Recognition of Military-Specific Physical Activities With Body-Fixed Sensors

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ABSTRACT The purpose of this study was to develop and validate an algorithm for recognizing military-specific, physically demanding activities using body-fixed sensors. To develop the algorithm, the first group of study participants (n = 15) wore body-fixed sensors capable of measuring acceleration, step frequency, and heart rate while completing six military-specific activities: walking, marching with backpack, lifting and lowering loads, lifting and carrying loads, digging, and running. The accuracy of the algorithm was tested in these isolated activities in a laboratory setting (n = 18) and in the context of daily military training routine (n = 24). The overall recognition rates during isolated activities and during daily military routine activities were 87.5% and 85.5%, respectively. We conclude that the algorithm adequately recognized six military-specific physical activities based on sensor data alone both in a laboratory setting and in the military training environment. By recognizing type of physical activities this objective method provides additional information on military-job descriptions.

INTRODUCTION

A mismatch between physical capability and physical job requirements can increase the risk of injury, jeopardize unit performance, and decrease overall morale.[1–4] Therefore, the importance of obtaining an accurate description of the job requirements in physically demanding occupations cannot be overestimated,[1,4] particularly in military organizations. Commonly used procedures to assess military- or fire fighting-specific job requirements include self-report questionnaires, interviews, observations, and physical measurements.[1,4–6] Bos et al.[7] recommend describing the exposure to work demands objectively in terms of duration, frequency, and intensity. To assess the duration and frequency of physical activities, direct observation or video observation are most precise but are impractical for large groups of participants. Using self-report questionnaires is the most practical approach in large-scale studies, but their reliability, validity, and objectivity are low.[8,9]

The most promising method of assessing the duration, frequency, and intensity of physical activities in large groups of participants is the use of body-fixed sensors. Several approaches have been shown to be effective in recognizing specific activities based on data of diverse body-fixed sensors.[10–12] However, none of these approaches has been adapted for a specific application in a military setting.

The most widely used body-wearable sensors measure acceleration (ACC) or heart rate (HR). Of the many different types of sensors, accelerometers supply the most useful data for activity recognition.[9] However, if worn only at the hip, additional physical efforts resulting from activities with low body movement but high muscle tension are not detected. The use of only a heart rate monitor is less useful for activity recognition because HR has a delayed reaction to activity changes and lacks specificity for any particular activity.

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A combination of ACC and HR data may enhance precision in activity recognition. The advantage of ACC is its immediate response to body movements and its information on respective intensity. On the other hand, even if HR has a delayed reaction to activity changes, it is more accurate when describing activities with low body movement but high physical intensity than is ACC data.

However, body-fixed sensors must meet several demands to be applicable in military workday life. They need enough memory and battery lifetime to record data continuously over at least 1 week. Sensors have to be waterproof, shock resistant, and wearable with all military equipment. In the present study, data provided by the sensors were used to recognize the most relevant physically demanding activity classes in the context of armed forces. Authors in previous studies[1,2,13–16] defined activities as physically relevant in military service if they are a frequent part of physically demanding tasks during daily military routine. Walking, marching with backpack, lifting and lowering loads, lifting and carrying loads, digging, and running were named most often in those publications and are therefore investigated in the present study.

The aim of this study was to recognize physically relevant, military-specific activities using easy-to-handle body-fixed sensors, thereby demonstrating that it is possible to objectively assess the duration and frequency of physically demanding, military-specific activities using this technology.

METHODS

Study Design

There were three steps in the data acquisition (see Figure 1). First, 15 volunteers performed six single, military-specific activities according to protocol. Their data were used to develop algorithms for activity recognition. Second, 18 volunteers performed the same six isolated activities to estimate the accuracy of the activity recognition system. In the third step, sensor-based activity recognition was compared to observation-based activity assessment on 24 volunteers during daily military routine.

Participants and Anthropometric Parameters

All participants were male recruits from the Swiss Army (Table I). All were volunteers recruited from two selected military occupational specialties (rescue technician and infantry recruits). The volunteers received comprehensive information about the study and provided written informed consent for their participation as approved by the Cantonal Ethics Committee of Bern, Switzerland and from the Swiss Army Sports and Preventions Competence Center. Age, body weight, and height data were collected in the first 2 weeks of military service. All volunteers were measured by the same examiner using a calibrated digital balance and a measuring tape.

