Detection of Daily Activities and Sports With Wearable Sensors in Controlled and Uncontrolled Conditions

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***Abstract*—Physical activity has a positive impact on people's well-being, and it may also decrease the occurrence of chronic diseases. Activity recognition with wearable sensors can provide feedback to the user about his/her lifestyle regarding physical activity and sports, and thus, promote a more active lifestyle. So far, activity recognition has mostly been studied in supervised laboratory settings. The aim of this study was to examine how well the daily activities and sports performed by the subjects in unsupervised settings can be recognized compared to supervised settings. The activities were recognized by using a hybrid classifier combining a tree structure containing *a priori* knowledge and artificial neural networks, and also by using three reference classifiers. Activity data were collected for 68 h from 12 subjects, out of which the activity was supervised for 21 h and unsupervised for 47 h. Activities were recognized based on signal features from 3-D accelerometers on hip and wrist and GPS information. The activities included lying down, sitting and standing, walking, running, cycling with an exercise bike, rowing with a rowing machine, playing football, Nordic walking, and cycling with a regular bike. The total accuracy of the activity recognition using both supervised and unsupervised data was 89% that was only 1% unit lower than the accuracy of activity recognition using only supervised data. However, the accuracy decreased by 17% unit when only supervised data were used for training and only unsupervised data for validation, which emphasizes the need for out-of-laboratory data in the development of activity-recognition systems. The results support a vision of recognizing a wider spectrum, and more complex activities in real life settings.**

***Index Terms*—Activity classification, context awareness, physical activity, wearable sensors.**

I. Introduction

CHRONIC noncommunicable diseases (NCDs) cause 60% of global deaths and the figure is expected to rise to 73% by 2020 [1]. Such diseases include, for example, cardiovascular diseases, diabetes, osteoporosis, and certain types of cancer. Physical inactivity is a major risk factor for these deaths, and it is estimated to cause 2 million unnecessary deaths per year. There is, thus, an urgent need to promote more active lifestyle.

There is strong evidence that regular physical exercise decreases the risk of cardiovascular disease (e.g., [2]), which is the leading cause of death in many developed countries. Risk factors associated with cardiovascular diseases include smoking, obesity, and high blood pressure, the last two of which are closely related to physical inactivity. Type II diabetes is strongly associated with obesity that, in turn, has a well-known relation to physical inactivity [3]. There is evidence that exercise improves the physiological control of glucose metabolism [4]. Falls are also a major health hazard to elderly people resulting often in hip fracture requiring surgical operation and long rehabilitation. It is suggested that muscle strength, neuromuscular coordination, postural stability, steadiness of gait, and the structural properties of bone all influence fall frequency [5]. Each of these can be directly enhanced by physical training.

Estimating energy expenditure is a common way to assess the activity level of a subject. Traditional devices for the estimation of energy expenditure are not suited for unobtrusive ambulatory monitoring. Recently, wearable devices have become available for that purpose and studies have shown that accelerometer-based estimation of energy expenditure can be obtained with relatively good accuracy [6], [7]. However, energy expenditure is only one important aspect of physical activity. An international consensus statement regarding physical activity, fitness, and health [8] identifies six areas affected by physiological effort: body shape, bone strength, muscular strength, skeletal flexibility, motor fitness, and metabolic fitness. All of these have their own distinct impact on an individual's general well-being, and thus, estimating energy expenditure alone is not sufficient in order to assess the overall impact of the physical activities on the individual's well-being.

A more detailed analysis of physical effort can be obtained by activity recognition, i.e., by detecting the exact form of activity the subject is performing. Previous studies have applied activity recognition, e.g., for elderly care [9]. We believe that another important application domain for the activity recognition lies in preventive healthcare (prevention of NCDs). In order to avoid the vicious circle of illnesses and related reduced ability to perform physical activities, the monitoring of the changes in physical activity needs to start before the physical ability of an individual starts to decline.

Accelerometers are currently among the most widely studied wearable sensors for activity recognition, thanks to their accuracy in the detection of human body movements, small size, and reasonable power consumption [10]. Recent reviews have described the use of accelerometers in movement and activity detection [10], [11]. In laboratory settings, the most prevalent everyday activities (sitting, standing, walking, and lying) have

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been successfully recognized with accelerometers [12]–[18]. However, the applicability of these results to out-of-laboratory monitoring is unclear. Long-term out-of-laboratory monitoring often means less-controlled user-annotated data collection, which introduces several challenges such as the following.

