Master's Thesis

Detection of physical activity types with accelerometers in adolescents during semi-structured free-living

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ABSTRACT

Background Few algorithms are available for detection and classification of physical activity (PA) types in adolescents, and existing algorithms are only validated in controlled laboratory settings. The performance of such algorithms outside of the laboratory in adolescents remains unexplored. Several algorithms have been developed and validated for adults but it is uncertain if these algorithms are valid for detection and classification of PA in adolescents.

Aim The aim of this study was to evaluate the validity of an algorithm developed for detection of PA in adolescents (NTNU^{ADOL}). A comparison was made against the performance of an algorithm developed for detection of PA in adults (NTNU^{ADUL}). The evaluation of the validity was based on the algorithms performance in detecting PA types in adolescent during semi-structured free-living.

Methods Twelve adolescents (6 boys, 6 girls, mean age 14.7 years, range 13-16 years) were equipped with two accelerometers (Axivity AX3) and a chest-mounted camera. A semi-structured free-living session for detection of PA types was carried out. Video recordings were used as validation criterion, and PA types were defined and used as guidelines for annotation of the video-recordings. Two algorithms, NTNU^{ADOL} and NTNU^{ADUL}, were developed and used for analysis. To test the performance of the NTNU-algorithms a reference was made against an existing algorithm developed for adults (Acti4) in a separate analysis. Walking, standing, sitting, lying down, shuffling, walking stairs, running and other vigorous PA was analyzed. Overall accuracy was calculated for each algorithm. Sensitivity, specificity and accuracy were calculated for each PA type. Confusion matrices were included to show the distribution of correctly and incorrectly classified instances.

Results Overall accuracy was 87% for NTNU^{ADOL} and 85% for NTNU^{ADUL}. Both algorithms could detect walking, standing, sitting, lying down and running with sensitivity above 80%. Specificity and accuracy was high (>87%) for both algorithms. The NTNU^{ADOL} showed highest sensitivity for detection of walking, standing, sitting, lying down, running, walking stairs up and other vigorous PA, while NTNU^{ADUL} showed higher sensitivity for shuffling and walking stairs down. Most misclassifications were due to insufficient discrimination between shuffling, walking and standing, and between walking stairs and horizontal walking

Conclusion Both algorithms were able to detect walking, sitting, standing, lying down and running with acceptable to high performance. There were no major differences between the algorithms. The most evident differences were found for detection of other vigorous PA with the NTNU^{ADOL} being superior and shuffling with the NTNU^{ADUL} being superior.

SAMMENDRAG

Bakgrunn Et fåtall algoritmer for deteksjon av ulike typer fysisk aktivitet (FA) eksisterer for ungdom, og alle er validert under kontrollerte omgivelser i et laboratorium. Algoritmenes prestasjon for deteksjon av FA typer hos ungdom utenfor laboratoriet er ukjent. Flere algoritmer har blitt utviklet og validert for voksne, men om disse algoritmene er også er valide for ungdom er fortsatt ukjent.

Mål Målet med denne studien var å evaluere validiteten til en algoritme utviklet for deteksjon av typer FA hos ungdom (NTNU$^{\mathrm{ADOL}}$). En sammenlikning ble gjort mot en algoritme utviklet for voksne (NTNU$^{\mathrm{ADUL}}$). Evaluering av validitet ble basert på algoritmens prestasjon for deteksjon av FA hos ungdom i en semi-strukturert naturlig setting.

Metode Tolv ungdommer (6 gutter, 6 jenter, gjennomsnittsalder 14.7 år, range 13-16 år) ble utstyrt med to akselerometre (Axivity AX3) og et kamera på brystet. En semi-strukturert protokoll utenfor laboratoriet ble gjennomført for deteksjon av ulike typer FA. Video ble brukt som validerings kriteria og ulike typer FA ble definert og brukt som retningslinjer for annotering av video-opptakene. To algoritmer, NTNU$^{\mathrm{ADOL}}$ og NTNU$^{\mathrm{ADUL}}$, ble utviklet og brukt for analyse. For å teste prestasjonen til NTNU-algoritmene ble det gjort en referanse til en allerede eksiterende algoritme utviklet på voksne, Acti4, i en separat analyse. Gå, stå, sitte, ligge, shuffling, gå trapp opp og ned, løping og annen vigorøs FA ble analysert. Overordnet nøyaktighet (‘accuracy’) ble beregnet for hver algoritme. Sensitivitet, spesifisitet og nøyaktighet (‘accuracy’) ble beregnet for hver FA type. ‘Confusion matrices’ ble inkludert for å vise korrekte og feilaktig klassifiserte tilfeller.

Resultat Overordnet nøyaktighet var 87% for NTNU$^{\mathrm{ADOL}}$ og 85% for NTNU$^{\mathrm{ADUL}}$. Begge algoritmene kunne detektere gå, stå, sitte, ligge og løpe med sensitivitet over 80%. Spesifisitet og nøyaktighet var høy (>87%) for begge algoritmene. NTNU$^{\mathrm{ADOL}}$ viste høyest sensitivitet for deteksjon av gå, sitte, ligge, løpe, gå trapp opp og annen vigorøs FA, mens NTNU$^{\mathrm{ADUL}}$ viste høyere sensitivitet for shuffling og gå trapp nedover. De fleste missklassifiseringene var mellom shuffling, gå og stå, samt mellom trappegang og horisontal gange.

Konklusjon Begge algoritmene kunne detektere gå, sitte, stå, ligge og løpe med akseptabel til høy sensitivitet, spesifisitet og nøyaktighet. Det var ingen store forskjeller mellom algoritmene. Den tydeligste forskjellen ble funnet for deteksjon av annen vigorøs FA der deteksjon var mest nøyaktig med NTNU$^{\mathrm{ADOL}}$ og for shuffling, der NTNU$^{\mathrm{ADUL}}$ var mest nøyaktig.

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INTRODUCTION

Low levels of physical activity (PA) is associated with reduced longevity[1] and increased risk of several non-communicable diseases (e.g., type 2 diabetes and coronary heart disease)[1,2]. It is well documented that PA during adolescence has important impact on several health outcomes, such as musculoskeletal health, cardiovascular health, overweight, blood pressure and mental health[3]. Adolescents are recommended a minimum of 60 minutes of moderate to vigorous-intensity PA (MVPA) during the day[4], but only 20% of the world's adolescent population fulfills this recommendation[4,5].

A detailed assessment of the PA types occurring during everyday life offers an interesting approach to studying PA pattern, determining level of PA, compliance with guidelines, effectiveness of PA interventions and understanding the relation between PA and health in adolescents. PA is a complex behavior consisting of several components, such as frequency, duration, type and intensity along with contextual and psychological factors. Contextual factors encompasses several different activities such as recreational or leisure time PA, occupational PA, transportation, and sports[6]. Several subjective and objective methods are available for measurement of PA[7] but reliability and validity differs extensively between methods. Self-reporting of PA by questionnaire is one of the most common methods used to estimate PA[8]. However, questionnaires are hampered by recall bias and subjective interpretation and have limited reliability and validity compared to objective measurements[7,9-11]. For example, substantial disagreement between self-reported and objectively measured sitting time has been found[12]. Thus, objective measurements of PA have become more attractive and the rapid development of wearable technology makes it possible to objectively record free-living PA for several days and weeks. Typically, devices for long-term recordings of PA include small light-weight accelerometers able to collect and store raw acceleration data. Tri-axial accelerometers measure acceleration in three directions and are sensitive to both gravitational- and dynamic acceleration. Thus, by means of accelerometers it possible to derive information about tilt, frequency, duration and intensity of body movements[13,14].

Several studies have used accelerometer recordings to estimate energy expenditure (EE)[15]. However, recent research has shown that self-reported PA types such as standing, sitting and walking have independent effects on health outcomes[16-18]. For example is excessive time spent sitting or lying found to increase the risk of cardiovascular- and all-cause mortality even in physically active individuals[16,19]. Thus, during the last years more attention has been directed towards the need for measuring different types of PA during daily life, rather than focusing on EE.

Provided a suitable placement of accelerometers on the body it is possible, based on the accelerometer signal, to derive information about different types of PA, such as standing, sitting, walking, running and cycling among others[20]. Several different approaches exist for development of custom-made algorithms for detection of PA types from one or several accelerometers with different configurations of the sensor placement[21]. Previous studies have shown that increasing the number of accelerometers from one to two gives a more accurate activity classification, but increasing from two to several are less beneficial. Moreover, placing one accelerometer on the upper- and one on the lower body has been suggested for optimal activity recognition[20]. A large amount of studies have developed and validated algorithms for detection of PA types in adults e.g.,[22,23-27]. Most notably, Skotte and colleagues developed an algorithm able to detect walking, standing, sitting, walking stairs, running, lying down and cycling from two accelerometers placed at the hip and thigh[22,23]. This algorithm has been validated against video recordings with sensitivity ranging from 75.4% to 99.4% in a controlled laboratory setting and from 49.9 to 98.5% in free living[23]. These results are better than or compare well with to those found by others[24-27]. Overall, findings from validation studies mimicking free-living show decreasing performance[23,24,27], indicating that measuring PA types with accelerometers in a controlled laboratory setting is not directly transmissible to everyday life.

The PA level and pattern is found to differ between adolescents and adults. The most prominent decline in PA is found during late adolescence[28]. A decrease in active transportation and increase in screen-time (television-time and computer-time) have led to high levels of sedentary behavior in adolescents[29,30]. However, studies show that adolescents participate in more regular, vigorous PA, sports and planned exercise compared to adults[28,29]. Thus, MVPA and organized sports are an important contributor to daily EE in adolescents[31,32]. The contextual and behavioral differences between adolescents and adults stress the importance of developing algorithms that are valid and usable for detecting different types of PA in adolescents.