Instruments

ActiGraph uniaxial accelerometers (GT1M, ActiGraph LLC, Fort Walton Beach, Florida) were used to monitor volunteers' waist ACC in vertical direction and step frequency. A second GT1M was mounted on the backpack to register backpack carrying. The intermonitor variability between different GT1M's is very small (<1%).[17] The GT1M is lightweight (27 g), compact (3.8 cm × 3.7 cm × 1.8 cm), and splashproof. Its rechargeable battery is capable of providing power for over 14 days without recharging, and it has a memory capacity of 1 megabyte. More detailed specifications have been described elsewhere.[18] In the present study, accelerometers were wrapped in waterproof plastic and were placed in a belt pouch on the waist over the right anterior axillary line and on the side strap of the personal backpack. The GT1Ms were programmed to record acceleration and step-count data in 2-second intervals so that data could be gathered over 6 continuous days.

A Suunto monitor (Suunto Smartbelt, Suunto, Fantaa, Finland) was used to measure volunteers' HR. A Suunto Smartbelt is a lightweight (61 g) and waterproof stand-alone monitor worn on the chest. Its exchangeable battery is capable of providing power for over 4 weeks of continuous measurement. One million heartbeats can be stored in the internal memory, enough for more than 1 week of continuous measurement. A Suunto Smartbelt registers HR as long as the chest strap is worn. In the present study, data were transferred to a computer, after a 5-day monitoring period, at 2-second intervals using Suunto Training Manager version 2.2.0.

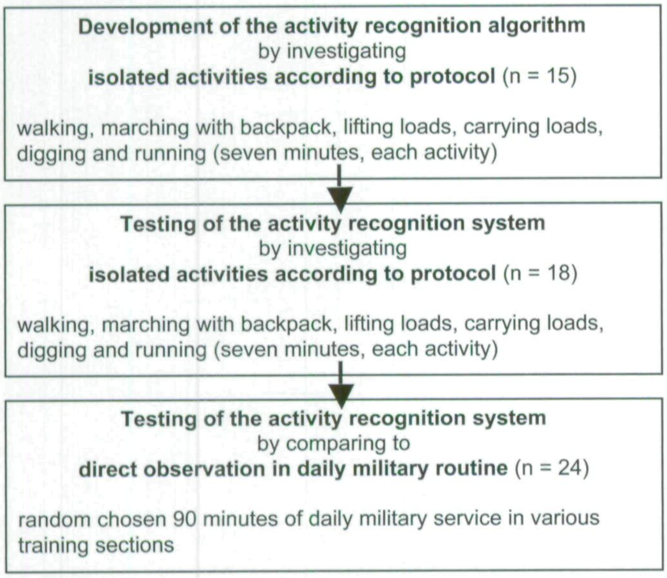

FIGURE 1. Three steps to data acquisition in the present study.

Data Collection Protocol

In a laboratory setting, 33 volunteers (Table I) completed six activities—walking, marching with backpack (10–15 kg), lifting and lowering loads (30 kg), lifting and carrying loads (30 kg, 10–40 m), digging, and running—for 7 minutes each with 2 minutes rest between activities. Apart from running, which was the last activity for all volunteers, the order of the activities was random. Data from 15 randomly chosen volunteers were used to develop algorithms for activity recognition. Data from the remaining 18 volunteers were used to estimate the accuracy of the activity recognition system.

During daily military routine, 24 randomly chosen volunteers (Table I) from two different troops were individually observed in situ over a 90-minute period to estimate the accuracy of the algorithm for activity recognition during daily military routine. An examiner observed the volunteers in various training sections and classified their activities in 20-second intervals. Observation was always done by the same examiner. In addition, two scientists joined the observation of 14 volunteers to investigate the inter-rater reliability of direct observation.