1) Annotations of the data are more unreliable causing difficulty in classifier training and also degrading classification results.
2) People perform activities in many different ways that are hard to categorize. For example, a person may lie down on a sofa in a way that cannot be said to be either sitting or lying.

In a few studies, data have been collected outside the laboratory. In [16], 24 subjects spent approximately 50 min outside the laboratory. Accelerometers were placed on sternum, wrist, thigh, and lower leg. Nine patterns (sitting, standing, lying, sitting and talking, sitting and operating PC, walking, stairs up, stairs down, and cycling) were recognized from presegmented data using similarity measures with a total accuracy of 66.7%. In the same study, the accuracy in laboratory settings was 95.8% illustrating the difficulties introduced by out-of-laboratory settings. In [19], five biaxial accelerometers attached to hip, wrist, arm, ankle, and thigh were used to recognize 20 everyday activities such as walking, watching TV, brushing teeth, vacuuming, etc. Data were collected for 82–160 min from 20 subjects. Four different classifier structures were used of which decision tree provided the best results accuracies ranging from 41% to 97% for different activities.

In our previous study on activity recognition [20], 16 test persons went through an approximately 2 h recording session with a supervisor during which the following activities were executed: lying, rowing (with a rowing machine), cycling (with an exercise bike), sitting, standing, running, Nordic walking, and walking. The recognition accuracies for different activities varied for the best classifier between 58% and 97%.

In this study, new data were collected that also contained unsupervised out-of-laboratory period. Our aim was to study the effects of such environment to the classification accuracy.

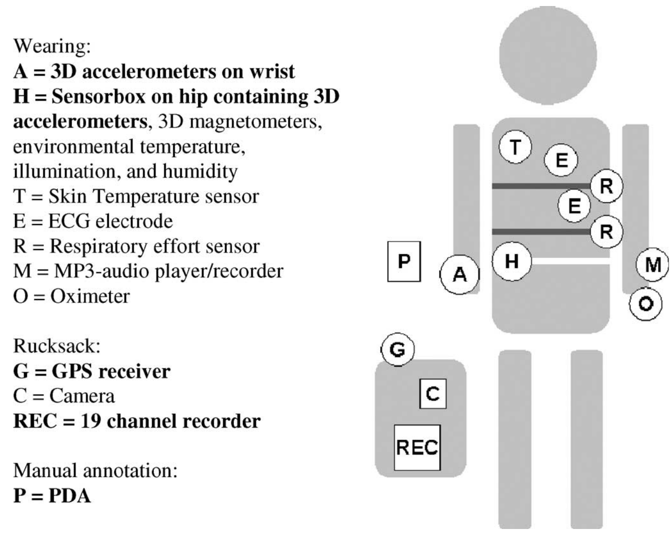

Fig. 1. Data collection and annotation system. The sensors and devices relevant for this study are printed in bold.

TABLE I
TEST PROTOCOL FOR DATA COLLECTION

Supervised indoor activities	**Time [min]**
Lying	3
Sitting and doing computer work	20
Lying	3
Sitting and reading comics	5
Lying	3
Cycling with an exercise bike	5
Lying	3
Exercising with a rowing machine	5
Lying	3
Standing and reading a poster	5
Supervised outdoor activities	**Time [min]**
Cycling with a regular bike	5
Walking to a park	5
Playing football	5
Walking back from park	5
Nordic walking to park & back	5
Running to park & back	5
Drinking water indoors	2
Unsupervised free period	**Time [min]**
Changing clothes	5
Free period (min. duration)	240

II. METHODS

A. Data Collection

The devices used in the data collection and their locations on the body are illustrated in Fig. 1. Although this figure includes sensors from which data are not used in this study, they are shown in the figure for more complete picture of the data-collection system.

