Activity Scores of Older Adults based on Inertial Measurement Unit Data in Everyday Life

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Abstract: The trend of an ageing population is becoming more and more obvious. Staying healthy in old age is an important social issue. Thereby, physical activity is essential for the preservation of physical function. We developed an algorithm for determining the activity level of seniors in everyday life. The proposed algorithm is based on machine learning activity detection using inertial measurement unit data. A series of activity scores is obtained by executing the algorithm from data on the type of activity, total activity time and activity intensity. To evaluate the performance of the proposed algorithm, a study with 251 participants aged above 70 (75.41 $\pm$ 3.88) years was conducted and the correlation between individual activity scores and clinical mobility assessments was determined. Results showed a relation between the Six Minute Walking Test and the total score in terms of activity level as well as the walk score. Additionally, the MVPA- and walk-score show a clear trend regarding the frailty status of the participants. Therefore, these scores are indicators of the physical function and hence validate the utility of the developed algorithm.

1 INTRODUCTION

Healthy ageing is becoming increasingly important, due to the demographic change and the increasing number of older people. In general, maintaining the fitness and independence of older adults to stay at home as long as possible is of high relevance. Early detection of functional changes allow interventions which improve or at least maintain physical function, which in consequence may reduce fall rates or the level of dependency (Beswick et al., 2008). Sufficient exercise is of main importance for healthy ageing. The results of Morey et al. (Morey et al., 2008) suggest that physical activity predicts functional status and negative changes in activity levels can indicate a reduction in physical functions. Similarly, according to Koroukian et al. (Koroukian et al., 2016), functional limitations may indicate poor health in older adults.

Early changes in functional status can be detected by clinical assessments. An alternative approach is the continuous monitoring of physical activity in everyday life with sensors, e.g. simple pedometers, accelerometers or presence sensors. By using wearable accelerometers, duration, intensity and type of activity can be determined via machine learning. In comparison to conventional assessments continuous monitoring reduces personnel and time expenditure and leads to a higher amount of everyday life results as technical monitoring avoids an examination situation and the active contribution of the subject.

This paper presents an unobtrusive approach for determining the activity level of seniors in everyday life using an inertial measurement unit. An algorithm was developed which evaluates the different activities in daily life. In consequence, the use of this methodology may result in early-stage interventions to prevent or reduce muscle loss by developing an individual training plan as soon as changes of the activity behavior of older people were identified.

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2 STATE OF THE ART

As already mentioned, changes in the physical activity of older adults can be a predictor of muscle loss and a possible loss of mobility. Thereby, physical activity can be measured both in terms of activity behavior and energy consumption. There are several methods to estimate the activity. For example, the recording of physical activity can be carried out using movement sensors as well as questionnaires (Ainsworth, 2009). Acceleration sensors were used in several studies to measure physical activity (Yasunaga et al., 2017; Loyen et al., 2017; van Ballegooijen et al., 2019) and a method to denote generic physical activity phenotypes from long-term accelerometer data was presented in (Marschollek, 2013).

However, Copeland et al. have shown, based on a literature search, that the sedentary time in the case of surveys compared to the time measured by devices is estimated too low (Copeland et al., 2017). When recording activity using questionnaires, the time of physical activity is often overestimated. The gold standard for determining energy expenditure is the double-marked water method using isotopes, but this is expensive and not suitable for everyday use. Therefore, a technical measurement of activity superiors questionnaires and clinical measurements and is preferable.

In literature, the activities were often assigned by an intensity unit based on their share of energy metabolism. The intensity unit is defined in MET (metabolic equivalent of task).

Table 1: Activity classification and corresponding MET-value.

activity	MET
sedentary behavior	≤ 1.5
mild physical activity	1.5 to 3.0
moderate to strong physical activity	≥ 3.0

A MET is defined as the energy conversion during quiet sitting, which means an average oxygen consumption of about $3.5\, ml \cdot kg^{-1} \cdot min^{-1}$ or $1\, kcal \cdot kg^{-1} \cdot h^{-1}$ for an adult (Ainsworth et al., 1993). Table 1 shows a basic classification, whereby physical activity can be classified according to their intensity in sedentary behavior, mild physical activity and moderate to vigorous physical activity. For example, Fortune et al. have developed an algorithm for the classification of activity levels for persons with rheumatoid arthritis, in which the activities are classified in class A (3-5 METs), class B (2-3 METs) and class C (1-2 METs) (Fortune et al., 2011). Class A activities are walking, stair climbing and cleaning tasks, class B activities are dressing, washing, drying dishes and class C are reading and writing.