Analysis

Statistical comparisons of volunteer's anthropometric data between study groups of three parts of data acquisition were

TABLE I. Volunteers' Respective Age, Weight, Height, and Military Training School in Three Parts of Data Acquisition of the Present Study

Data Acquisition	*n*	Military Training School	Age (y)	Weight (kg)	Height (cm)
Development of the Activity Recognition Algorithm	15	Swiss Army Rescue Technicians' School	20.7 ± 1.1	75.6 ± 10.3	179.3 ± 6.5
Testing of Activity Recognition System in Isolated Activities	18	Swiss Army Rescue Technicians' School	21.0 ± 0.8	75.4 ± 8.6	176.8 ± 8.0
Testing of Activity Recognition System During Daily Military Routine	24	Swiss Army Rescue Technicians' and Infantry School	21.3 ± 2.7	77.3 ± 9.5	180.9 ± 5.2

performed with SPSS for Windows (version 16.0, SPSS, Chicago, Illinois) with an α level of 0.05 to indicate statistical significance. Therefore a one-way analysis of variance (ANOVA) with Tukey post hoc analysis was conducted.

All ACC and HR data were synchronized for every volunteer by a self-programmed application using Matlab (Matlab 5.3, MathWorks, Natick, Massachusetts). Mean heart rate was calculated using a sliding window with a window size of 2 minutes on 5 days of continuous heart rate data for every 2 seconds. The lowest value found in such a window was used as resting heart rate. Implausible data, caused by short duration artifacts in the signal, were detected by visual inspection of the plotted raw data. These data were excluded from the identification process of resting heart rate.

Development of the Activity Recognition Algorithm

The development of an activity recognition algorithm was focused on the most frequent military-specific, physically demanding activities such as (1) walking, (2) marching with backpack, (3) lifting and lowering loads, (4) lifting and carrying loads, (5) digging, and (6) running.[1,2,13–16] Apart from these, daily military routine contains many other activities. The purpose of the present study is to recognize the six specific activities only and to assign all remaining activities to the "other activities" class. Box plots for hip acceleration (H-ACC), heart rate above resting heart rate (HRaR), step frequency (SF), and backpack acceleration (BP-ACC) were plotted for every activity class (Fig. 2). The box plots were used to verify the discrimination of the activity classes by their inherent sensor data. The specific activity classes were determined as data within the 1.5 × interquartile range of corresponding labeled data. Areas out of specific data ranges of the six activity classes represent the "other activities" class. Based on the activity classes-specific data ranges, the nodes of the decision tree were defined. Classifications were made in 2-second intervals. In a postprocessing step, first activity assignments (0.5 Hz) were filtered to reduce the number of short-duration misclassifications.[10] The used filter replaces short activities with the surrounding longer duration activity. Therefore, first-classified data were buffered in 60-second time segments. If at least 20 of the 30 decisions in a 60-second time segment were the same, the respective activity class was assigned.

Testing of the Activity Recognition System

The recognition rates of activities classified based on sensor data were calculated and presented in a confusion matrix.[19] Each row of the confusion matrix represents the instances in an actual activity class, while each column represents the instances in a predicted activity class. The recognition rate is defined by the number of true positive-classified instances divided by the number of total instances of the respective actual activity class. The overall recognition rate is defined by the sum of all true positive-classified instances of all activity classes divided by the total number of investigated instances.

RESULTS

Participants

Age, weight, and height of the volunteers in three parts of data acquisition of this study did not differ ($p = 0.702$, 0.776, and 0.142, respectively, see Table I).