Acceleration signals were measured with ADXL202 accelerometers (Analog Devices, Norwood, MA), and were stored on a flash-card-memory-based, 19-channel recorder (Embla A10, Medcare, Reykjavik, Iceland). Sampling frequency was 20 Hz, and the range of the sensor output was ± 10 g. Location information was stored on a Garmin eTrex Venture GPS receiver (Garmin Ltd., Olathe, KA) once per 20 s. Accelerometers were attached to their data-storage unit by cables. Cables were taped to the body so that they did not restrict normal movements. Also, the cables were placed so that it was possible to place the rucksack with the data-storage unit on the floor, for example, when sitting down.

Twelve subjects [aged 27.1 ± 9.2 years, body mass index (BMI) 23.8 ± 1.9, ten males, two females] were recruited by advertisements at a local university. A written consent was obtained from each volunteer. Approximately 6 h of data were collected with each subject. The 6 h measurement session was further divided into two phases: 1) a supervised period with exact scenario and accurate supervisor-made annotations and 2) an unsupervised period with subject-made annotations. The test protocol is described in Table I.

During the supervised data-collection session, the subject was accompanied by a supervisor, who used a personal digital

Fig. 2. Annotation application on PDA.

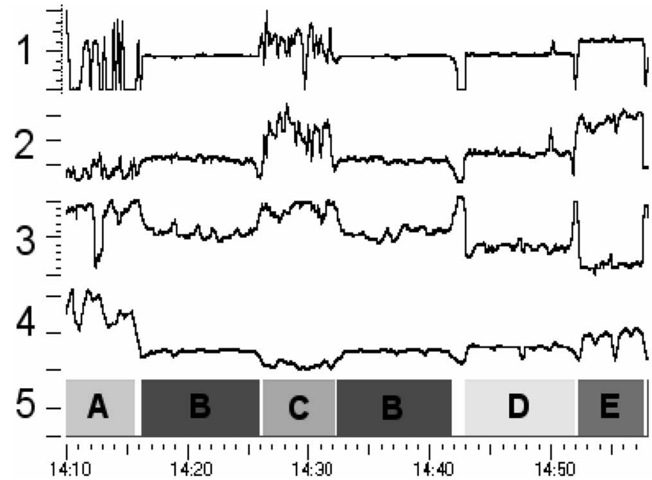

Fig. 3. Selected signal features during different activities in excerpt from the supervised data. Panels from top to bottom: 1) peak frequency of up-down acceleration (feature A); 2) range of up-down acceleration (feature B); 3) spectral entropy of up-down acceleration (feature F); 4) speed; 5) activity: A) cycling; B) walking; C) playing football; D) Nordic walking; E) running.

assistant (PDA) and a custom-made application to mark changes in activity and context for reference purposes (Fig. 2). After the supervised phase, the use of the PDA application was instructed to the test person, and he/she made the annotations himself/herself throughout the unsupervised period.

Exercise bike and *rowing machine* were each used for 5 min indoors. The user was given the freedom to choose a comfortable pace in each activity. *Cycling* was performed outdoors with real bikes. Most test persons used their own bikes. *Football* was played in a nearby park. In practice, this meant kicking a ball with the supervisor and running after the ball every now and then, not real football game with 22 players. *Nordic walking* is an activity that has recently become popular in northern and middle Europe. In short, it is fast-pace walking using poles similar to skiing poles. It also enables the training of the upper body during walking. During the unsupervised period, many people went to work or attend lectures. Some people performed different activities such as bowling, driving a car, walking to different places like library, cottage, etc. One person went home and took a nap.

Fig. 2 depicts the annotation application [21]. In each panel, the options are exclusive. The context value was changed by tapping another value. "Activity" panel was used to mark the true activity of the subject. "Location" was used to tell whether the subject was indoors, outdoors, or in a vehicle. "Eating" described eating and drinking in general. "Annotator" is "assistant" during the supervised activities and "self" during the unsupervised period. "Sync" was used to mark the start and end markers for synchronization. For some annotated context, there was also an option for transition ("$*$" in the application UI) such as the transition from sitting to standing, which was used only by the supervisor. It was not in use during the free period, as marking the transitions from one activity to another was considered too challenging to be done by the subject alone while performing the activities.