A small number of studies have validated accelerometers for detection of PA types in adolescents, and results have been inconsistent[33,34]. In a controlled laboratory setting, one accelerometer at the hip was validated against direct observation. Percentage of time spent sitting and lying was correctly classified 15% and 20% of the time respectively, while standing was correctly classified 94% of the time[34]. In another study comparing an accelerometer on the thigh with one on the waist, overall accuracy for detection of sitting, stranding and walking was 99.1% for the waist-worn accelerometer and 66.7% for the accelerometer on the thigh[33]. Both studies used proprietary software provided by the manufacturer. They are often restricted to one accelerometer and a few PA types. For example, differentiating between sitting and lying, and sitting and standing, have proven difficult[33,34]. Moreover, the low performance found with proprietary software limits their usability for detection of PA types during free-living, where a more variety of PA types may occur and complexity of PA may increase.

Furthermore, two studies have developed algorithms for detection of PA in children and adolescents aged 5 to 18.9 years[35,36]. Both algorithms were validated against EE and known duration of the protocol. Moreover, both studies developed algorithms based on only one accelerometer (hip or wrist). Lying down, sitting, standing, walking, running, playing basketball and dancing[36] and sedentary activity, light household and games, moderate-to-vigorous games and sports, walking and running[35] were detected. Classification accuracy ranged from 64% to 97% and from 75% to 98% respectively. However, validation of algorithms for detection of PA types from accelerometer data in adolescents during free-living are currently lacking. Further, although several custom-made algorithms for detection of PA types have proved to have high validity in adults, it is unknown whether these algorithms have similar precision for detection of PA in adolescents.

The aim of this study was to evaluate the validity of an algorithm developed for detection of PA in adolescents (NTNU^{ADOL}). A comparison was made against the performance of an algorithm developed for detection of PA in adults (NTNU^{ADUL}). The evaluation of the validity was based on the algorithms performance in detecting PA in adolescent during semi-structured free-living. It was hypothesized that the NTNU^{ADOL} algorithm would be more precise in detecting and discriminating between different types of physical activities in adolescent than the NTNU^{ADUL} algorithm. For the purpose of making a comparison between the NTNU^{ADOL} and NTNU^{ADOL} possible, definitions were established for the types of PA to be included in the analyses. In addition to comparing the two NTNU-algorithms, a reference was made to an existing algorithm for activity detection (Acti4)[22].

2. METHODS AND MATERIAL

2.1 Sample

Twelve healthy adolescents (6 boys, 6 girls) from Charlottenlund lower secondary school in Trondheim, Norway, were recruited to the study. Characteristics of the participants are presented in Table 1. Inclusion criteria were 1) able to move around without walking aids and 2) able to take verbal instruction. The participants were informed about the general content and aim of the study prior to participation, and parents had to give their written approval. The study protocol was approved by the Regional Committee for Ethics in Medical Research and the study was carried out according to the Declaration of Helsinki.

Table 1. Characteristics of the participants. Values are mean ± standard deviation (range).

	Boys (n=6)	Girls (n=6)
Age (years)	14 ± 1.1 (13 – 15)	15.3 ± 0.5 (15 – 16)
Weight (kg)	57.1 ± 12.1 (44.0 – 71.2)	59.4 ± 6.5 (50.2 – 67.8)
Height (cm)	168 ± 7.2 (160 – 179)	167 ± 5.7 (160 – 171)
Body mass index (kg/m^2)	20.1 ± 3.4 (17.0 – 25.5)	21.3 ± 1.7 (19.1 – 23.1)

2.2 Instrumentation

PA was measured using the Axivity AX3 (Axivity[i], UK) device (Figure 1). The AX3 is a tri-axial accelerometer (dimensions 23x32.5x7.6 mm; weight 11g). Due to its open-source firmware platform and sampling of raw acceleration data, the AX3 allows for open data processing.

The AX3 can record accelerations between 12.5 to 3200 Hz, with range ±2/4/8/16 g. In the present study, the accelerometers were set to a sample rate of 200 Hz, with a dynamic range of ±8 g. All raw data was stored in a 512 Mb internal memory and downloaded as a binary file (Continuous Wave Accelerometer [CWA] format) for visualization and further analysis.

[i] http://axivity.com/

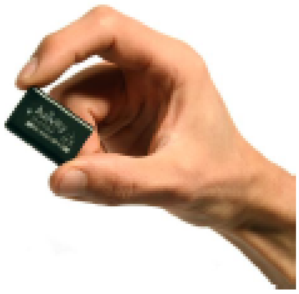
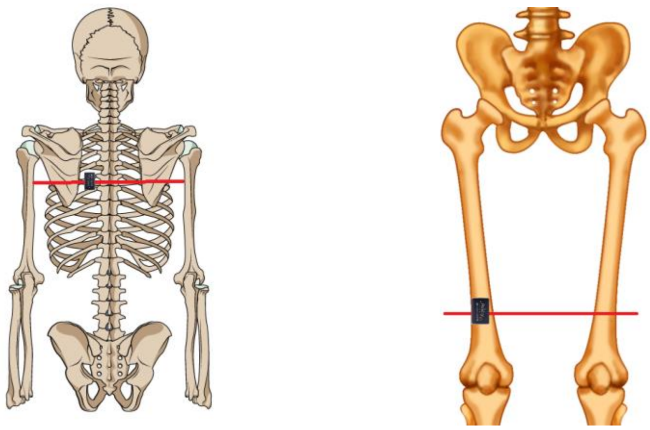


Figure 1. The AX3 accelerometer.

Two accelerometers were attached directly to the skin of the participants. One was placed at the upper back, approximately 1-2 cm to the left of the spinous process of T5 (Figure 2a; Figure 3a), and the other on the right thigh, approximately 10-12 cm above the upper border of the patella (Figure 2b; Figure 3b). The x-axis of the accelerometer corresponds to the body's longitudinal axis (gravitational axis), the z-axis to the anteroposterior axis and the y-axis to the mediolateral axis. The accelerometers were wrapped in plastic foil, attached to the skin with toupee tape and 5x5 cm of Fixomull (BSN Medical[ii]), and covered by Flexi Fix (Smith & Nephew[iii]) in accordance with procedure used in previous studies[22]. The AX3 accelerometers were initialized using the software provided by the manufacturer (OmGui Configuration and Analysis Tool, Open Movement project, version 1.0.0.28[iv]) before use.



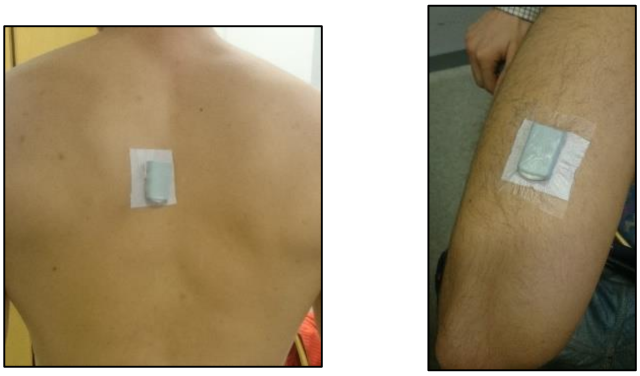
(a) Back sensor. (b) Thigh sensor.

Figure 2. Illustration of the anatomical placement of the accelerometers.

[ii] http://www.bsnmedical.com/bsn-medical-global.html
[iii] http://www.smith-nephew.com/professional/
[iv] https://github.com/digitalinteraction/openmovement/wiki/AX3-GUI

A GoPro camera (type Hero 3+, Figure 4b) was used for video recordings (video resolution 720 pixels, 30 frames per second [fps]). The camera was attached to the chest with a chest harness (Figure 4a) pointing downwards and filming only the legs.

The two accelerometers had to be synchronized with each other and the video-recording. Synchronization was achieved by making a reference point. Heel-drops were chosen, as they are easy to perform, and the impact between the heel and ground is easily spotted in the acceleration signal from both the thigh and the back, as well as in the video. Three heel-drops were conducted both at the start and end of the data collection.



(a) Back sensor. (b) Thigh sensor.

Figure 3. The accelerometers were wrapped in plastic foil and attatched to the skin on the upper back (a) and on thigh (b). FlexiFix was used to cover the accelerometers (not shown in picture).

(a) Chest mounted. (b) GoPro camera.

Figure 4. GoPro camera attached to chest (a) and illustration of GoPro Hero 3+ (b).

2.3 Semi-structured free-living protocol

Prior to the measurements, demographic data such as gender and age were collected, and weight and height were measured (in light clothing, no shoes). The accelerometers and the GoPro camera were attached to each participant by a test-leader, ensuring the correct placement.

A semi-structured free-living protocol for detection of PA types was carried out. A test-leader was present during the start-up of the session, explaining the content and order of the protocol. The participants performed a rebus consisting of several tasks requiring the participants to carry out the PA types of interest. This included walking, standing, sitting, running, lying down, shuffling, bending/picking, walking stairs and other vigorous PA. The rebus can be found in Appendix 1. The first 10 minutes of the rebus was for detection of sports-like PA types consisting of rapid leg movements with rapid changes in movement direction as well as sideway and backward movements. Three agility drills were set-up and the participants were told to finish each a minimum of three times. For a more detailed illustration of the set-up of the agility drills, see Appendix 2. Most of the remaining tasks in the protocols were stated as goals rather than requests to minimize the participant's awareness of the data collection. For example, the participants were told to 'go find the exhibition with the skeleton at the top floor' to implement walking stairs up and down. The order of the rebus was set, but the participants did not have any further restrictions. They were encouraged to behave as naturally as possible. The complete protocol lasted for approximately 45 minutes.

2.4 Definition of physical activity types

Currently, there is no consensus on which types of PA to include in accelerometer validation studies, neither on how to define different PA types. Due to the lack of consensus, a major part of this study was to develop and establish definitions for different PA types prior to the data collection. This involved both *selection* of PA types, *why* they should be included and *how* they should be defined. This selection was based on 1) possible relevance for health, 2) how common and relevant the PA type is across age and 3) how common the PA type is in daily life. The included PA types are illustrated in Figure 5 and the complete list of definitions can be found in Appendix 3.