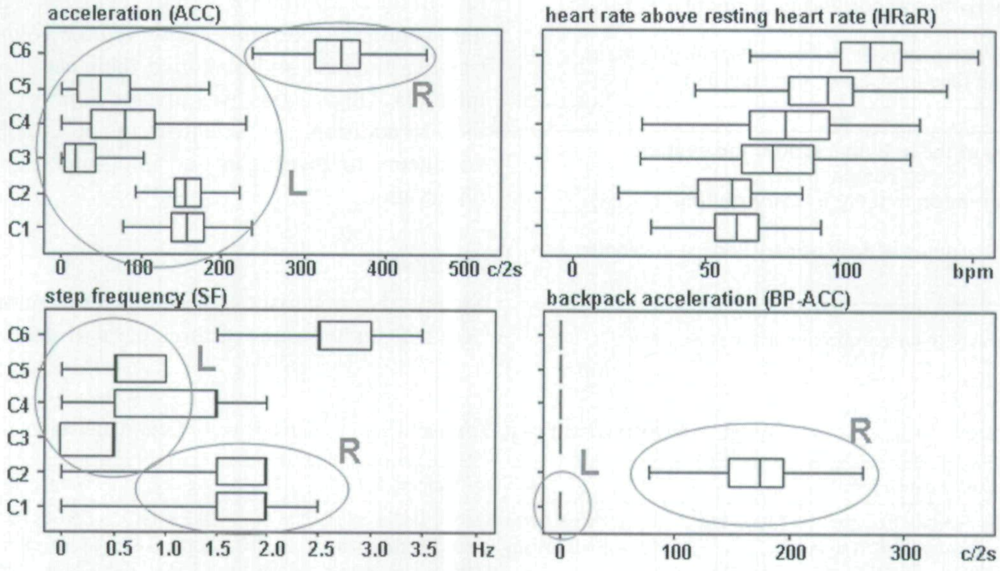

FIGURE 2. (A–D) Box plots are used to determine nodes of the decision tree by visual inspection. Decision nodes are outlined with two corresponding circles. Activities marked with R fall into right branch and those marked with L fall into left branch of node. C1, walking; C2, marching with backpack; C3, lifting and lowering loads; C4, lifting and carrying loads; C5, digging; and C6, running.

Discrimination of Military-Specific Activity Classes by Sensor Data

First, running can be separated from the other five military-specific activities using H-ACC data (see Figure 2A). Furthermore, walking and marching can be separated from two materials-handling classes (lifting and lowering loads, digging) using SF (see Figure 2B). Finally, walking and marching with backpack can be distinguished by BP-ACC (see Figure 2D). The discrimination power of the registered data does not allow the separation of the three materials-handling classes. Discrimination of the six military-specific activity classes by HRaR was weak (see Figure 2C). However, HRaR is relevant to distinguish between the six specific and other less physically demanding activities of the "other activity" class.

Decision Tree

Activities were first classified in 2-second time segments without considering temporal connections (see Figure 3A). The problem of the three materials-handling classes not being able to be separated still remained; therefore, simple temporal logic was used in a second step. First-classified data were buffered in 60-second time segments. If at least 20 of the 30 decisions in a 60-second time segment were the same, the respective activity class was assigned (see Figure 3B). If the assigned class was the cumulative class of materials handling, it was further separated into lifting and lowering loads (H-ACC < 42 c/2 s) or digging (H-ACC ≥ 42 c/2 s), depending on the mean H-ACC. For the class lifting and carrying loads, the 30 decisions in 60-second time segments were analyzed further. In this segment, short classifications as cumulative materials handling and walking alternated cyclically. On average, 44% of the 30 two-second decisions in the 60-second time segment of lifting and carrying loads was assigned as materials-handling activity, 33% as walking, and 23% as other activities. Based on that distribution, the last decision was made. If in a 60-second time segment at least 11 first decisions were materials handling and 8 were walking or marching, the lifting and carrying loads class was assigned. Otherwise, the segment was assigned to the heterogeneous "other activities" class (Fig. 3).

Testing of the Activity Recognition System in Isolated Activities

The overall recognition rate of isolated activities assessed in a laboratory setting was 87.5% (walking, 95%; marching with backpack, 95%; running, 85%; and materials-handling classes, 76%). Within the materials-handling classes, 60% of lifting and lowering loads was classified true positive and 22% was incorrectly classified as digging. Also, 60% of digging was classified true positive and 15% was incorrectly classified as lifting and lowering loads. Only 42% of the lifting and carrying loads class was classified true positive, while 33% was incorrectly classified as walking and 6% as lifting and lowering loads.

