a chair in a sequence of five times. Therefore, the analysis of one transition can be unobtrusively measured in a home-assessment. But we do not intend to create a test situation. Therefore, the suitability of this assessment item for home-assessments is fairly low.
The **balance** tests need expensive measuring devices such as force platforms or other floor sensors. The installation of these sensors requires a greater effort to avoid an increase of the fall risk. For this reason, the measurement of these balance tests by ambient technology is not quite suitable yet and needs further studies (e.g. considering the suitability of a balance sensor as part of a scale).
Consequently, in the following we want to concentrate on the investigation of the parameter mobility: Under consideration of these aspects and the afore mentioned suitability requirements, walking tests with short distances (SPPB, Frailty, TUG) are most suitable for mobility measurements in domestic environments. Therefore, we developed an assessment system for the analysis of functional performance based on walking speeds for short distances.

4. TECHNOLOGY-SUPPORTED HOME-ASSESSMENT / DOMESTIC EVALUATION SYSTEM

As discussed, transferring sensor-based mobility assessments into domestic environments would hold various advantages such as continuous long-term measurement and an unbiased and more current perspective on the health of patients. However, since these environments/settings are not standardized, the approach's practicability has to be confirmed regarding its ability to generate clinical meaningful and relevant insights.
Thus, we investigated the transferability of mobility assessments into real-life environments by comparing the mobility status measured in both settings (manually and by technology) in a field trial with 20 participants with a mean age of 84.25 years.
For long-term monitoring in domestic environments, a home automation system with motion detectors, reed contact sensors and current sensors has been installed in the homes and collected data over ten months. In addition, the physical performance of the participants was manually assessed monthly in their domestic environments by medical professionals e.g. via the $4\,m$-walk test (as part of the SPPB) and the TUG Test. The test procedures were approved by the local ethics committee (ethical vote: Carl von Ossietzky University Oldenburg No. Drs27/2014) and conducted in accordance with the Declaration of Helsinki.
The proposed ambient home-based assessment system measures the transition times between different regions within the domestic environments via low-cost motion-detectors. The resulting region-transitions are filtered, and an individualized subset of the most frequently used transitions is aggregated into monthly mobility statistics, which are suited to indicate trends over time, as described in the following subsection in greater detail.
The low-cost motion detectors (MDs) are energy-efficient and, therefore, they are battery-operated and can work continuously for months without battery replacements. Due to

the independence from the availability of power supplies the positions of MDs can be selected less restricted than the positions of light barriers (LBs). Furthermore, single MDs already support coverage of complete regions/rooms, while LBs can only detect passing a small area. In order to identify indicators for the mobility of a participant by these MD sensors, the duration for changing regions (described as region-transitions) is considered as a potentially reliable indicator. These durations are calculated based on presence information as follows: Regions represent areas of detection of a person's presence via single MD sensors. These regions can be even combined into larger logical units, e.g. to cover complete rooms (exemplary see Room L in Figure 2 a. MD sensors are marked as yellow boxes).
However, battery-operated MD sensors typically hold the following drawback: Due to radio-regulatory-demands, the minimum transmission interval between two events of one sensor is set to several seconds up to few minutes. Therefore, leaving a region can not be detected directly by the related MD. However, entering a region can be determined immediately if the minimum transmission interval of the related sensor has been expired. Region-transitions are defined between the available regions within the domestic environment. Each definition consists of a start region, a destination region and at least one intermediate region. The definition of regions and region-transitions takes the requirement into account that the area between adjacent regions is small and limited. Thus, the position of a person entering a region is known and, therefore, the behavior of this approach is similar to the behavior of LBs. Thereby, a region-transition (as detected by the regions' MD) is assumed to achieve a similar time-accuracy as LBs, if they would be mounted in doorways between two regions. The duration of a region-transition is calculated as the temporal difference between entering the first intermediate region and entering the destination region.
The durations of region-transitions are used to calculate an indicator. The sequence of these indicators is compared to the sequence of assessment results. In order to receive a characteristic and robust value the detected region-transitions are filtered by a two-step procedure: Firstly, region-transitions within multiperson periods are removed and secondly, frequently performed region-transitions are identified and used for further analysis.