Although it is difficult to accurately characterize the amount of physical activity which is required to maintain functional independence, it seems that moderate to higher activity levels are more effective than mild activities. It can be assumed that there might be a threshold of at least moderate activity for significant outcomes (Paterson and Warburton, 2010). Yasunaga et al. showed that replacing low sedentary behavior times (e.g., television and desk work) with medium to high levels of physical activity can contribute to improving physical function in older adults (Yasunaga et al., 2017). Loyen et. al have found that one-third of the participants did not meet the physical activity recommendations of the World Health Organization (WHO) based on total time in moderate to vigorous-intensity physical activity (MVPA), while more than 70% did not meet the recommendations based on time in MVPA bouts of at least 10 minutes (Loyen et al., 2017). In most articles with sensor-based activity estimation, the time in sedentary behavior (SB), light-intensity physical activity (LIPA) and moderate to vigorous-intensity physical activity (MVPA) were distinguished. Whereby, the wearing period of the accelerometer was at least four days (including one weekend day) with at least 10 hours recording (600 minutes) per day.

In most cases, the questionnaires evaluate the frequency, duration and type of activity in order to determine the level of physical activity. In the work of Huy and Schneider, a tool for measuring activity was developed for the German-speaking countries (Huy and Schneider, 2008) and compared following questionnaires: Dijon Physical Activity Score, Modified Baecke Questionnaire for Older Adults (MBQ), Physical Activity Scale for the Elderly (PASE), Yale Physical Activity Survey (YPAS) and Zutphen Physical Activity Questionnaire (ZPAQ). Trampisch et al. compared the MBQ, ZPAQ, PASE, YPAQ and CHAMPS Physical Activity Questionnaire for Older Adults (Trampisch et al., 2011). Since the questionnaires MBQ (Voorrips et al., 1991), PASE (Washburn et al., 1993), YPAS (Dipietro et al., 1993) and ZPAQ (Caspersen et al., 1991) have been used in both articles and are suitable for our target group of older adults starting at 60 years, they will also be considered in the present analysis.

These questionnaires identified the following areas of physical activity: sports, leisure, household, gardening, occupation, locomotion and rest periods (Huy and Schneider, 2008). All questionnaires use an overall score that summarizes all surveyed physical activities into a single result. Each activity is assigned a weighting. For YPAS and ZPAQ, this weighting is based on the MET value, which corresponds to the energy consumption during the performance of the physical activity and an intensity score was assigned to each specific activity area. MBQ and PASE result in a total score. MBQ calculates the sum of the activity areas sports, household and leisure with different weightings and PASE calculates the sum of 12 activity-subareas with different weightings.

3 METHODS

The aim of the present analysis was the calculation of an individual activity score based on the performed activities in daily life. The score should hold crucial information about the functional status and should be sensitive for changes in the activity behavior of the older adults to recognize first signs of functional deterioration occurring with age.

The study design and the algorithm for the score calculation are presented in the following subsections.

3.1 Study Design and Sample

We conducted a study with 251 participants aged 70 at minimum. The characteristics of our study sample are listed in Table 2. 148 participants were female and 103 male.

Table 2: Characteristics of the study sample (n=251), SD stands for standard deviation.

	min	max	mean (SD)
age [years]	70	87	75.41 (3.88)
height [cm]	145.8	192.5	167.10 (9.27)
weight [kg]	46.85	123.45	76.85 (14.15)

The participants performed first a comprehensive clinical assessment, which included besides other tests the Six Minute Walking Test (6MWT) (Butland et al., 1982), the Short Physical Performance Battery (SPPB) (Guralnik et al., 1994), the Timed Up and Go Test (TUG) (Podsiadlo and Richardson, 1991), the Frailty Index (FI) (Fried et al., 2001) and the Stair Climb Power Test (SCPT) (Bean et al., 2007). All functional tests were measured by physical therapists in a conventional manner as well as technology-based. The description of the whole study can be found in (Hellmers et al., 2017). Besides medical products and ambient sensors like light barriers, an inertial measurement unit (IMU) integrated into a belt was also used. The used sensor unit consists of a 3D accelerometer, gyroscope, magnetometer and a barometer.