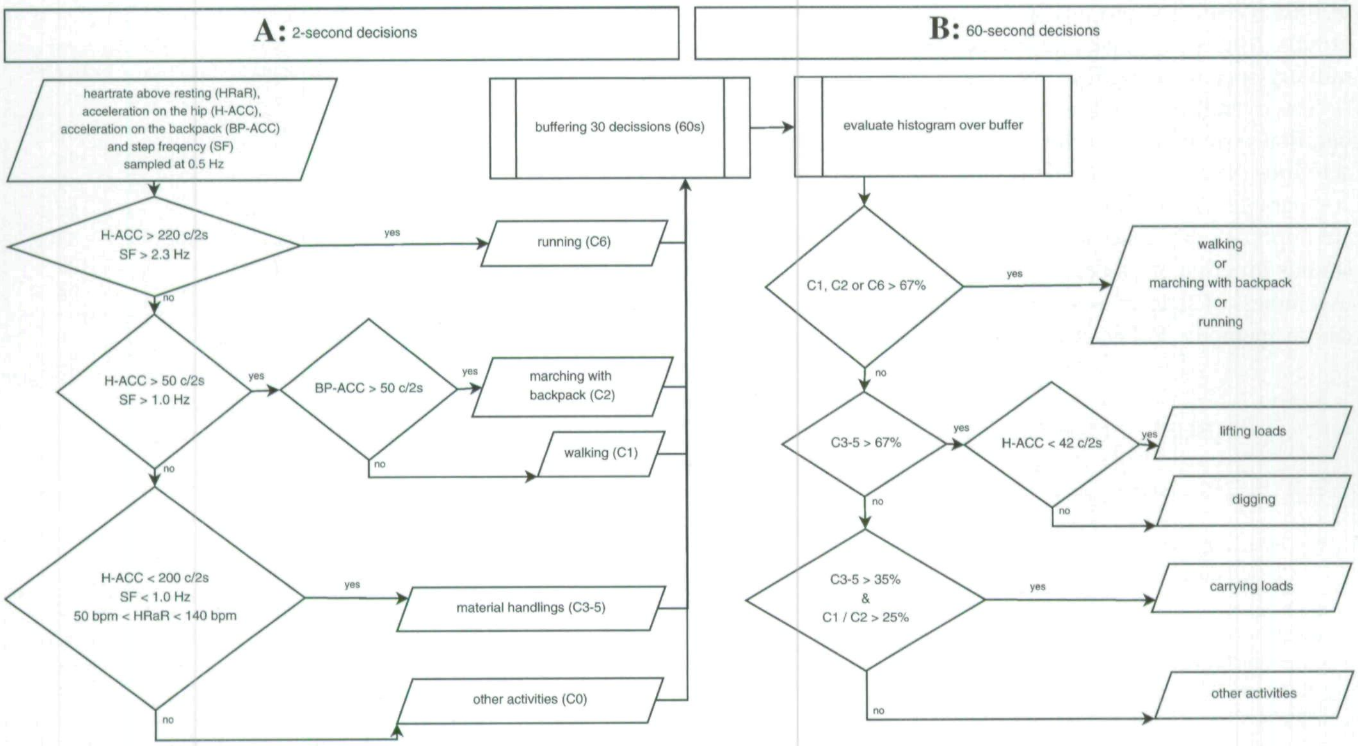

FIGURE 3. (A and B) Decision tree in two phases as an activity classifier. In phase A, sensor data sampled at 0.5 Hz is used to distinguish between walking (C1), marching with backpack (C2), materials-handling activities (C3–C5), running (C6), and other activities (C0). In phase B, results of part A are buffered in 60-second sequences to filter short duration misclassifications and to distinguish between all six relevant, military-specific physically demanding activity classes and the "other activities" class.

Comparison of the Activity Recognition System With Observation During Daily Military Routine

The overall recognition rate of activities classified by the sensor-based activity recognition system compared to observation-based activity classification during daily military routine was 85.5%. True positive recognition for the military-specific activity classes ranged from 48% (materials-handling classes) to 89% (marching with backpack; see confusion matrix in Table II).

Inter-rater Reliability of Direct Observation

Total data from three examiners matched 91.8% to 92.6% of the pairwise-compared instances. The concordance of activity classification based on observation for the six activities ranged from 51% between examiners one and two in lifting and carrying loads to 100% between examiners two and three in running (see Table III).

DISCUSSION

Direct observation,[20] energy expenditure estimations by doubly labeled water (DLW),[21,22] and self-report questionnaires[23,24] are the most common methods of assessing job requirements in armed forces. Unfortunately, direct observations are not feasible for large-scale studies; DLW does not differ between activity classes, and self-report questionnaires are of low objectivity. Established body-fixed sensors were used in the present study to objectively assess duration and frequency of military-specific physically demanding activities in larger groups. Algorithms have thus been developed to recognize six military-specific activities.