4.1 Exclusion of Region-Transitions within Multiperson Periods

When multiple persons stay within an apartment, the calculated transition-durations might be faulty. Thus, these region-transitions are excluded from further consideration. For this reason, multiperson periods are computed by means of the recorded sensor events and the topology of the regions. Violations of a sensor graph (regions as nodes and edges between adjacent regions) and of minimum transition durations are used in consideration of apartment-specific thresholds to determine multiperson periods, as proposed in [22].

4.2 Initial Identification of Relevant Region-Transitions

In order to identify a characteristic and robust subset of region-transitions, the most frequently performed transitions are ascertained. Therefore, one month after the installation of the system, the recorded region-transitions are analyzed to obtain the most frequently region-transitions as follows:
For each region-transition-definition the number of detected region-transitions is computed. After that, region-transition-definitions are sorted in ascending order depending on the frequencies. Based on this series of definitions/frequencies the absolute cumulative frequencies are calculated and used to identify a minimal set of region-transitions which includes more than 50% of all region-transitions. For this purpose, those region-transitions with a relative cumulative frequency greater or equal 50% are selected for computing the desired indicators.
The region-transition-definitions are sorted in ascending order depending on their frequencies and numbered from 1 to n and let $H_1, H_2, \ldots, H_n$ be the related frequencies, the k^{th} absolute cumulative frequency can be calculated as follows:

$$F_{abs}(k) = \sum_{i=1}^{k} H_i, 1 \leq k \leq n$$

The k^{th} region-transition is selected if relative cumulative frequency is greater or equal 50%:

$$\frac{F_{abs}(k)}{F_{abs}(n)} \geq 0.5$$

Figure 3 shows the absolute cumulative frequencies for participant A. The three region-transitions on the right side are selected.

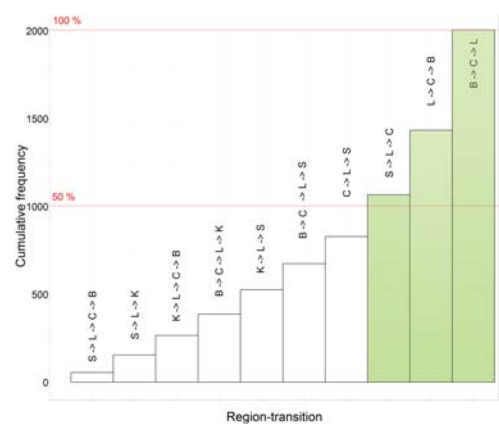
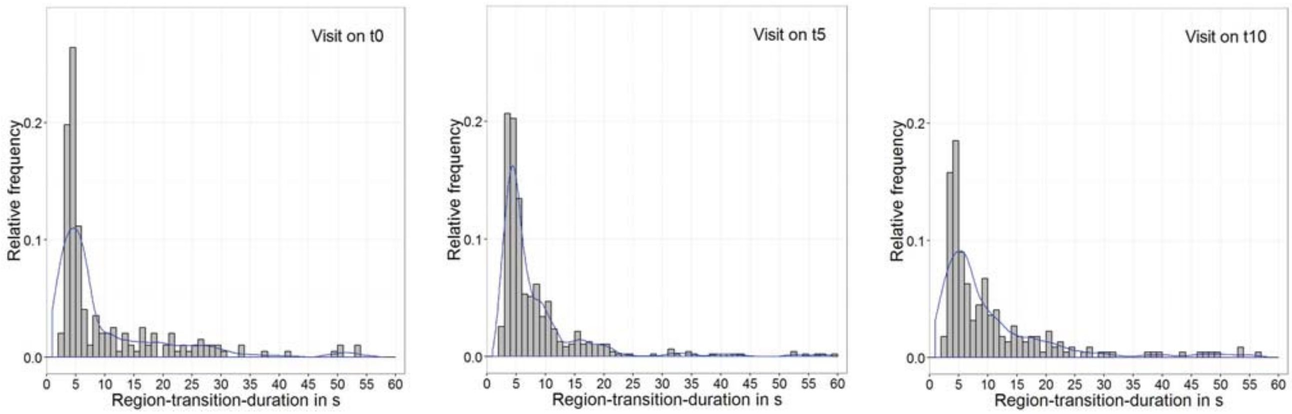


Figure 3: Cumulative frequency of region-transitions for participant A. The abbreviations stand for living room (L), corridor (C), bathroom (B), bedroom (S) and kitchen (K).