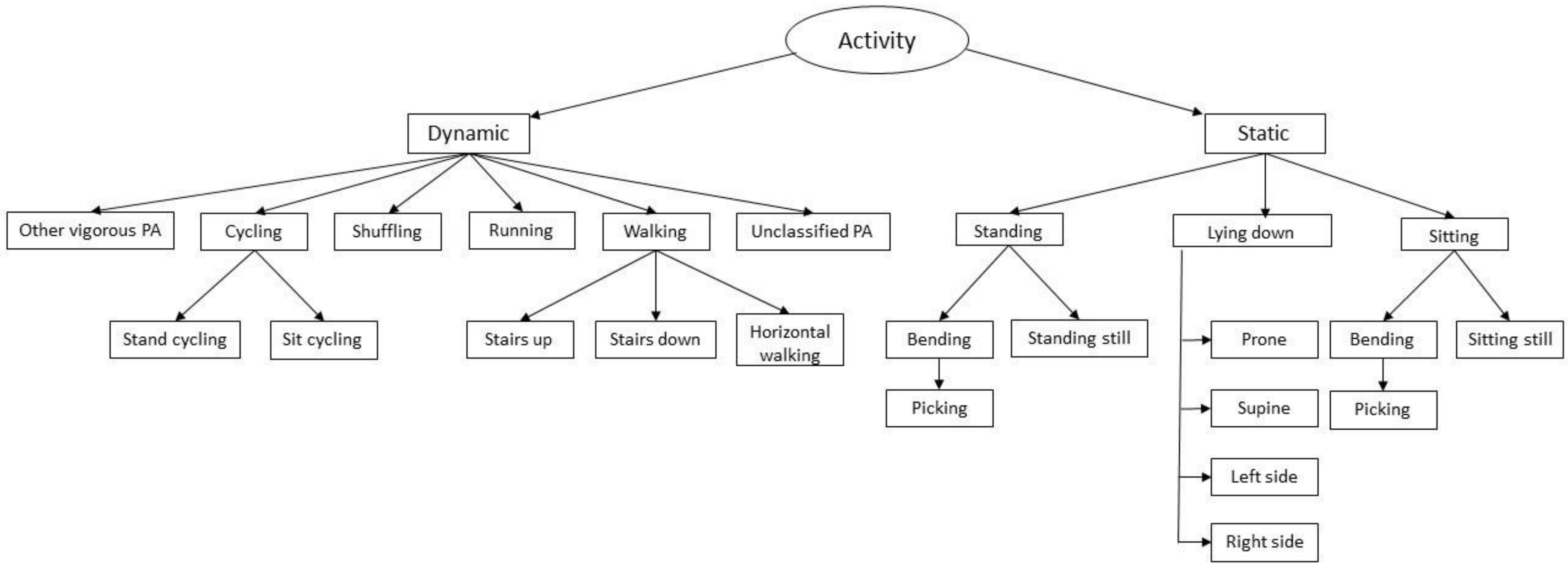


Figure 5. Hierarchical overview of the PA types defined for the video analysis. The main PA categories and corresponding possible sub-categories are illustrated.

The definitions were developed in collaboration with a validation study for detection of PA types in adults and one for detection of PA types in children. Thus, the definitions were designed to apply for all age-groups. First, the most common types of PA were defined. This included walking, sitting, standing, lying down, running, cycling and walking stairs. Shuffling was included to account for feet-movements that do not classify as walking. Other vigorous PA was included as a collective term for sports-like PA because this is a common PA type in children and adolescents participating in sports and physical education. Bending, picking and transitions were included because they are of relevance for functional ability, especially for the elderly. Moreover, a category of unclassified PA and a category of undefined PA were included. Unclassified PA accounted for all PA that could be recognized but did not fit into one of the other definitions. This could for example include crawling, skipping or falling. Undefined was included to account for periods when it was not possible to state what type of PA that was conducted, for example periods when the camera was blocked.

In addition to defining the specific types of PA, postural transitions were described. This was to ensure coherence regarding when a PA-type ends and a new one begins. Two types of transitions are described: 1) transitions actually classified separately as a 'transition'. They occur between lying and sitting/walking/standing or from sitting/walking/standing to lying and from sitting to walking/lying/standing or from walking/lying/standing to sitting. In this case, a separate transition is defined. 2) The transition-period between two activities or postures. This describes when one activity/posture ends and another one begins, without there being a separate transition between them. Definitions of the transitions can be found in Appendix 3.

2.5 Data analysis

2.5.1 Video annotations

The analysis of the video recordings was used as gold standard for the validation of the PA types identified with the algorithm. Before annotation, the video was converted from AVI to MP4 format and from 30fps to 25fps.

Videos were annotated according to the definitions (Appendix 3). Annotation was done by using the Anvil Video Annotation Research Tool version 5.1.13[v]. An overview of

[v] http://www.anvil-software.org/

the annotation window is presented in Figure 6. Annotation was done frame-by-frame (1 frame = 1/25 sec) for each participant. A total of 14 different types of PA were annotated. This includes walking, shuffling, running, standing, sitting, lying down, walking stairs up, walking stairs down, bending, picking, transitions, other vigorous PA, unclassified PA and undefined activity. Additionally, the heel-drop was annotated. The completed annotations were thereafter exported to text format for further use. This process was repeated for each subject. All observations classified as undefined were excluded from further analysis. The annotations of the heel-drop were also excluded from all other analysis, except for the synchronization process. Annotations for bending and picking were combined into one category consisting of all annotations and renamed to bend/pick.

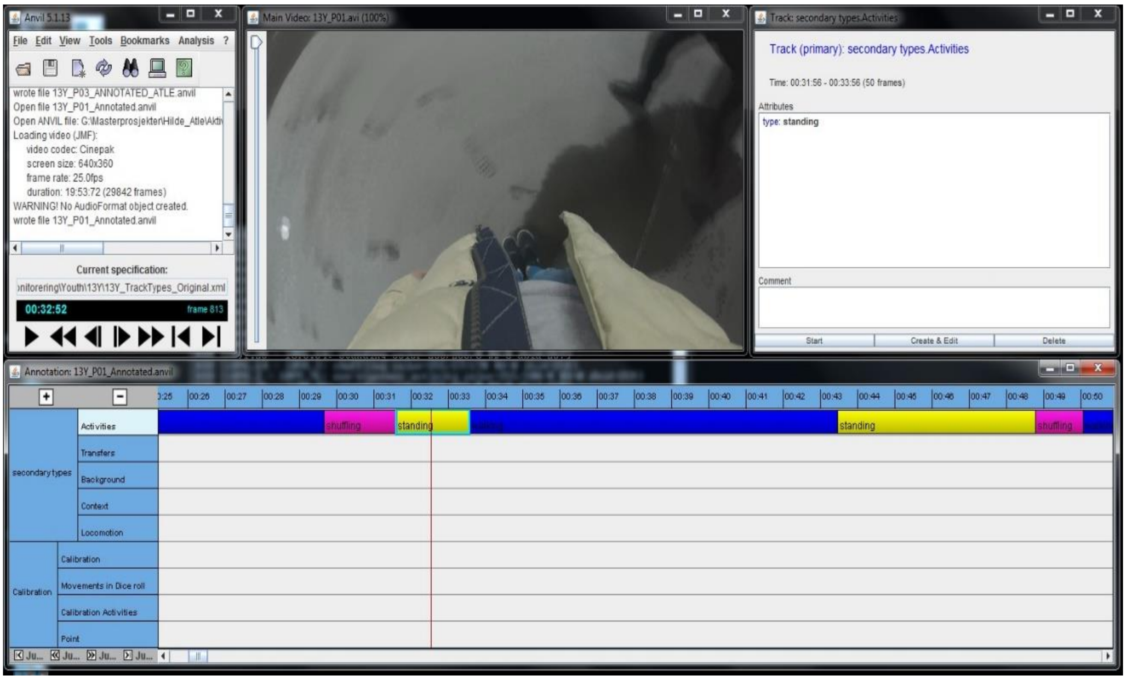


Figure 6. Illustration of the annotation window in Anvil. Activities are annotated in the upper line and color-coded so that they are easily recognized.

In order of calculating inter-rater reliability (IRR), three persons annotated the same video for one participant. The video lasted for approximately 50 minutes and consisted of the complete protocol for one adolescent. IRR was calculated as Cohen's kappa coefficient *(κ)* for all annotator pairs (Table 2). Then, the arithmetic mean of these values was calculated[37]. The resulting mean Cohen's kappa value was 0.92.

Table 2. Calculated Cohen's kappa for all three annotator pairs.

	κ -value
Annotator 1 versus annotator 2	0.92
Annotator 1 versus annotator 3	0.92
Annotator 2 versus annotator 3	0.92

2.5.2 Resampling and synchronization of accelerometer data

The raw acceleration files ([CWA-format]) were transferred to a computer by using the OmGui software. The raw acceleration data and associated video-annotations were then processed in Matlab (The MathWorks Inc., US) before further analysis.

The sampling rate of the AX3 was shown to vary within each sensor unit during a sampling period. For example, if the sensor was configured to sample at 200 Hz it could deviate from this (e.g., 198.3 Hz at one point and 201.1 Hz on another). Thus, the raw acceleration signals had to be resampled. Originally, they were set to 200 Hz for inclusion of gait-parameters, but because this was not of interest in this study, the acceleration data was resampled from 200 Hz to 100 Hz.

Synchronization of the acceleration data and the video-annotations was achieved by a correlation analysis. First, a template-window consisting of the first three heel-drops was created. By sliding this template across the signal and using correlation, the frame annotated as heel-drop was matched with the visually spotted impact in the acceleration signals. This is illustrated in Figure 7. Synchronization was done for each subject, both at the beginning and end of the signal.