The overall recognition rate of the presented activity recognition system of 87.5% for isolated activities and 85.5% for activities observed during daily military routine is high and comparable with findings in other studies.[10–12] However, there are important differences concerning the methods between the studies in terms of choice and number of assessed activities, in numbers of sensors used and their data density, and in validation methods. Pober et al.[12] achieved a mean recognition rate of 80.8% by classifying four activities (walking, walking uphill, vacuuming, and computer work) with one sensor signal (chest acceleration, 1 Hz) in a laboratory setting. Pärkkä et al.[10] found a mean recognition rate of 86% by classifying five activities and three posters (running, nordic walking, walking, rowing, cycling, sitting, standing, and lying) with 22 different signals (synchronized by 1 Hz) in an out-of-laboratory environment. Aminian et al.[11] showed a mean recognition rate of 89.3% by classifying three posters and two activities (sitting, standing, lying, dynamic activities, and other activities) with two sensor signals (chest and thigh acceleration, 10 Hz) in a laboratory setting.

The recognition rate of specific activities investigated during daily military routine was lower than in isolated activities performed after protocol. This is due to a greater variability in activity durations and intensities during daily military routine. Especially, activities with short durations have a lower recognition rate because with every change of activity, a difference between sensor-based and observation-based activity classification is likely. If the activity changes often, direct observation is more difficult and subjective appraisal is more important, such as in frequent changes between walking and standing, for example. Misclassifications of activities with short duration explain why walking achieves a lower recognition rate than marching with backpack as an example of an

TABLE III. Accordance of Observation-Based Activity Classification by Three Different Examiners Following, Simultaneously, the Same Volunteer

Activity Class	Examiner 1 vs. 2	Examiner 1 vs. 3	Examiner 2 vs. 3
Walking (%)	81	81	87
Marching With Backpack (%)	99	99	98
Lifting and Lowering Loads (%)	83	57	79
Lifting and Carrying Loads (%)	51	72	54
Digging (%)	63	100	83
Running (%)	92	85	100
Other Activities (%)	96	97	94

Twelve volunteers were observed for 90 minutes each.

TABLE II. Confusion Matrix With Actual (Observation Based) vs. Predicted (Sensor Data Based) Activity Classes Assessed During Daily Military Routine

Observation Based Activity Classes, minutes (%)	Sensor-Based Activity Classes, minutes (%)							
	Walking	Marching With Backpack	Lifting and Low Loads	Lifting and Carry Loads	Digging	Running	Other Activities	Sum
Walking	**92 (66)**	0 (0)	2 (1)	8 (6)	0 (0)	1 (1)	37 (26)	140 (100)
Marching With Backpack	0 (0)	**197 (89)**	1 (0)	8 (4)	1 (0)	0 (0)	15 (7)	222 (100)
Lifting and Lowering Loads	0 (0)	0 (0)	**46 (48)**	1 (1)	3 (3)	0 (0)	45 (47)	95 (100)
Lifting and Carrying Loads	7 (10)	2 (3)	9 (13)	**14 (20)**	1 (1)	0 (0)	37 (53)	70 (100)
Digging	0 (0)	0 (0)	4 (18)	1 (5)	**11 (50)**	0 (0)	6 (27)	22 (100)
Running	1 (4)	1 (4)	0 (0)	1 (4)	0 (0)	**16 (70)**	4 (17)	23 (100)
Other Activities	15 (1)	2 (0)	79 (5)	24 (2)	3 (0)	0 (0)	**1510 (92)**	1633 (100)
Sum	115	202	141	57	19	17	1,654	2,205

In 24 volunteers a total of 2,205 minutes of daily military activities was measured. True positive classifications are printed boldface.

activity with longer durations. All materials-handling classes show only moderate recognition rates (see Table II). However, with over 90 minutes of data collection per subject, on group level, false negative and false positive misclassifications cancel each other at random. Table II shows that the total sum of instances classified on the basis of sensor data are similar to the total sum of observed instances for all activity classes.