Derivation of Relevant Parameters

In order to achieve assessment-equivalent parameters, an indicator is calculated for each selected region-transition. The trend of these indicators is used to assess the mobility of the person. The trend is calculated for each selected region-transition and then compared to the trend of the clinical assessment parameters. In order to get a meaningful trend, an indicator is determined monthly. Therefore, a monthly subset of detected region-transitions for each selected definition is built. Then an indicator is calculated for each subset. For this purpose, a kernel density estimator is used to estimate



(a) t0 (b) t5 (c) t10

Figure 4: Histograms of the region-transition-durations for the transition $bathroom \rightarrow corridor \rightarrow livingroom$ at the time t0 (a), t5 (b) and t10 (c). The blue line represents the estimated kernel density. The maximum of this function is the computed indicator for the considered month.

the distribution of the region-transition-durations. The Epanechnikov kernel is applied for this type of data. The indicator is the mode of the computed distribution.
Figure 4 shows three histograms of the region-transition-durations for one definition, namely the transition $bathroom \rightarrow corridor \rightarrow livingroom$. The blue line represents the estimated kernel density. The maximum of this function is the computed indicator for the considered month.

5. EVALUATION OF THE AMBIENT HOME-BASED ASSESSMENT SYSTEM

In order to investigate the sensitivity of the proposed ambient home-based assessment system, we have evaluated the system within a field trial with 20 participants with a mean age of 84.25 years, living alone. Each participant's domestic environment was equipped with a home automation system that mainly used MDs as sensors. The physical performance of the participants was manually assessed monthly in their domestic environments by medical professionals including the $4\,m$-walk test (as part of the SPPB) and the TUG Test.
To investigate if the longitudinal and technical calculated assessment-results correspond with the ones of the established clinical assessments, we compare the temporal trends (calculated as linear regression (LR)) of the manually measured TUG (TUG-LR) and SPPB Walking test (SPPB-LR) with the corresponding one of the technical-derived duration-indicators (TDDI-LR) for each selected region-transition for two participants of the trial.
Figure 5 shows the temporal trends for the gold standard procedures, the TUG-LR (Figure 5 a) and the SPPB-LR (Figure 5 b), as well as for the three most frequent region-transitions (Figure 5 c-e) which consider at least 50% of all region-transitions. These trends and the meaningful relation among each other is typical for the cohort of the trial. The trends indicate the similarity of the results and support our assumption that clinical relevant trends can be derived from home-assessment systems that measure transition-durations via low-cost ambient motion-detectors. For the exemplarily selected trends of participant A, shown in Figure 5, a general decrease over the considered ten months is apparent (as indicated by the lines' slope). While the trends of the two assessments and the three region-transitions are similar, this does not necessarily hold true for the separate monthly indicator-values for the following reasons: Since TUG and SPPB are performed once per month, they only assess the mobility at that moment. Therefore, they are affected by the physical performance of that day and the inter-tester variability and thus, are much more susceptible to temporal variations than the proposed continuous and long-term detection of region-transitions and computation of the indicators.
However, the following discrepancy should be pointed out: Even though the durations for performing the SPPB walking test (shown in Figure 5 b) and for executing a region-transition [$livingroom \rightarrow corridor \rightarrow bathroom$] (Figure 5 d) are comparable with approximately 7.5 seconds, it must be considered that the corresponding distances vary by approximately 50% of 4m and 2m, respectively. This discrepancy is a consequence of the different types of circumstances, namely the capacity during assessment-conditions in contrast to assessing performance in daily living situations as discussed by [13]. Furthermore, unlike the SPPB walking test, the paths of the region-transitions are normally not straight.
While in many considered domestic settings a sufficient sensitivity was achieved, in some cases the trends were not similar. Therefore, the case of participant B which's overall TDDI-LRs trends do not fit to its SPPB-LRs and TUG-LRs (as shown in Figure 6) represents a suitable example. Herein, the given discrepancy among the trends is a result of an unintended repositioning of a motion detector in month 7: The sensor was attached to a TV-cupboard which was located in the right corner of the living room. This cupboard was rotated by approximately 60 degree anticlockwise, and thus the