B. Signal Processing

Signal features were calculated for each second of the data collection. Time-domain features calculated were mean, variance, median, skew, kurtosis, 25% percentile, and 75% percentile. Frequency-domain features included the estimation of power of the frequency peak and signal power in different frequency bands. Speed was calculated from GPS location data. Spectral entropy S_N [22] of the acceleration signals for the frequency band 0–10 Hz was calculated as

$$S_N(f_1, f_2) = \frac{-\sum_{f_i=f_1}^{f_2} P(f_i)\log(P(f_i))}{\log(N[f_1, f_2])} \tag{1}$$

where $P(f_i)$ represents the power spectral density (PSD) value of the frequency f_i. The PSD values are normalized so that their sum in the band $[f_1, f_2]$ is 1. $N[f_1, f_2]$ is the number of frequency components in the corresponding band in PSD.

The feature selection proceeded by identifying for each activity the feature having the best performance in discriminating the corresponding activity from other activities. The performance of each feature was evaluated by the area under the receiver operator characteristic (ROC) curve.

Figs. 3 and 4 show examples of how different signal features behave during different activities. The following signal features were selected for activity classification:

1) peak frequency of the up–down acceleration measured from the hip;
2) range of the up–down acceleration measured from the hip;
3) mean value of the up–down acceleration measured from the hip;
4) peak frequency of the horizontal acceleration measured from the wrist;
5) sum of variances of 3-D acceleration measured from the hip;
6) spectral entropy of the up–down acceleration measured from the hip;
7) speed measured from the GPS.

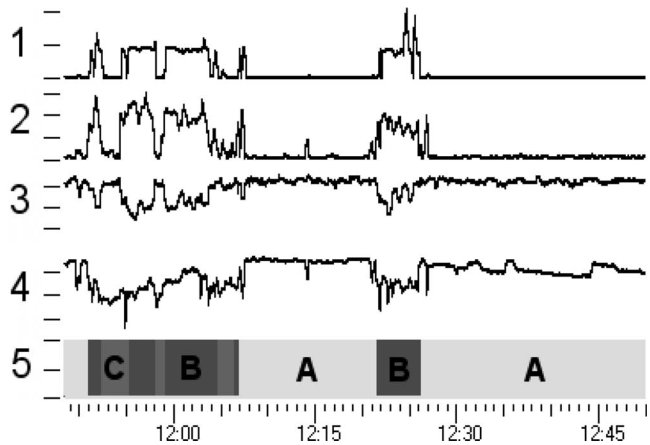

Fig. 4. Selected signal features during different activities in excerpt from the unsupervised data. Panels from top to bottom: 1) peak frequency of up-down acceleration (feature A); 2) range of up-down acceleration (feature B); 3) spectral entropy of up-down acceleration (feature F); 4) mean value of up-down acceleration (feature C); 5) activity: A) sitting; B) walking; C) standing. Also, shorter segments with corresponding shades of gray represent the same activities.

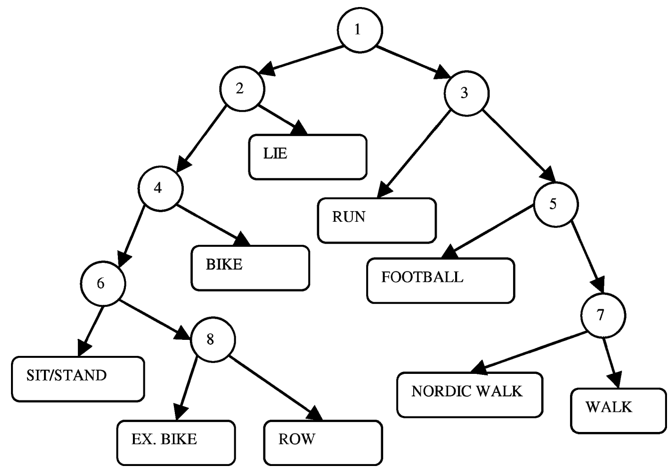

Fig. 5. Structure of the custom decision tree and hybrid model.

The following nine target classes were used for the activity recognition: 1) lying; 2) sitting and standing (see Section IV for the reason why these activities were combined into a single group); 3) walking; 4) running; 5) Nordic walking; 6) rowing with a rowing machine; 7) cycling with an exercise bike; 8) cycling with real bike; and 9) playing football. Compared to our earlier study, two activities were novel: cycling with a real bike and playing football. Although cycling with a regular bike and with an exercise bike are very similar activities, we wanted to keep them as separate classes because in everyday life they can be performed with different purposes: exercise bike is used only for exercising aerobic fitness, whereas regular bike is often used for transportation. Football was included to test the feasibility of the system to detect a more complex type of activity, as football comprises walking, standing, running, kicking the ball, etc.