2.5.3 NTNU-algorithms

This study is a part of a larger collaborative project. Algorithms for detection of PA types were developed in parallel to the present study. It is not the scope of this study to give a detailed description of the development of these algorithms as this can be found elsewhere[38]. In brief, adaptive machine learning systems capable of learning the pattern and recognize features of complex data was used to develop two novel algorithms, $\text{NTNU}^{\text{ADOL}}$ and $\text{NTNU}^{\text{ADUL}}$. By training the algorithms on realistic data and extracting features from the acceleration signal these algorithms can provide classification of different types of PA[21]. The core of the algorithms is based on the random forest technique, which work as a collection of de-correlated decision trees where N random subsets are created with a corresponding decision tree. Each instance is classified in every decision tree, and the label (PA-type) with the most votes is chosen[39]. A 10-fold cross-validation (*k-fold* cross-validation) method was used to split the original data-set into ten different sub-sets with equal size. Nine of the sets were used for training the algorithm, and the last one was used for testing. This process was repeated ten times and results in ten different classification algorithms. The results obtained from the classification algorithms are then averaged and used in further analyses[40]. Thus, no data will be tested on a model it has been trained on. The widow-size was fixed at 1 sec and in the current context one instance corresponds to 0.5 sec. Further, a sliding window technique with 50% overlap was used (i.e., the first window contains sample 0 to 100, the second window from 50 to 150 and so forth).

The NTNU[ADOL] was both trained and tested on data from the present study (n=12). The NTNU[ADUL] was trained on data from the parallel study on adults (n=23) while the data from the present study (n=12) was used as test-data. The protocol used for development of the NTNU[ADUL] is found in Appendix 4.

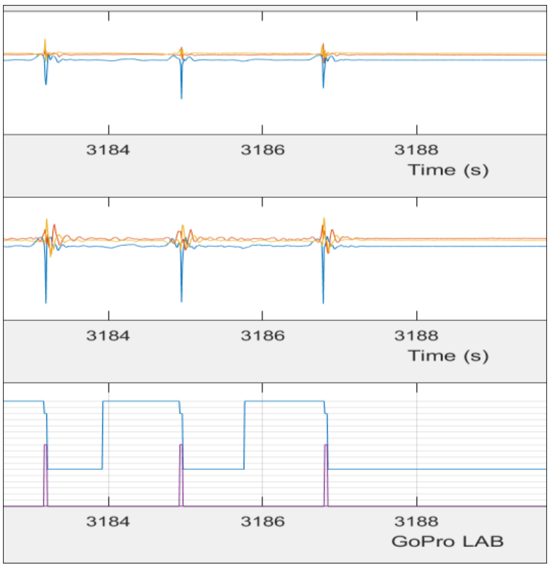


Figure 7. Synchronized data for one subject. Synchronization is from the beginning of the protocol. A correlation analysis was used to match the heel-drops from all three signals. The top traces show the signal from the accelerometer attached to the back, the middle traces show the signal from the accelerometer attached to the right thigh while the bottom traces indicate the video annotation.

2.5.4 Acti4

To test the performance of the novel NTNU-algorithms, a reference was made to an already existing algorithm, Acti4 (version 1602a The National Research Centre for the Working Environment, Copenhagen, Denmark and Federal Institute for Occupational Safety and Health, Berlin, Germany). Acti4 is a custom-made software developed by Skotte and co-workers[22]. It has proven to have high validity in classifying different types of PA, both in a controlled laboratory setting[22,23] and during free-living[23]. For a more detailed description of the development of the Acti4-software, reference is made to additional literature[22].

Data collected on adolescents was tested in Acti4. Acti4 was validated for the same PA types included in the NTNU algorithms for proper comparison, and the sensitivity, specificity and accuracy from Acti4 were compared to the corresponding values for $\text{NTNU}^{\text{ADOL}}$. Processing of the acceleration data from the AX3 sensors and the video-annotations had to be done prior to- and after analysis in Acti4. For a more detailed description of Acti4, the Acti4 set-up used in this study and the data processing, see Appendix 5.

2.6 Statistics

Statistical analyses were conducted in Excel (Microsoft Office 2016) and IBM SPSS Statistics for windows (version 22, SPSS Inc., Chicago).

Correctly and incorrectly classified instances for each algorithm are presented in confusion matrices. From the confusion matrix it is possible to derive information about the distribution of true positives (TP), true negatives (TN), false positives (FP) and false negatives (FN). Sensitivity, specificity and accuracy was calculated for each PA type. Weighted overall accuracy was calculated for each algorithm. Sensitivity is defined as the proportion of measurements correctly identified within the number of measurements actually belonging to that PA type (TP/[TP+FN]). Specificity is defined as the proportion of measurements correctly identified within the number of measurements not belonging to that PA type (TN/[TN+FP]). Accuracy is defined as the proportion of correctly classified observations among all observations included in the analyzes ([TP+TN]/[TP+TN+FP+FN]). The confusion matrices were used to examine patterns of misclassification.

The data material included walking, sitting, standing, lying down, shuffling, walking stairs up, walking stairs down, running, bending/picking, transitions, unclassified PA and other vigorous PA. Bend/pick and transitions were considered less important for the present sample. Unclassified PA is a collective term consisting of several different movements not formally defined (i.e., not fitting into the main categories listed above). In the present study the confusion matrices include all raw data and to illustrate potential misclassifications the unclassified PA, transitions and bend/pick were also included. Moreover, the NTNU^{ADUL} was trained to classify sit and stand cycling and is therefore included in the confusion matrix for NTNU^{ADUL}. The PA types included in this study was walking, standing, sitting, lying down, shuffling, running, walking stairs up and down and other vigorous PA.

There is no consensus about the acceptable level for sensitivity, specificity and accuracy for detection and classification of different types of PA. Guidelines for *k*-values[41] have been used for interpretation of sensitivity, specificity and accuracy where previous studies have regarded values greater than 60% as acceptable and above 80% as almost perfect[25]. In this study, values above 80% were regarded as acceptable and values above 90% were regarded high.

3. RESULTS

3.1 Detection of physical activity types

Overall accuracy for detection and classification of all PA types included in the original analysis was slightly higher for the NTNU^{ADOL} compared to NTNU^{ADUL} (87% versus 85%). Table 3 shows sensitivity, specificity and accuracy for all PA types. Both NTNU^{ADOL} and NTNU^{ADUL} showed sensitivity above 80% for walking, standing, sitting, lying down and running. Sensitivity was low for detection of shuffling and walking stairs with both algorithms. There were no major differences in specificity and accuracy between the NTNU^{ADOL} and NTNU^{ADUL} with specificity and accuracy ranging from 89% to 100%. The most evident differences between the two algorithms were found for sensitivity for detection of shuffling (29% for NTNU^{ADOL} versus 36% for NTNU^{ADUL}) and detection of vigorous PA (84% for NTNU^{ADOL} versus 76% for NTNU^{ADUL}) (Table 3).

For Acti4, overall accuracy was 80%. There were no major differences in the performance of the NTNU^{ADOL} and Acti4 overall. The most evident differences were in sensitivity for walking stairs (92% for Acti4 versus 71% for NTNU^{ADOL}), standing (90% for NTNU^{ADOL} versus 72% for Acti4) and shuffling (61% for Acti4 versus 29% for NTNU^{ADOL}) (Table 3).

3.2 Misclassification of physical activity types

Table 4 and Table 5 show the confusion matrices with correctly and incorrectly classified instances for the NTNU^{ADOL} and NTNU^{ADUL}, respectively[vi]. Of a total of 64228 instances, the NTNU^{ADOL} misclassified 8136 instances and NTNU^{ADUL} misclassified 9762 instances.

NTNU^{ADOL} misclassified shuffling 71% of the time, while the NTNU^{ADUL} misclassified shuffling 64% of the time. Most of the misclassified instances were identified as standing (34% by NTNU^{ADOL} and 33% by NTNU^{ADUL}) or walking (36% by NTNU^{ADOL} and 28% by NTNU^{ADUL}). NTNU^{ADUL} misclassified some instances of standing as shuffling (8%) or walking (5%). Walking stairs down was partly misclassified as horizontal walking by both algorithms (40% by NTNU^{ADOL} and 20% by NTNU^{ADUL}). Likewise, walking stairs up was mostly misclassified as horizontal walking (28% by NTNU^{ADOL} and 27% by NTNU^{ADUL}). Some periods of walking stairs down were misclassified as running (12%) by NTNU^{ADUL}. Other vigorous PA was misclassified 15% of the time by NTNU^{ADOL}, with the majority of instances being misclassified as walking (9%), compared to NTNU^{ADUL} where the majority of instances were misclassified as running (15% of a total 24%). NTNU^{ADUL} also misclassified some periods of running as other vigorous PA (10%).

[vi] The confusion matrix of correctly and incorrectly classified instances for Acti4 can be found in Appendix 5.

Table 3. Sensitivity, specificity and accuracy for the NTNU^{ADOL}, NTNU^{ADUL} and Acti4.

Activity	Sensitivity (%)			Specificity (%)			Accuracy (%)		
	NTNU^{ADOL}	NTNU^{ADUL}	Acti4	NTNU^{ADOL}	NTNU^{ADUL}	Acti4	NTNU^{ADOL}	NTNU^{ADUL}	Acti4
Walking	95	92	90	89	91	93	92	92	91
Standing	90	86	72	95	95	97	94	93	91
Sitting	98	97	98	100	100	100	98	100	99
Lying down	94	92	99	100	100	100	100	100	99
Running	88	84	81	100	99	100	99	99	99
Shuffling	29	36	61 [a]	98	96	87 [a]	93	91	85 [a]
Stairs down	43	44	-	100	100	-	100	99	-
Stairs up	71	67	92 [b]	100	100	99 [b]	99	99	99 [b]
Other vigorous PA	84	76	-	100	99	-	99	99	-

Note: Stairs down and other vigorous PA do not exist as PA types in Acti4 and cannot be classified.

[a] Shuffling equals Acti4 category moving.

[b] Stairs up includes annotations for walking stairs up and down as Acti4 combines walking stairs up and down.

Table 4. Confusion matrix of annotated and classified activities from the NTNU$^{\mathrm{ADOL}}$. The numbers in the cell are instances (top, in black) and percentage (%) of the total number of instances for each PA type (bottom, in grey). Correctly classified instances and sensitivity (%) for each PA type are in the diagonal.