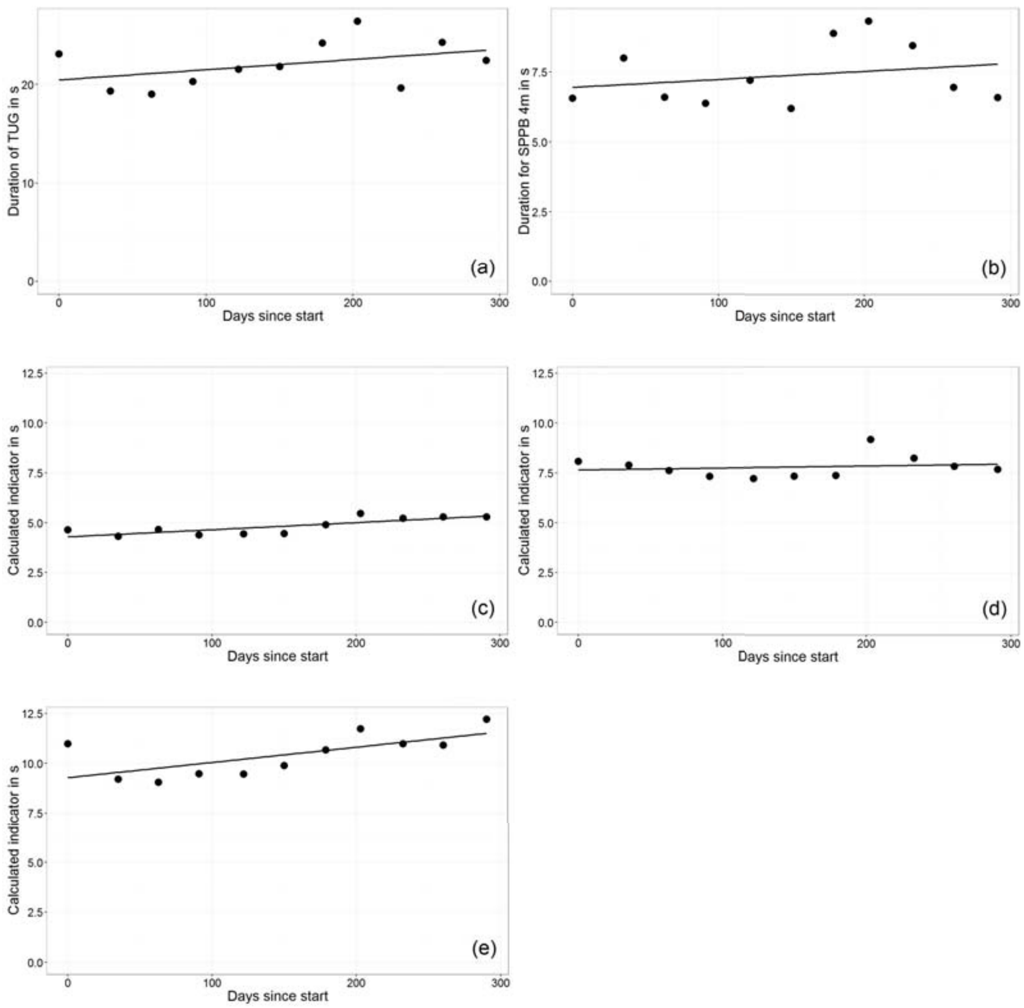


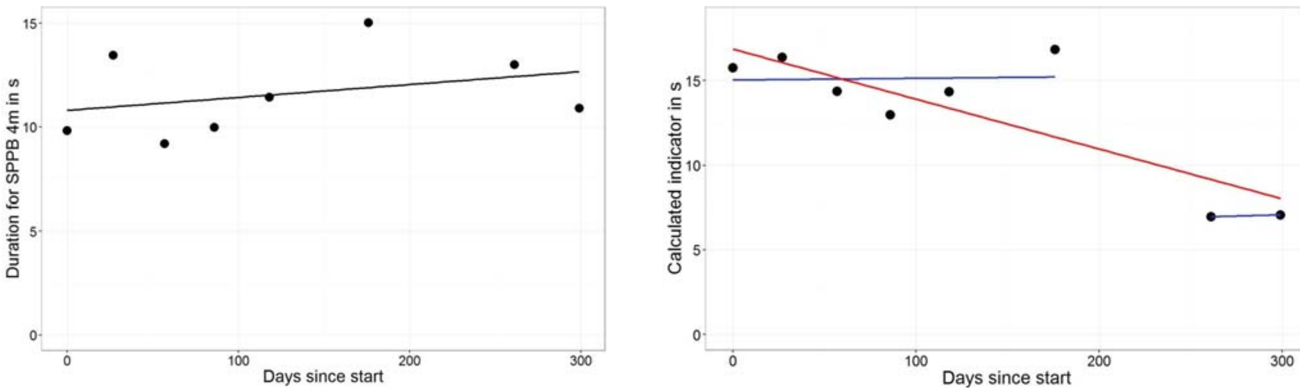
Figure 5: Trends for duration of TUG (a) and SPPB (b) walk test for participant A and the trends for calculated indicators for the region transitions: $Bathroom \rightarrow corridor \rightarrow livingroom$ (c), $Livingroom \rightarrow corridor \rightarrow bathroom$ (d) and $bedroom \rightarrow livingroom \rightarrow corridor$ (e).