Following the assessment, the participants wore the IMU-based sensor belt for seven days in their everyday life. To compare the results of the sensor with a gold standard measure, they were asked to write an activity diary.

In this analyses, data of 231 participants were included. 20 subjects were excluded, due to too short measurements with a duration below 4 days or a mean duration of fewer than 10 hours per day, incorrect wearing of the belt (deviating sensor orientation) or technical problems. The criterion of a minimum measurement time was chosen on the basis of the literature research (see Section 2).

3.2 Hierarchical Classification Model and Score Algorithm

To develop an adequate algorithm for the score calculation, the sensor measurements were analyzed via a machine learning classifier regarding the performed activities. We used a hierarchical classification model with four classifiers. After a low pass filtering of the raw data, the first classifier distinguished between static and dynamic activities, as well as transitions. If the state was classified, the other classifiers characterized the activities in detail. The selection of the trained activities was chosen regarding the activities in the conducted assessment tests. Figure 1 illustrates the hierarchical classification model. The state classifier is based on boosted decision trees, whereby the other classifiers are based on multilayer perceptrons (MLP). The MLP-classifier for the static activities consists of 5 hidden layers (HL) and 7 hidden nodes (HN), the classifier for dynamic activities of 3 HL and 44 HN, and for transitions of 4 HL and 40 HN. Further details of the different classifiers, used window sizes, step widths, filters and feature sets can be found in (Hellmers et al., 2018; Hellmers et al., 2019).

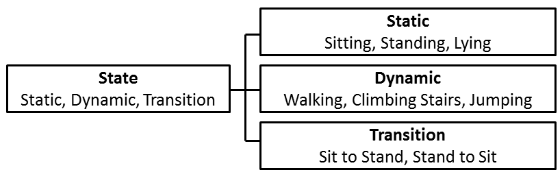

Figure 1: Hierarchical classification model. The first classifier distinguished between the state. The following classifiers recognized the possible activities of each state.

After the classification of the performed activities, an activity score can be calculated. Therefore, each activity is assigned an intensity weighting. The weightings are based on the MET-values found in the literature (see Section 2) and listed in Table 3.

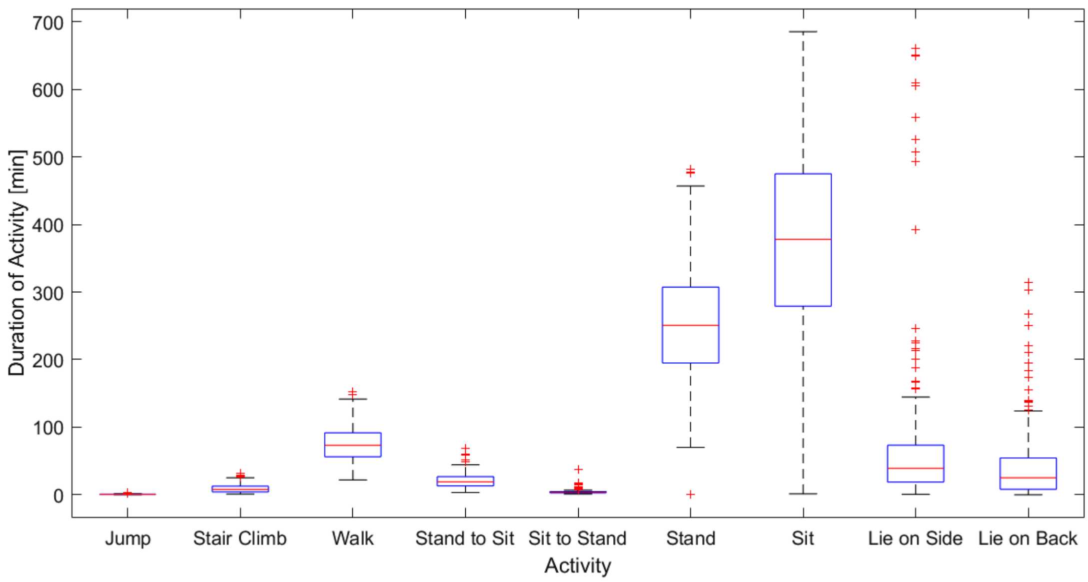

Figure 2: Average time in minutes of each activities per day over 231 participants.