Annotated activity	Classified activity												Total instances
	Walk	Run	Shuffle	Stairs up	Stairs down	Stand	Sit	Lying down	Trans.[a]	Bend/ pick[a]	Other vig. PA	Unclass.[a]	
Walk	31075 95	63 -	605 2	31 <1	2 <1	765 2	2 <1	0 -	12 <1	14 <1	71 <1	0 -	32640
Run	129 7	1601 88	2 <1	7 <1	1 <1	10 1	0 -	0 -	0 -	0 -	66 4	0 -	1816
Shuffle	1721 36	14 <1	1423 29	3 <1	2 <1	1642 34	6 <1	0 -	1 <1	2 <1	24 <1	0 -	4838
Stairs up	264 28	6 1	5 1	672 71	0 -	0 -	0 -	0 -	0 -	0 -	6 1	0 -	953
Stairs down	142 40	2 1	3 1	20 6	152 43	22 6	0 -	0 -	0 -	0 -	12 3	0 -	353
Stand	904 6	5 <1	727 4	0 -	2 <1	14559 90	2 <1	0 -	1 <1	4 <1	31 <1	3 <1	16238
Sit	5 <1	0 <1	1 <1	4 <1	0 -	0 -	3798 98	1 <1	60 2	0 -	0 -	0 -	3869
Lying down	0 -	0 -	0 -	0 -	0 -	0 -	1 <1	876 94	51 5	0 -	0 -	0 -	928
Trans.[a]	59 9	0 -	26 4	2 <1	0 -	5 1	76 12	64 10	379 61	9 1	2 <1	0 -	622
Bend/ pick[a]	31 19	0 -	8 5	0 -	0 -	5 3	0 -	0 -	0 -	115 71	4 2	0 -	163
Other vig. PA	151 9	70 4	10 1	7 <1	3 <1	20 1	0 -	0 -	0 -	0 -	1377 84	0 -	1638
Unclass.[a]	35 21	3 2	12 7	1 1	0 -	50 29	0 -	0 -	0 -	0 -	0 -	69 41	170

Note: Percentages are rounded to the nearest whole percentage; Trans. – transitions; Other vig. PA – other vigorous PA; Unclass. – unclassified activity
[a] PA type included in original analysis but not included or discussed further in this study.

Table 5. Confusion matrix of annotated and classified activities for NTNU$^{\text{ADUL}}$. The numbers in the cell are instances (top, in black) and percentage (%) of the total number of instances for each PA type (bottom, in grey). Correctly classified instances and sensitivity (%) for each PA type are in the diagonal.

Annotated activity	Classified activity: Walk	Run	Shuffle	Stairs up	Stairs down	Stand	Sit	Lying down	Trans.[a]	Bend/ pick[a]	Sit cycl.[a b]	Stand cycl.[a b]	Other vig. PA	Unclass.[a]	Total instances
Walk	29993 92	140 <1	1247 4	209 1	87 <1	705 2	1 <1	0 -	72 <1	11 <1	0 -	13 <1	162 <1	0 -	32640
Run	61 3	1525 84	5 <1	27 1	11 1	9 <1	0 -	0 -	0 -	0 -	0 -	0 -	178 10	0 -	1816
Shuffle	1347 28	29 1	1757 36	19 <1	15 <1	1574 33	4 <1	0 -	48 1	6 <1	0 -	3 <1	36 1	0 -	4838
Stairs up	262 27	1 <1	3 <1	635 67	14 1	0 -	0 -	0 -	8 1	0 -	0 -	0 -	30 3	0 -	953
Stairs down	71 20	41 12	3 1	28 8	155 44	31 9	0 -	0 -	1 <1	0 -	0 -	1 <1	22 6	0 -	353
Stand	862 5	18 <1	1268 8	4 <1	4 <1	13986 86	13 <1	0 -	13 <1	18 <1	0 -	0 -	45 -	7 <1	16238
Sit	0 -	0 -	0 -	2 <1	0 -	0 -	3767 97	0 -	99 3	1 <1	0 -	0 -	0 -	0 -	3869
Lying down	0 -	0 -	0 -	0 -	0 -	0 -	2 <1	855 92	71 8	0 -	0 -	0 -	0 -	0 -	928
Trans.[a]	34 5	0 -	13 2	2 <1	0 -	9 1	65 10	82 13	407 65	5 1	0 -	0 -	5 1	0 -	622
Bend/ pick[a]	14 9	0 -	3 2	3 2	0 -	5 3	21 13	0 -	36 22	71 44	0 -	1 1	9 6	0 -	163
Sit cycl.[a b]	0 -	0 -	0 -	0 -	0 -	0 -	0 -	0 -	0 -	0 -	0 -	0 -	0 -	0 -	0
Stand cycl.[a b]	0 -	0 -	0 -	0 -	0 -	0 -	0 -	0 -	0 -	0 -	0 -	0 -	0 -	0 -	0
Other vig. PA	66 4	247 15	18 1	23 1	9 1	27 2	0 -	0 -	5 <1	2 <1	0 -	0 -	1241 76	0 -	1638
Unclass.[a]	24 14	3 2	13 8	3 2	0 -	46 27	1 1	0 -	2 1	0 -	0 -	0 -	2 1	76 45	170

Note: Percentages are rounded to the nearest whole percentage; Trans. – transitions; Other vig. PA – other vigorous PA; Unclass. – unclassified activity; Sit cycl. – sit cycling; Stand cycl. – stand cycling.

[a] PA type included in original analysis but not included or discussed further in this study.

[b] Activity is included in the NTNU$^{\text{ADUL}}$ and can be classified by the algorithm, but was not included in the protocol and data-set for this study

DISCUSSION

The purpose of this study was to evaluate the validity of an algorithm developed for detection of PA in adolescents (NTNU^{ADOL}). A comparison was made against the performance of an algorithm developed for detection of PA in adults (NTNU^{ADUL}). The evaluation of the validity was based on the algorithms performance in detecting PA in adolescent during semi-structured free-living. The overall accuracy for all PA types included in the original analysis was 87% for the NTNU^{ADOL} and 85% for the NTNU^{ADUL}. Both algorithms could detect walking, standing, sitting, lying down and running with acceptable to high sensitivity. Specificity and accuracy was acceptable to high for all PA types detected with both algorithms. The NTNU^{ADOL} showed highest sensitivity for detection of walking, standing, sitting, lying down, running, walking stairs up and other vigorous PA, while NTNU^{ADUL} showed slightly higher sensitivity for shuffling and walking stairs down.

Both the NTNU^{ADOL} and the NTNU^{ADUL} showed sensitivity, specificity and accuracy above 80% for detection of walking, sitting, standing, lying down and running. These values are comparable to or higher than results in other studies. Trost and colleagues compared one accelerometer on the hip with one on the thigh in children and adolescents. Accuracy ranged from 79% to 97% for detection of walking, sitting, standing, lying down and running in a laboratory[36]. In another laboratory study on children and adolescents, accuracy ranged from 75% to 94% for detection of a similar PA types[35]. Both the aforementioned studies used only one accelerometer, and the higher values found in the present study may be because of the inclusion of a second accelerometer. In adults, two accelerometers (hip and thigh) detected walking, sitting and standing with sensitivity ranging from 49.9% to 98.5% and specificity from 92.6% to 100%. The participants performed two free-living sessions with different complexity at their work place[23]. Moreover, by combing four accelerometers, lying, sitting, standing and dynamic activity was detected with sensitivity values from 58% to 100%. The participants performed given activities in a living room, at their own initative[24]. Thus, the values found in the present study are comparable to or higher than what has been found previously for adults during free-living.

Compared to self-reporting of PA, use of accelerometers offer a substantial improvement in the possibilities for quantifying PA pattern, level of PA and compliance with PA recommendations. Self-reporting of PA has shown poor validity, especially for reporting of daily sitting time[12]. Moreover, self-reporting methods often overestimate MVPA[11] and underestimate sedentary behavior[10], and light intensity PA (such as walking and standing) are often difficult to remember. The current study indicates that both NTNU^{ADOL} and NTNU^{ADUL} produce acceptable estimates of common daily PA types in adolescents during free-living. For example, being able to accurately detect and differentiate sitting from lying down and standing makes it possible to estimate total daily sitting time, breaks in sitting time, and duration of low intensity PA (walking, standing) with high precision.

The most evident difference in sensitivity between the two algorithms was found for detection of other vigorous PA; the NTNU^{ADOL} was superior to NTNU^{ADUL} (84% versus 76%). Most misclassifications of other vigorous PA were as walking or running, and this finding is similar for both algorithms. The slightly lower sensitivity of the NTNU^{ADUL} in detecting other vigorous PA was due to a more prominent misclassification of other vigorous PA as running compared to the NTNU^{ADOL}. The NTNU^{ADUL} also misclassified running as other vigorous PA, showing that the limitation with the NTNU^{ADUL} is lack of ability to differentiate running from other vigorous PA. It is not surprising that vigorous PA was misclassified as running, because some overlap may exist between these two PA types. Running often occurs together with modes of other vigorous PA and both show increased acceleration in the vertical direction. Also, the agility drills used in this study did contain transitions from running to other vigorous PA and misclassifications often occur as the previous or following PA type. On the other hand, the misclassification as walking was not expected. However, accurate detection of other vigorous PA will depend on the quality (e.g., intensity) of the performance. Lower degree of performance (e.g., low intensity, less prominent sideways movement and less rapid feet-movement) could explain why other vigorous PA is misclassified as either running or walking. It is possible that some participants did walk or run more than they did use sideways movement. Previously, moderate-to vigorous sports and games (basketball and dance) were detected in children and adolescents, with accuracy ranging from 64% to 86%[35,36]. Both studies were laboratory studies using only one accelerometer. Additionally, playing football has been detected outside of the laboratory in adults. Two accelerometers were placed on the hip and wrist, and accuracy was found to be 88%[27]. The accuracy found for detection of other vigorous PA in the present study are higher than previously reported accuracies. In the present study, two accelerometers were used and the high accuracy may be explained by their placement (upper and lower extremities). Also, a broad definition was used which can be easier to detect compared to more specific definitions, such as dance and basketball.