corridor (room 3) became a part of the coverage area of the attached sensor (see Figure 2b). As a result, the path length of the region-transition was shortened, resulting in a reduced region-transition-duration (as shown in the red line in Figure 6 b). When excluding these unintended measures from consideration for the TDDI-LR, the trend corresponds with the SPPB-LR trend much better (as shown in the left blue line in Figure 6 b). In addition, in this deployment of participant B a loss of measurements occurred during the months five, seven and eight, leading to missing TDDIs for the corresponding months and thus, affecting the overall trend generation. The reasons for this loss were that the participant was in an institution for short-term care (between months four and five) and the system was shut-down unintendedly due to health-related changes of the domestic environment within the months seven and eight. While most results support the systems practicability, further work is still required to identify and overcome such unintended changes of the system. In addition, these preliminary results have to be confirmed in a larger cohort. A further point is the detection of untypical behavior and generating alarms for caretakers. A first approach is introduced in [30].

6. SUMMARY AND DISCUSSION

We have developed a minimized unsupervised technical assessment of physical performance in domestic environments that is expected to generate clinical meaningful and relevant insights about the functional status.Therefore, we identified the three functional parameters ”mobility and endurance”, ”strength” and ”balance” as essential components of functional mobility in a typical assessment (based on 20 assessment items on a geriatric study) via an exploratory factor analysis. However, the categorization of the items into this three functional parameters seems to be logical, because according to Cooper et al. strength, balance and walking are key components of physical performance [4].

Furthermore, we identified a minimal subset of assessment items which covers all identified factors and is suitable for



(a) Trend of duration for SPPB 4m for participant B.

(b) Trend of calculated indicators for participant B. Region-Transition: living room - corridor - bathroom.

Figure 6: Durations for walking distances: 4m SPPB walk test (a), region-transition (b).

unsupervised home-assessments: While the strength can be easily measured via handgrip dynamometers or even scales, the investigation of balance needs further studies to clarify most suitable measures. Focusing on the measurement of mobility, the measurement of short walking distances is most suitable for home-assessments. Finally, we investigated the transferability of the mobility measures by developing an ambient unsupervised assessment system and evaluate it in a ten month trial with 20 elderlies. The system measures region-transition-durations via motion detectors and identifies trends for the physical performance. For our investigations we take the most frequently performed region-transitions into account. In a further study we want to select and evaluate the region-transition according to their topology (straight sections or distances comparable with SPPB walking test). By examining the meaningfulness of these trends in comparison to the trends over regular TUG and SPPB tests, as common gold-standard measures, we could confirm a general fitting of the technical and clinical results.

While the results of such domestic assessments may not be directly comparable to clinical assessment tests, the problem of the incompleteness of assessment results (due to the applicability of only a subset of clinical assessment tests in domestic environments) could be minimized by our approach of an exploratory factor analysis and the meaningful reduction to a subset of essential assessment items. But our results show that the uncertainty and the contextual dependency are still problems, and it is necessary to check the results for plausibility.

However, we could introduce a minimized unsupervised assessment for functional performance and confirm the feasibility of our approach.Unsupervised technical home-assessments offer a good opportunity to enable high frequent or even long-term measurements of the functional status of the persons at risk. We look forward to using this approach to develop an alert system for critical changes in the persons' mobility or cases of emergency in further studies.

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