The total activity score S is calculated by the whole duration of an activity A_i per day

$$A_i = \sum_{k=1}^{m} Z_k/T, \tag{1}$$

with Z_k as duration of activity and T number of measuring days, multiplied by the intensity weighting I_i

$$S = \sum_{i=1}^{n}(I_i \cdot A_i), \tag{2}$$

with n as total number of recognized activities. Alternatively, specific scores like the sedentary behavior score can be calculated by only taking the corresponding activities into account:

$$S_{SB} = I_{sitting} \cdot A_{sitting} + I_{lying} \cdot A_{lying} \tag{3}$$

LIPA-, MVPA-Scores and scores of specific activities can be calculated analogously.

4 RESULTS

Figure 2 shows the activities per day in minutes over the total study sample. As expected, the participants showed most of the time a sedentary behavior with in average 484.43 ± 126.88 minutes. The second most frequent activity was standing with 250.30 ± 25.61 minutes per day. The average walking time is about 75.28 ± 25.61 minutes per day. Due to the limited selection of recognized activities, there are some missclassifications identified from the diaries of the participants. For example, housework and gardening are recognized as standing in most cases.

Table 3: Intensity weightings and categories of each activity. The abbreviations stand for: Sedentary behavior (SB), light-intensity physical activity (LIPA) and moderate to vigorous-intensity physical activity (MVPA).

activity	intensity weighting	category
sitting	1	SB
lying	1	SB
standing	2	LIPA
walking	3.5	MVPA
transitions	5.5	MVPA
climbing stairs	6.85	MVPA
jumping	10	MVPA

Another important activity for our target group is cycling. Cycling is often classified as climbing stairs, walking, sitting or standing. In a self-experiment it could be shown that the speed of cycling has a significant influence on the classification. Thus, very slow riding is classified as sitting while fast riding is recognized as climbing stairs. Since driving faster means a higher energy consumption, this ”missclassification” is categorized correctly regarding the intensity weighting.

In terms of METs, the activities also fall into the right category: for example, slow-cycling (5.5 mph) corresponds to 3.5 METs, while faster cycling (10-11.9 mph) corresponds to 6.8 METs (Ainsworth et al., 2011). These values are similar to the intensity weightings of 3.5 for walking and 6.85 for climbing stairs.

In a second analysis, the study participants were categorized into four different groups regarding the