The sensitivity of the NTNU^{ADOL} was better than for NTNU^{ADUL}, and this could be an important difference. Adolescents are known to participate in organized sports[28,29]. Moreover, studies indicate that a majority of daily MVPA comes from sports activities, and adolescents reporting high levels of organized sports are more likely to achieve PA recommendations[31,32]. Thus, accurate detection of such modes of PA are important for this age-group. However, the difference between the algorithms was small, and it is uncertain if it would have practical relevance. Although the detection of other vigorous PA was acceptable during the present conditions, the performance of the algorithms under different settings is unknown.

The PA type with lowest sensitivity with both algorithms was shuffling. This was also one of the PA types with an evident difference between the algorithms, with a higher sensitivity found for the NTNU^{ADUL} (29% versus 36%). A high percentage of the shuffling instances were misclassified as either walking or standing. This finding is consistent for both algorithms. The better sensitivity of the NTNU^{ADUL} in detecting shuffling is mainly explained by better differentiation between shuffling and walking compared to the NTNU^{ADOL}. Adults may have a more evident distinction between shuffling and walking compared to adolescents, making them easier to differentiate. The insufficient differentiation between shuffling, walking and standing is not surprising. Shuffling varies from almost equal to standing to almost equal to walking. Moreover, short periods of shuffling often occurred in-between periods of standing and walking. The window size in the algorithms was set to 1sec, but the video-annotations were at 25fps. Thus, one window could contain several PA types of short duration, leading to misclassifications. In a previous study on adults, a category called 'moving' was included to account for all feet-movements that do not classify as walking, running or walking stairs. In two free-living sessions with different complexity at the participants work place, sensitivity for moving was 58.3% and 78.7%[23]. These values are slightly higher than those found in the present study, but the definition and parameters used for detection of 'moving' are not directly comparable to shuffling. Even though there was a small difference in the performance of NTNU^{ADOL} and NTNU^{ADUL} for detection of shuffling, the sensitivity of both algorithms was poor during free-living for adolescents.

For walking stairs up and down, sensitivity was relatively low for both algorithms (43% to 71%) and there were no major differences in performance between the two algorithms. Most misclassifications of walking stairs up and down were as horizontal walking. It was a difference between the NTNU^{ADOL} and NTNU^{ADUL} for walking stairs down regarding the direction of the misclassifications. For NTNU^{ADOL} most misclassifications of walking stairs down were horizontal walking. For the NTNU^{ADUL} however, some instances were misclassified as running or as other vigorous PA in addition to horizontal walking. Thus, the intensity of descending stairs may be higher in adolescents compared to adults, and be more similar to running. Also, the vertical acceleration of walking stairs down is similar to the vertical acceleration found during running[14]. As mentioned, most misclassifications of both modes of walking stairs was as horizontal walking. This may be explained by the type of stairs found in the buildings. Walking shorter and less steep stairs often resembles a movement pattern that is very similar to horizontal walking. Differentiating between horizontal walking and walking stairs has been mentioned as a challenge in previous studies on adults[23,25] and the results from this study are in line with these. In a previous study on adults, two accelerometers (hip and thigh) could detect walking stairs during free-living with a sensitivity of 54.6%[23]. However, in the aforementioned study walking stairs up and down were not differentiated so these values are not directly comparable. In a separate analysis (data not shown) where walking stairs up and down was combined, sensitivity was higher than what is previously reported (65% for NTNU^{ADOL} and 64% for NTNU^{ADUL}). Because of the minor misclassification in-between walking stairs up and down, the present study show that it is possible to differentiate between walking stairs up and down when using two accelerometers placed on the upper back and thigh.

A reference was made to Acti4, and no major differences were found for walking, sitting and running. Acti4 showed higher sensitivity for lying down, shuffling and walking stairs up, indicating that the definitions in Acti4 may be more appropriate for detection of these PA types. For example, Acti4 uses a stair threshold and this seems to differentiate horizontal walking from walking stairs. Most misclassifications were due to insufficient differentiation between standing, walking and shuffling. As expected, Acti4 could not detect other vigorous PA because it is not set up for this PA type. Mostly, other vigorous PA was misclassified as shuffling, and this is surprising because it was expected that other vigorous PA would be misclassified as running. However, the agility drills did contain rapid change in direction and movement of the feet, and this may be more similar to the Acti4 definition of moving (renamed to shuffling for this purpose). Because the definitions used for validation and for development of Acti4 are different, and due to differences in window-size, sampling rate and data processing prior to and after analysis in Acti4, direct comparison is not possible. However, Acti4 proves valid for detection of common daily PA types in adolescents, and some of the definitions used in Acti4 may be more accurate than those used for development of the NTNU-algorithms.

It is beyond the scope of this study to discuss in detail the development of the NTNU-algorithms. However, some important issues may have affected the results. The NTNU-algorithms are pattern recognition algorithms. The algorithms isolate features from the acceleration signal and are thereafter trained to identify these features and classify the PA types. The performance of the algorithms is higher for those PA types with a large training-set. This could potentially explain the difference in performance for other vigorous PA, where the adolescents' data-set did contain a larger amount of activity data. However, the overall difference in the size of the data-sets were small, and the effect on the final result is likely to be trivial. Further, a fixed 1 sec window with 50% overlap was used. Thus, more than one activity could occur in one window, and this would cause short-duration movements to be misclassified. This is a limitation, especially for children and adolescents, because the pattern of PA may entail more abrupt and frequent changes in the type of activity than among adults.

There are many ways of defining the same PA type, and because of the lack of common nomenclature they may vary from study to study, making direct comparison difficult. A major part of this study was to develop a list of PA definitions and there are some important aspects that needs further discussion. First, shuffling was included to account for leg-movements that do not classify as walking. It is questionable, and unknown, if shuffling has independent effect on health, and thus, combining shuffling with standing (small movements) and walking (stepping) is possible. Second, other vigorous PA was defined as a collective term, but because of the diversity of the PA types belonging to this definition possible sub-categories could have been defined. However, there will always be a tradeoff when deciding the level of detail when it comes to relevance for health, classification accuracy, practical importance and usability, among others. Further, the term other vigorous PA indicates some kind of intensity measure, and this was not used. Sports and exercise is not solely vigorous, but includes bouts of MVPA and renaming this to 'sports and exercise' may be more intuitive. Including heart rate monitoring and global positioning systems provide a more detailed method for defining and detecting sports activities. This may also make it possible to examine the necessity of different sub-categories of other vigorous PA, and for improving the definitions in general. Lastly, the definitions are designed to apply for all ages. However, differences in PA and movement pattern across age may call for algorithms trained on age-specific definitions. Crawling and climbing could be of importance for children, and walking pattern may differ substantially from childhood, to adulthood and for the elderly.

Thus, it may be important to train the algorithms on age-specific definitions, and not just different populations.

4.1 Future research and practical implications

At date, there is no consensus when it comes to validation of accelerometers for use in research. The variety in accelerometer brands, accelerometer-set up, protocols and choice of analytic tools makes comparison of results across studies difficult. Different accelerometer set-up (number and placement of accelerometers), design of the protocol (laboratory versus free-living, PA types included) and choice of analytic tool and outcome measure, may explain the variation in validity. These limitations could have implications on the usability of such algorithms because researchers across studies do not speak the same language. This calls for a common agreement and standardized guidelines for validation and use of accelerometers. Few accelerometer brands provide access to the raw acceleration signal. Instead they process the signal before analysis, and this processing is often based on 'black box' algorithms. Because the raw acceleration signal is almost similar for all accelerometer brands, access to this would open for development of algorithms that can be used for several accelerometer brands. Moreover, development of open-source algorithms based on raw acceleration signals, similar accelerometer set-up, PA types and definitions, protocols and outcome measures would allow for comparison across studies and for future pooling of data.

Furthermore, future studies should aim to validate classification algorithms under more representative conditions, such as during real free-living including leisure time PA, occupational PA, household, transportation among other. For example, the agility drills used for detection of other vigorous PA did not cover the variety of this PA type. By validation during real free-living it would also be possible to examine more thoroughly if it is necessary to develop algorithms specific for adolescents.

Knowledge about type of PA can provide detailed information about PA pattern and level of PA in a population. However, accelerometers do not provide information about some aspects that cannot be measured directly, such as context and motivational factors. These aspects may have implications on PA, and thus, future research could aim to combine accelerometers with other methods (e.g., questionnaire data). Furthermore, using multisensory systems, such as accelerometers, heart rate monitoring and global position systems could provide more detailed information about PA (e.g., context, perceived intensity), improve PA definitions and classification accuracy.

Adolescence represent a window of opportunity for promotion of PA, and a positive attitude towards PA and health that can be maintained throughout adolescence and adulthood. Including accelerometers in interdisciplinary education programs could link subjects such as mathematics, social studies, information technology, physical education and health science. Accelerometer out-put could be analyzed and put into context with health and current social development, raising awareness of the importance of PA and health.

4. 2 Strengths and limitations

To my knowledge, this is the first study to validate algorithms for detection of PA types in adolescents during free-living. Controlled laboratory settings do not directly replicate the PA pattern found during free-living. Being under observation and guidance may influence the PA pattern and PA during free-living tend to become shorter of duration and more complex in character, making it more difficult to detect. Thus, the primary strength of this study is the free-living protocol. A second strength is the comparison of an algorithm developed for adolescents with one developed for adults for examination of the necessarily of such. The inclusion of two accelerometers, one at the upper and one on the lower body, also strengthens this study. Definitions of PA types were established and video analysis was used as criterion measure (IRR = 0.92). Also, the AX3 accelerometer provides access to the raw accelerometer data and the NTNU algorithms are open-source with all data being available to others.