Four different classifiers were used: 1) custom decision tree; 2) automatically generated decision tree; 3) artificial neural network (ANN); and 4) hybrid model. Classifiers 1–3 were included mainly for comparison purposes to evaluate the performance of the classifier 4. For all classifiers, results were acquired by 12-fold leave-one-subject-out cross validation. Each classifier had the same seven-signal features at their disposal. Data sample order was randomized before the training phase. The following describes the classifier structures in detail.

1) *Custom decision tree*: In custom decision tree, each decision is made by a simple thresholding mechanism [20]. The structure of the tree was built using *a priori* knowledge and our own intuitive modeling of different activities. The obtained tree had eight binary decision nodes. The structure of the tree is depicted in Fig. 5. Specific questions can be assigned to each of the numbered decision nodes: a) footsteps? b) lying? c) running? d) cycling? e) playing football? f) doing indoor exercise? g) Nordic walking? h) rowing? The tree has been built so that "walk" and "sit/stand" are default groups for any activity the decision tree is not familiar with. For example, if footsteps are detected, but not the characteristics of running or Nordic walking, the activity falls through the tree to a class "walk". Similarly, if no footsteps are recognized and also none of the characteristics of lying, cycling, cycling on exercise bike, or rowing, the activity falls to "sit/stand".
2) *Automatically generated decision tree*: An automatically generated decision tree was used in order to compare how well the human-made rules and tree structure perform compared to automatic classification. The tree was generated using a Matlab (MathWorks, Inc., Natick, MA) Statistics Toolbox function "treefit."
3) *Artificial neural network (ANN)*: A multilayer perceptron with a hidden layer of 15 nodes and with resilient back propagation as the training algorithm was used as the ANN classifier.
4) *Hybrid model*: As a novel method, we combined the best qualities of the custom decision tree model and neural networks. Our observations suggested that though implementing *a priori* knowledge into a classifier structure improved the results in general, it also resulted in simpler rules, which degraded the recognition accuracy in some aspects. Thus, the purpose was to achieve a model that could combine the best properties of the human *a priori* knowledge of the activities with the accurate nonlinear classification properties of the ANNs. In the hybrid model, the simple thresholding decisions made in each decision node of the custom decision tree (Fig. 5) were replaced by small multilayer perceptron networks (size 7:5:1). Each node gave as output a value between 0 and 1. A value of 0.5 was considered the decision boundary when selecting which branch of the tree to proceed.

III. Results

The total amount of data used for the analysis was 68:28:32 (hh:mm:ss), 21:08:57 of which were supervised data and 47:19:35 were unsupervised. The data consisted of the following percentages of activities: 1) lying 7.3%; 2) rowing 1.5%; 3) cycling with an exercise bike 1.4%; 4) sitting and standing

TABLE II
SUMMARY OF THE ACTIVITY-RECOGNITION RESULTS USING BOTH SUPERVISED AND UNSUPERVISED DATA FOR TRAINING AND TESTING OF THE CLASSIFIERS (PERCENTAGES)

	Custom Decision Tree	Automatic Decision Tree	Artificial Neural Network	Hybrid Model
Lie	**98**	96	**98**	97
Row	58	84	85	**87**
ExBike	20	**79**	4	18
Sit/ Stand	94	53	96	**97**
Run	**91**	83	90	89
Nordic walk	**85**	66	66	70
Walk	50	62	67	**71**
Football	63	55	47	**78**
Bike	52	**74**	67	72
TOTAL	83	60	87	**89**

TABLE III
DETAILED ACTIVITY-RECOGNITION RESULTS OF THE HYBRID MODEL USING BOTH SUPERVISED AND UNSUPERVISED DATA FOR TRAINING AND TESTING OF THE CLASSIFIER (PERCENTAGES)