Only the true positive classification of the lifting and carrying loads class was apparently low. However, parts of lifting and carrying loads activities were classified as either walking and marching (33% in laboratory setting and 13% during daily routine) or lifting and lowering loads (6% in laboratory setting and 13% during daily military routine, see Table II). These classifications are not entirely wrong because the class carrying loads contains walking and, to a small extent, lifting. Apart from that, there are no systematic misclassifications between the six military-specific activity classes.

Possibilities for Enhancing Output in Activity Recognition

The lifting and carrying loads class is important in the military setting because walking with heavy loads is much more physically demanding than simply walking. It is worthwhile to attempt to enhance the respective recognition rate of the used method. We suggest investigating temporal patterns in the data using hidden Markov models,[25] for example. Temporal patterns are suggested to be useful in recognizing lifting and carrying loads because this activity class is composed by cyclic alternations of a small number of short activities. To test such an approach, a new dataset with higher resolution and precision of the label segments is needed. With the use of more complex sensors, higher data density and additional sensors placed elsewhere on the body, the accuracy of the activity recognition system may be increased. Unfortunately, continuously assessing physical activities over 1 week of military service puts very high restrictions on sensors and body positions. Therefore, it is important to maintain a balance between accuracy and feasibility, especially in this setting.

Limitations

Although direct observation was found to have good interobserver reliability in general, it is unlikely that it is entirely precise. The comparison of observations of three examiners showed enhanced variances in short duration activities. The concordance for the lifting and lowering loads class between different examiners was only 51–72%, for example (see Table III). The use of video observation would have been ideal, as it may provide a more accurate reference for sensor-based activity recognition. Video analysis allows for watching a specific sequence several times, using slow motion and other software functions that facilitate the task, allowing for definition of label segments with a higher resolution and precision. However, the use of video was not allowed in the Army's daily routine and video analysis can be expensive.

In the presented study, volunteers were observed during randomly chosen 90 minutes of their daily military routine. The disadvantage of this approach is its unequal outcome in duration and frequency of different military-specific activities. Unfortunately, the dataset sampled during daily military routine contained only 22 minutes of digging and 23 minutes of running. Each of these activities represents 1% of the registered activity time (see Table II). However, to counter this limitation, the military-specific activity recognition system was additionally compared to isolated activities performed after protocol containing the same duration for every activity class in every subject.

Strengths

The developed algorithms for military-specific activity recognition are validated not only in isolated activities in a laboratory setting but also during daily military routine. Therefore, the results are more meaningful for future applied studies.

The presented classification method is simple to use and comprehensible.

Additionally, the algorithm of this study can be combined with algorithms from prior studies to estimate activity intensities.[26,27] Those algorithms for energy expenditure estimation are based on the same sensor signals (uniaxial accelerometry and HR monitors). However, such algorithms have to first be validated in a military setting.

Relevance for Future Applications

Body-fixed sensors have been applied successfully in recent studies to investigate job requirements in military occupations.[21,28,29] With the algorithm presented in the current study body-fixed sensors deliver not only previously used indexes of activity intensities (ACC and HR)[21,29] and walking distances (SF),[28] but also information on type, duration, and frequency of military-specific activities.

The advantages of the chosen body-fixed sensors for future investigations in military live action are the ability to collect and store data of many participants, without any technical support or recharging over 1 week. In contrast to prior observation studies,[24,30] there is no need for a researcher to accompany the participants during military field exercises with the current approach. A limitation of this approach when applied in the field may be the reduced control of participants' commitment to wearing the sensors.

The presented algorithm was developed to provide scientific answers in the field of occupational medicine, injury prevention, and physical training in military settings. Additionally, physical activities and demands can be determined to develop job descriptions in military organizations. So far, a relation between general physical demands and injury incidence has been demonstrated.[31–33] The present method can provide useful information to further specify physical demands-related injury risk factors. Therefore, progression, type, amount, and frequency of physical demands during military basic training can be assessed and compared with occurrences of injuries, dismissals, or changes in physical performances.

CONCLUSION

Established, easy-to-handle body-fixed sensors deliver data for specific and valid activity recognition in a military setting. With the discussed sensors and the developed algorithm, military-specific activities can be recognized in 1-minute intervals over six continuous days. The presented method allows investigators to objectively assess type, occurrence, duration, and frequency of military-specific physical activities.

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