There are some limitations to the present study. First, the free-living protocol was semi-structured. This was a compromise to ensure inclusion of certain PA types and the choice of tasks covered a very large range of PA types found during daily life. However, PA during daily life may be more specific or occur as mixed behavior not captured in the present study. To facilitate natural behavior, the tasks in the rebus was mostly stated as goals rather than requests. However, the agility drills were set, phrases such as ‘go for a run’ or ‘take a break in three different chairs’ were used and a chest-mounted camera was used during the complete session. Thus, it impossible to say whether the participants managed to behave naturally or was too aware of the data collection. Second, of practical reasons certain PA types, for example riding a bicycle and upper body exercise, were not included even though they may be common PA types in adolescents. Third, it was not examined whether arm-movements could be detected, and these movements could be of interest for detection of upper body exercise and other PA types including arm-movements (e.g., carrying loads). Fourth, the study sample was small (n=12) and relatively homogenous. In population studies, the sample could be more heterogeneous and whether the algorithms are valid under such conditions remains unexplored. The algorithms are pattern recognition algorithms and they perform well when applied to populations and/or PA types they have been trained on. The NTNU$^{\text{ADOL}}$ was both trained and tested on the same sample and the validity of this algorithm in an independent sample and during different settings (e.g., school, household, sports) should be explored further. Thus, the level of external validity is unknown. Lastly, confidence intervals were not included, making it impossible to state if the difference between the two algorithms are significant. However, the observed differences were in most cases small and may not be of practical relevance.

4.3 Conclusion

Both algorithms were able to detect walking, sitting, standing, lying down and running with acceptable to high sensitivity, specificity and accuracy. For accurate detection of walking stairs and shuffling, more work is needed. There were no major differences between the algorithms for detection of PA types in adolescents during free-living. The most evident differences were found for detection of other vigorous PA, with the NTNU$^{\text{ADOL}}$ being superior, and for shuffling, with the NTNU$^{\text{ADUL}}$ being superior. However, the small differences between the two algorithms may indicate that for detection of daily PA types, there is no major advantages by developing algorithms specific for adolescents for daily-life activities. Future work should aim to validate these algorithms in an independent sample, for different PA types and in different settings, preferably during true free-living conditions.

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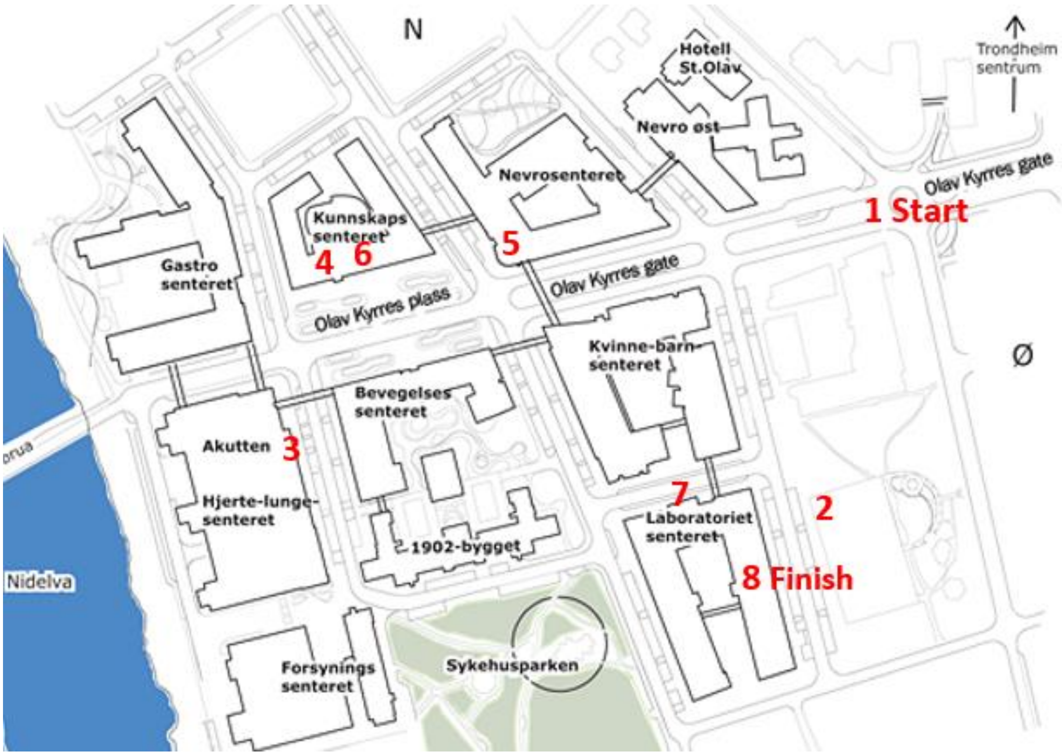
APPENDIX 1

REBUS – St. Olav's Hospital



MÅL: Ta et bilde på alle postene, og samle tre stein fra tre ulike steder.

1. Gjennomfør alle tre hurtighetsøvelsene minimum tre ganger

2. For å ha god helse er det viktig å bevege seg. Gå derfor til post 2 og løp ei runde rundt banen.

3. Hvis dere ikke hadde gjort dette, hadde dere gjort dere selv en bjørnetjeneste. Derfor er det bedre å gjøre en bjørn en tjeneste, gå og klapp bjørnen.

4. Som skoleelever lærer dere at kunnskap er viktig! Gå til bygget med mest kunnskap og sett dere godt til rette foran den store skjermen. En pust i bakken er viktig for å ha ei god helse, men det er viktig å ikke sitte for lenge av gangen. Alle tre skal derfor sitte i tre ulike stoler på denne plassen.

5. For å kunne ta til seg all kunnskapen, er det viktig med nok næring. Det er også viktig å kose seg her i livet. Gå til 7/11 og kjøp dere noe godt.

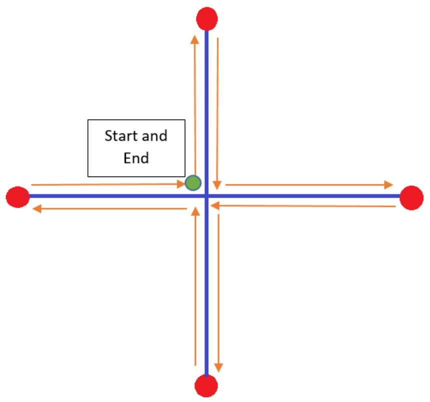
6. Nå som dere har fylt på med energi, er dere også klare til å fylle på med ny kunnskap. Gå til plassen hvor mye kunnskap er samlet i bøker. Finn skjelettet som er her.

7. Nå nærmer det seg slutt og dere er sikkert slitne. Gå til lab-senteret og finn benker dere kan legge dere på. Ligg på rygg, venstre side og høyre side.

8. Nå har dere hvilt og har masse energi, så ta dere en tur til den anatomiske utstillinga og finn et hjerte og ei lunge.

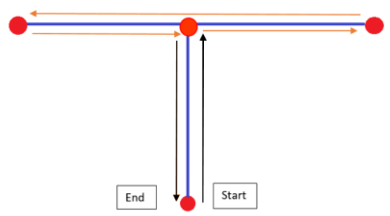
APPENDIX 2

Timeframe: Approximately 10 minutes



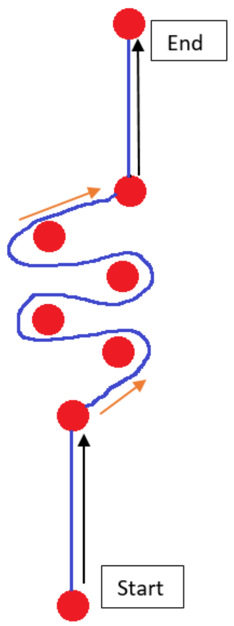
1: Cross: Starting position at the middle of the cross. High intensity movement with change in direction, and no stop in movement during implementation.

1. Rapid movement to the front cone and back to start position. Stand still.
2. Change in direction and rapid movement to the right cone and back to start position. Stand still.
3. Change in direction and rapid movement to the back cone and back to start position. Stand still.
4. Change in direction and rapid movement to the left cone and back to start position. Stand still.



2: T-drill: Starting position and end position at the bottom of the T.

1. Walk from starting position to the top of the T (along the black line).
2. Change direction and move rapidly to the right cone.
3. Change direction and move rapidly to the left cone.
4. Change direction and move rapidly to the center of the T.
5. Change direction and walk slowly back to start position.



3: Zigzag run: Start by the first cone and run to the next cone (approximately 15m). Move rapidly sideways around the next five cones as indicated by the blue line and orange arrows. Run the final stretch (approximately 15m) to the last cone.

APPENDIX 3

DEFINITION OF ACTIVITIES	
Activity	**Description**
Sitting	When the person's buttocks are on the seat of the chair, bed or floor. Sitting can include some movement in the upper body and legs; this should not be tagged as a separate transition. Adjustment of sitting position is allowed.
Standing	Upright, feet supporting the person's body weight, with no feet movement, otherwise this could be shuffling/walking. Movement of upper body and arms is allowed until forward tilt and arm movement occurs below knee height. Then this should be inferred as bending. **For chest mounted camera**: If feet position is equal before and after upper body movement, standing can be inferred. Without being able to see the feet, if upper body and surroundings indicate no feet movement, standing can be inferred.
Walking	Locomotion towards a destination with one stride or more, (one step with both feet, where one foot is placed at the other side of the other). Walking could occur in all directions. Walking along a curved line is allowed.
Shuffling	Stepping in place by non-cyclical and non-directional movement of the feet. Includes turning on the spot with feet movement not as part of walking bout. **For chest mounted camera:** Without being able to see the feet, if movement of the upper body and surroundings indicate non-directional feet movement, shuffling can be inferred.
Stair ascending/descending	**Start:** Heel-off of the foot that will land on the first step of the stairs. **End:** When the heel-strike of the last foot is placed on flat ground. If both feet rests at the same step with no feet movement, standing should be inferred.
Lying down	The person lies down. Adjustment after lying down is allowed if it does not lead to a change between the prone, supine, right and left lying positons. Movement of arms and head is allowed. Movement of the feet is allowed as long as it does not lead to change in posture. **Prone:** On the stomach. **Supine:** On the back. **Right side:** On right shoulder. **Left side:** On left shoulder.
Sit cycling	Pedaling while the buttocks is placed at the seat. Cycling starts on first pedaling and finishes when pedaling ends. **For outdoor bicycling:** Cycling starts at first pedaling, or when both feet have left the ground. Cycling ends when the first foot is in contact with the ground. **Not pedaling:** Sitting without pedaling should be tagged separate as sitting.
Stand cycling	Pedaling while standing. Cycling starts on first pedaling and finishes when pedaling ends. Standing without pedaling should be tagged separate as standing.
Running	Locomotion towards a destination, with at least two steps where both feet leave the ground during each stride.