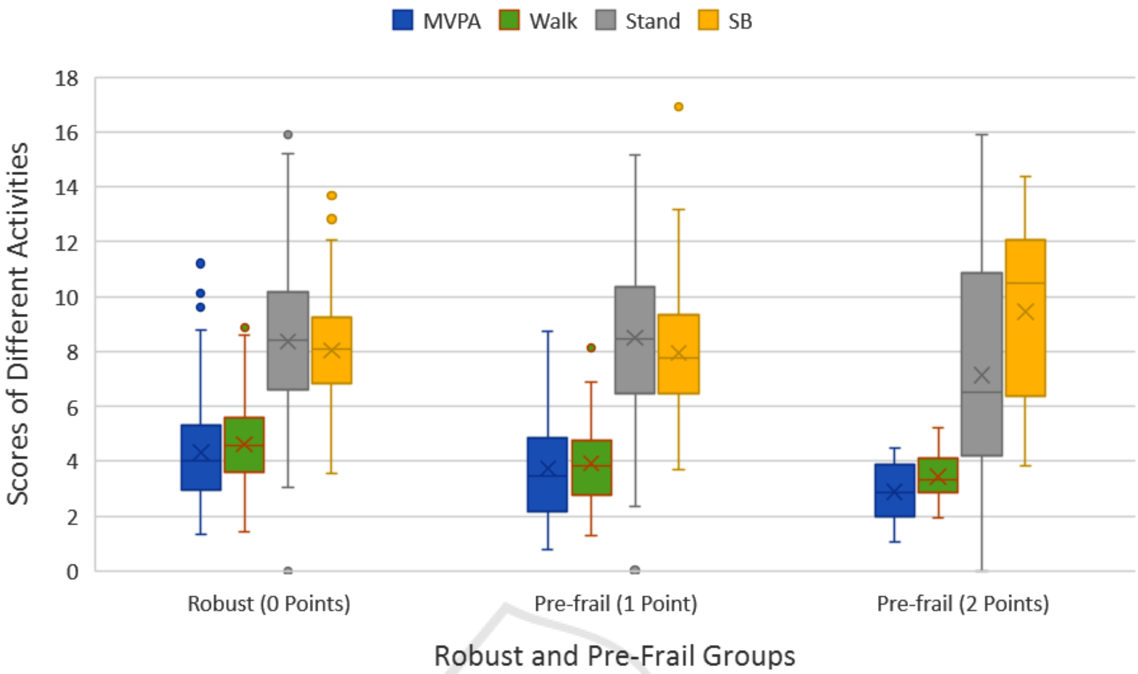

Figure 3: Average MVPA-score, walk-score, stand-score and sedentary behavior-score (SB) for the different frailty groups regarding the Fried phenotype.

Fried phenotype: robust (0 points) , pre-frail (1 point and 2 points) and frail ($\leq$ 3 points). The distribution of the 231 subjects among the groups is as follows: 160 (robust - 0 points), 60 (pre-frail - 1 point), 11 (pre-frail - 2 points). Figure 3 shows the results of the MVPA-score, walk-score, stand-score and SB-score for the different frailty groups. There is a clear trend that seniors with a low MVPA-score (decreasing active) are frailer. On average, the participants of the robust-group have a higher MVPA-score of 4.32 and (pre-) frail seniors have lower MVPA-scores of 3.74 and 2.88. This trend can also be observed in the walking score. Therefore, the walking-score could also be a predictor of frailty. However, the SB-score seems to be not a sure sign of frailty. Due to the disbalanced group sizes, these results should be considered with caution.

The scores also reflect the long times spent standing or in a sedentary behavior.

Figure 4 presents the results of the walking score in comparison to the results of the Six Minute Walking Test (6MWT). Correlation analysis shows a light significant correlation with a p-value of $p < 0.001$ and a correlation coefficient of 0.48. The dashed line shows the calculated regression line.

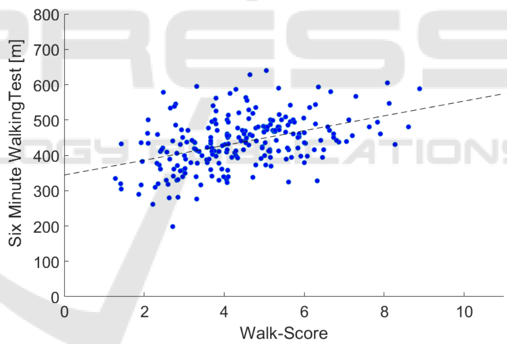

Figure 4: Correlation of the walking-score with the results of the Six Minute Walking Test.

5 CONCLUSIONS

We developed an algorithm for the estimation of an activity level of older adults based on inertial measurement unit measurements in daily life. We conducted a study with 251 participants aged 70 years and above and analyzed the activities recognized via a hierarchical machine learning classification model. Different activity scores were calculated, whereby the MVPA- and walk-score show a clear trend regarding the frailty status of the participants. Correlation analyses with the results of clinical mobility assessments showed a significant correlation between the walk-score and the Six Minute Walking Test.

Therefore, we presented a promising approach that provides information on the health status through unobtrusive everyday measurements. Further investigation about the significance of the scores are necessary. Concerning the miss-classifications, an expansion of the recognizable activities would be valuable to improve the meaningfulness of the scores.

However, we are optimistic that this approach will be able to detect changes in the activity behaviour of seniors and thus is suitable to give early indications of the necessity of interventions in the event of a beginning functional decline.

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