Annotation	Recognized Activity								
	Lie	Row	Ex-Bike	Sit/ Stand	Run	Nordic walk	Walk	Foot-ball	Bike
Lie	97	0	0	3	0	0	0	0	0
Row	0	87	0	13	0	0	0	0	0
ExBike	0	0	18	66	0	0	16	0	0
Sit/ Stand	0	0	0	97	0	0	2	0	0
Run	0	0	0	0	89	7	2	1	0
Nordic walk	0	0	0	1	5	70	24	0	0
Walk	1	0	0	21	0	5	71	1	1
Football	0	0	0	2	7	1	12	78	0
Bike	2	0	1	12	1	1	12	1	72

TABLE IV
DETAILED ACTIVITY-RECOGNITION RESULTS OF THE HYBRID MODEL USING ONLY SUPERVISED DATA FOR TRAINING AND TESTING OF THE CLASSIFIER (PERCENTAGES)

Annotation	Recognized Activity								
	Lie	Row	Ex-Bike	Sit/ Stand	Run	Nordic walk	Walk	Foot-ball	Bike
Lie	99	0	0	0	0	0	0	0	1
Row	0	97	3	0	0	0	0	0	0
ExBike	0	0	81	16	0	0	2	0	1
Sit/ Stand	0	1	3	95	0	0	0	0	0
Run	0	0	0	0	90	7	1	2	0
Nordic walk	0	0	0	1	6	78	13	1	0
Walk	0	0	1	0	3	12	81	2	1
Football	0	0	0	0	6	0	6	88	0
Bike	3	0	2	0	1	0	3	1	91

63.2%; 5) running 1.9%; 6) Nordic walking 2.8%; 7) walking 16.8%; 8) football 1.5%; and 9) cycling with a regular bike 3.6%. The classification results are summarized in Table II. The results of the hybrid model are described in Table III. To assess the importance and reliability of supervised and unsupervised data sets, the following results were also calculated.

1) The total classification accuracy was calculated using only supervised data both in training and testing of the model (leave-one-subject-out cross-validation). The test was performed in order to obtain activity-recognition results that are comparable to those of the earlier studies with laboratory data. The total classification accuracy was 90%, increasing by 1% unit compared to the result obtained by using all collected data in training and validation. The results are shown in Table IV.

TABLE V
DETAILED ACTIVITY-RECOGNITION RESULTS OF THE HYBRID MODEL USING SUPERVISED DATA FOR TRAINING AND UNSUPERVISED DATA FOR TESTING OF THE CLASSIFIER (PERCENTAGES)

Annotation	Recognized Activity								
	Lie	Row	Ex-Bike	Sit/ Stand	Run	Nordic walk	Walk	Foot-ball	Bike
Lie	98	0	1	1	0	0	0	0	0
Sit/ Stand	1	2	9	80	0	0	2	1	5
Walk	2	4	29	15	0	3	30	13	4
Bike	1	3	17	6	1	1	5	17	49

2) The supervised data were used for the training, whereas the unsupervised data were used for the testing of the model. The test was performed in order to assess the feasibility of a scenario in which an activity-recognition device would be trained with laboratory data and be used in out-of-laboratory settings. The total classification accuracy was 72% decreasing by 17% unit compared to the result obtained by using all collected data in training and validation. Only four activities were annotated by the subjects during the free period: lying down, sitting and standing, walking, and cycling. The results are shown in Table V.

IV. DISCUSSION

Activity data were collected for 68 h from 12 subjects, out of which the activity was supervised for 21 h and unsupervised for 47 h. Activities were recognized from the data by using 3-D accelerometers on hip and wrist and GPS information. The total accuracy of the activity recognition using both supervised and unsupervised data was 89%. In comparison to our previous study in which only supervised data were used and the total accuracy of 86% was achieved [20], the results obtained here show slightly improved performance.

The aim of the study was to assess the feasibility of activity recognition in out-of-laboratory settings. The 1% unit difference between the classification accuracy obtained using all data and that obtained using only supervised data suggest that activity recognition is also feasible in out-of-laboratory. However, the 17% unit decrease in the classification accuracy when only supervised data were used for training and only unsupervised for validation suggests that in order to obtain an activity-recognition algorithm feasible in out-of-laboratory settings, it must also be trained with annotated real-life data.