	For chest mounted camera: Running can be inferred when trunk moves forward is in a constant upward-downward motion with at least two steps. Running along a curved line is allowed.
Bending	While standing/sitting, bending towards an object placed below knee-height is bending.
Picking	This refers to picking/placing/touching an object from below knee height. Picking occurs when the trunk is at its lowest point and the person has touched/placed/picked an object. When the person starts to rise it's trunk, picking finishes, and bending begins.
Other vigorous PA	All non-cyclic rapid leg movements that do not classify as running. This includes sport like activities such as rapid change in direction and jumping. Can occur in all directions.
Unclassified PA	All non-cyclic movements that are recognizable, but do not classify according to the definitions. Can occur in all directions. Can be crawling, rolling etc.
Undefined	Until all the sensors are attached, or final adjustment made to position the video can be tagged as undefined. All postures/movements that cannot be clearly identified should be tagged as undefined.
DEFINITON OF TRANSITIONS	
Transitions	**Description**
Bending to picking from standing/walking/sitting	As soon as forward/sideways trunk tilt occurs, bending has started. Bending finishes when the person has reached the lowest point of the movement and picking occurs. When the person starts to rise up, picking finishes and bending begins. When the trunk is in an upright and stable position, bending finishes. This should be tagged as "bending-picking-bending". Steps can occur during bending.
Walking to posture	Walking ends when both feet are at rest, or at first evident forward tilt of upper body. Steps can occur during the transition from walking to posture.
Upright to sitting	Can be from walking or standing, as soon as forward trunk tilt occurs, or a lowering of the trunk, the transition has started. Steps can occur during the transition for positioning. Transition ends when buttocks are in contact with the seat of the chair, bed or floor.
Sitting to upright	Transition starts when the person's buttocks leave the chair and ends when the trunk has reached its upright position. Steps and turning can occur during the transition from sitting to upright.
Standing/walking/sitting to lying	When the trunk flexion begins, or a lowering of the center of mass, the transition has started. Transition finishes when the person is lying flat with the trunk in a stable position.
Lying to standing/walking/sitting	While lying, the transition begins with an upward movement of the trunk or leg movement that leads to a stable upright position or continuous walking. The trunk angle should be in a steady posture for the transition to finish. Steps can occur during the transition.
Standing to walking	As soon as heel-off occurs, walking has started.

Standing to shuffling	As soon as one foot moves, shuffling has started.
Shuffling/walking to standing	As soon as the feet stop moving, walking/shuffling has finished and standing has started.
Shuffling to walking	As soon as walking direction is set and heel-off occurs, shuffling has ended and walking starts.
Walking to shuffling	When walking is interrupted by stepping in place, non-cyclical, non-directional movement of the feet or turning on the spot, this should be tagged as shuffling.
Sit cycling to stand cycling / stand cycling to sit cycling	When the buttocks leave the seat, stand cycling can be inferred. When the buttocks are placed at the seat, sit cycling can be inferred.

APPENDIX 4

Standardized lab-protocol – Adults

	Activity	**Reps**
1	Stand – heel drop– stand	3
2	Stand – sit – stand	3
3	Stand – sit at table – stand	3
4	Stand – lie down on the back – turn to right/left/stomach – stand	3
5	Stand – bend with straight legs – pick object from floor forward/left/right – stand	3
6	Stand – lie - sit – lie – stand	3
7	Stand – bend with bent legs – pick object from floor forward/left/right – stand	3
8	Sit still – sit cycling – stand cycling – sit cycling – sit still	3
9	Stand – heel drop – stand	3
10	Stand – walk at preferred pace – stand	2
11	Stand – agility drill (forward/backwards/left/right) – stand	3
12	Stand – climb stairs (right foot first) – stand – descend stair (right foot first)	2
13	Stand – climb stairs (left foot first) – stand – descend stair (left foot first)	2
14	Stand – walk (slow speed) flat – stand	1
15	Stand - walk (normal speed) flat – walk (normal speed) 3% - walk (normal speed) 6% - walk (normal speed) 9% - walk (normal speed) 6% - walk (normal speed) 3% - walk (normal speed) flat - stand	1
16	Stand – walk (fast speed) flat – stand	1
17	Stand – walk flat – run flat - walk flat – stand	3
18	Stand – heel drop – stand	3

Semi-standardisert protokoll: I hverdagen - Voksne

I løpet av den neste timen ønsker vi at du gjennomfører aktivitetene som er listet opp under. Når en aktivitet er gjennomført setter du et kryss under "gjennomført". Etter at du har fullført hele listen, går du tilbake til lab for å levere utstyret.

NB: ikke ta av akselerometer eller kamera før du er tilbake i lab!

Subjekt ID: ______________

Aktiviteter	**Gjennomført**
Sitte - helst i to ulike stoltyper	
Stå stille	
Stå - shuffle (Beveg beina på stedet)	
Stå - løft en gjenstand fra bakken med bøyde bein	
Gå flatt	
Gå trapp opp og ned	
Ligge på rygg, høyre side og venstre side	
Løpe (varighet over 10sek)	
Tilbake i lab: Heel drop: Stå på tå - slipp hælene i bakken så hardt du kan. Gjennomføres tre ganger.	

APPENDIX 5

DATA PROCESSING AND ANALYSIS IN Acti4

The Acti4-software works as a rule-based algorithm. It uses the standard deviation of the acceleration in the longitudinal direction of the thigh to discriminate between dynamic and static activities. Dynamic activities are differentiated by a magnitude of the gravitation, while static activities are differentiated based on the inclination of the longitudinal axis of the hip or thigh accelerometer[22].

Acti4 is developed based on ActiGraph GT3X+ accelerometer data sampled at 30 Hz. Thus, the synchronized 100Hz acceleration data was resampled to 30Hz and converted to ActiGraph format ([.CSV-files]). Acti4 classifies sitting, standing, running, moving, lying down, moving, walking stairs, cycling and rowing. The window-size in Acti4 is activity based, and can be modified. For the purpose of this study, the window-size was set to 5sec for identification of walking stairs, sitting and lying down, 2sec for identification of running, walking, standing and moving, and 15sec for cycling and rowing.

The output from Acti4 is a 1Hz activity classification. For validation against the video-annotations, data were resampled from 1Hz to 25Hz to correspond with the video-annotations (25fps). A confusion matrix (Table 6) was developed showing correctly and incorrectly classified instances. One instance corresponds to 1/25 sec with no overlap. Annotations for walking stairs up and down were combined into walking stairs (up). For proper comparison, Acti4 category ‘moving’ was been renamed to shuffling, and annotations for other vigorous PA, bend/pick, transitions and unclassified PA were included for the validation.

Table 6. Confusion matrix of annotated and recognized activities from Acti4. The numbers in the cell are instances (top, in black) and percentage (%) of the total number of instances for each PA type (bottom, in grey). Correctly classified instances and sensitivity (%) for each type of PA are in the diagonal.

Annotated activity	Classified activity														Total instances
	Walk	Run	Shuffle	Stairs up	Stairs down[c]	Stand	Sit	Lying down	Cycle[a] [b]	Row[a] [b]	Trans.[a] [c]	Bend/ pick[a] [c]	Other vig. PA[c]	Unclass.[a] [c]	
Walk	376098 90	1262 <1	31868 8	2493 1	0 -	4966 1	1030 <1	28 <1	0 -	0 -	0 -	0 -	0 -	0 -	417745
Run	668 3	18380 81	3217 14	212 1	0 -	119 1	0 -	0 -	0 -	0 -	0 -	0 -	0 -	0 -	22596
Shuffle	11636 18	817 1	39902 61	767 1	0 -	12024 18	269 <1	0 -	0 -	0 -	0 -	0 -	0 -	0 -	65415
Stairs up	689 4	0 -	216 1	15901 92	0 -	376 2	50 <1	0 -	0 -	0 -	0 -	0 -	0 -	0 -	17232
Stairs down[c]	0 -	0 -	0 -	0 -	0 -	0 -	0 -	0 -	0 -	0 -	0 -	0 -	0 -	0 -	0
Stand	12680 6	363 <1	43562 21	234 <1	0 -	148658 72	133 <1	0 -	0 -	0 -	0 -	0 -	0 -	0 -	205630
Sit	210 <1	0 -	149 <1	0 -	0 -	99 <1	47232 98	710 1	0 -	0 -	0 -	0 -	0 -	0 -	48400
Lying down	70 1	0 -	0 -	0 -	0 -	0 -	40 <1	12057 99	0 -	0 -	0 -	0 -	0 -	0 -	12167
Cycle[a] [b]	0 -	0 -	0 -	0 -	0 -	0 -	0 -	0 -	0 -	0 -	0 -	0 -	0 -	0 -	0
Row[a] [b]	0 -	0 -	0 -	0 -	0 -	0 -	0 -	0 -	0 -	0 -	0 -	0 -	0 -	0 -	0
Trans.[a] [c]	810 10	0 -	537 7	0 -	0 -	76 1	2060 26	4470 56	0 -	0 -	0 -	0 -	0 -	0 -	7953
Bend/pick[a] [c]	222 10	0 -	1657 77	0 -	0 -	265 12	0 -	0 -	0 -	0 -	0 -	0 -	0 -	0 -	2144
Other vig. PA[c]	1273 6	1781 9	15692 78	1324 7	0 -	8 <1	0 -	0 -	0 -	0 -	0 -	0 -	0 -	0 -	20078
Unclass.[a] [c]	2040 84	163 7	168 7	0 -	0 -	60 2	0 -	0 -	0 -	0 -	0 -	0 -	0 -	0 -	2431

Note: Stairs up includes annotations for both walking stairs up and walking stairs down; Shuffling equals Acti4 category moving.

[a] PA type included in original analysis but not included or discussed further in this study. [b] Acti4 categories, but not included in protocol/video-annotations.

[c] Included in protocol/video-annotations but not classified by Acti4.