The hybrid model classifier proved to provide better results than the reference classifiers. It confirms our hypothesis that combining human *a priori* knowledge and the nonlinear classification process of neural networks may provide a basis for activity recognition with even greater variety of activities. However, with ANNs, an important issue is the noise and inaccuracy in the everyday activity data. For that reason, special care should be taken to obtain an adequate learning rate for the ANNs, as a very big rate can prevent the convergence of the model. As the hybrid model provided the best classification results, mainly its results are discussed in the following.

Cycling with an exercise bike and regular bike introduced difficulties in this study. In our earlier study, we had measured acceleration from the wrist and chest. In that study, cycling with an exercise bike was detected with the accuracy of 75–82% [20]. In this study, an accelerometer placed on the hip could not produce a signal that could discriminate cycling and footsteps as well. This can be observed, for example, in the result summary in Table II. One can observe a clear tradeoff between the accurate detection of the two cycling activities and the rest of the activities. Automatically generated decision tree was the only classifier that could recognize the two cycling activities with nearly acceptable accuracy. However, this resulted in decrease in the detection accuracies of the other activities as well as in the total detection accuracy. Other classifiers concentrated on the other activities, thus leading to a worse detection of the cycling activities. The detection of cycling with a regular bike outdoors has better accuracy, as the GPS signal provides additional information for this task.

Football playing was detected with 88% accuracy from the supervised data that was a surprisingly high accuracy. However, it seems that the unsupervised period has included some movements similar to football, which degraded the recognition accuracy to 78% when all data were considered. Nevertheless, we feel that the accuracy is encouraging for future research in the recognition of more complex sports.

In supervised data, walking was detected with acceptable accuracy of 81%. If Nordic walking and walking had been considered a single class, the recognition accuracy would have been 93%. Including the unsupervised period decreased the accuracy with 10% unit for the hybrid model, which seems acceptable because the exact annotation of walking in different day-to-day situations is difficult as the walking periods may be of short duration.

Lying was detected with 97% and sitting and standing were recognized with 97% accuracy, as well. Seventy-eight percent of the unsupervised data comprised lying, sitting, or standing. This supports the assumption that the recognition of these passive activities is of major importance, as everything else not belonging to these activities can be considered more health enhancing. Thus, as a simple index of subject's overall activity, a percentage showing the amount of time spent in any other activity than these three could be used. For that purpose, the recognition accuracies obtained for these three activities in out-of-laboratory settings are encouraging.

In our previous study, we had recognized that the absence of accelerometers on the lower body (below waistline) was a limitation in the sensor setup. This was especially noticed as the inability to differentiate sitting and standing. For that reason, we repositioned the 3-D accelerometer from the chest level to the hip, as there were indications that such a placement could enable the discrimination of these two activities [23]. However, it became clear that, in our study, this discrimination was not possible regardless of the accelerometer replacement. As the subjects in our study wore sport clothes, the belt with the accelerometers had to be placed on top of the clothes. For that reason, it was not tightly connected to other clothes or the body, and the position of the accelerometers did not stay fixed. It seems that in order to obtain more precise acceleration information on hip, special attention must be paid on the sensor location and attachment. However, also such subject-dependent factors as body shape influence the sensor orientation on the waist. For that reason, the accurate discrimination of sitting and standing using waist-level accelerometry without user-specific training is complicated.

In the previous study, we used accelerometers with the sampling frequency of 200 Hz. For the current study, we dropped the sampling frequency to 20 Hz, which consumes less power. This decision was also backed up by other studies [6], [24], suggesting that such a sampling frequency should be enough. However, this proved to be a wrong decision because the impulses produced, for example, by a foot hitting the ground during running and a pole hitting the ground during Nordic walking diminished notably, and as the signal features used for discriminating these activities were based on the impulses, the activity-recognition accuracy also decreased.

For this study, 2 g accelerometers were replaced by 10 g ones, as we had noticed that the -2 to 2 g range is not sufficient during vigorous exercise. In general, -10 to 10 g scale was enough for the exercises on our protocol. Larger scale resulted in decreased signal resolution, but it seems that the decrease had negligible influence on the signal features.

Our future challenges include adjusting the activity-detection algorithms to real-time performance and for mobile devices. That way, the continuous monitoring of daily activities could be performed unobtrusively, and the changes in the daily durations of different activities could be reported that could motivate the user to prevent chronic diseases associated with physical inactivity.

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