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Employing body-fixed sensors and machine learning to predict physical activity in military personnel: A customized approach

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ABSTRACT

Background

This was a feasibility pilot study aiming to develop and validate an activity recognition system based on a custom-made body-fixed sensor and driven by an algorithm for recognizing basic kinetic movements in military personnel. The findings of this study are deemed essential in informing our development process and contributing to our ultimate aim which is to develop a low-cost and easy-to-use BFS for military applications.

Methods

Fifty participants performed a series of trials involving walking, running and jumping under laboratory conditions in order to determine the optimal, among five machine learning, classifiers. Thereafter, the accuracy of the classifier was tested towards the prediction of these movements (15183 measurements) and in relation to participants' gender and fitness level.

Results

Random forest classifier showed the highest training and validation accuracy (98.5% and 92.9% respectively) and classified participants with differences in type of activity, gender and fitness level with an accuracy level of 83.6%, 70.0% and 62.2% respectively.

Conclusions

The study showed that accurate prediction of various dynamic activities can be achieved with high sensitivity using a low-cost easy-to-use sensor and a specific ML model. Whist this technique is in a development stage, our findings demonstrate that our body-fixed sensor prototype alongside a fully trained validated algorithm can strategically support military operations and offer valuable information to commanders controlling operations remotely. Further stages of our developments include the validation of our refined technique on a larger range of military activities and groups by combining activity data with physiological variables to predict phenomena relating to the onset of fatigue and performance decline.

KEY MESSAGES

- Accurate prediction of various dynamic activities in large number of troops through body-fixed sensors can be carried out at a very low cost and by using in-house resources.
- The design and deployment of such custom made BFS systems allows direct access and handling of the raw data, thus the whole pipeline is transparent and customisable, whereas commercial devices generally keep the details of data processing a secret.
- The selection of the optimal algorithm to accompany the BFS should be based on full validation experiments and not on algorithm popularity.

INTRODUCTION

During sustained military operations many stress factors are magnified due to sleep deprivation, incomplete exercise recovery, extreme environmental conditions and calorific deficit.[1] Under such conditions, forecasting the fighter's performance is vital, as it constitutes the army's most important military system in its efforts to accomplish a mission.

Towards that direction, the U.S. Army has developed sensor and wireless communication technology, thereby improving the integration of wearable systems monitoring the war fighter.[2] However, this technology is not accessible by most developed countries which may fall short of efficient prognostic tools regarding the fighter's operational readiness. Particularly in South East Europe where no data are available on wearable systems, the development of a portable, low-cost, and easy-to-use sensor system, such as body-fixed sensors (BFS), poses as an effective alternative. Research over the past decade has suggested that BFS are considered as the most promising method, amongst other techniques, for assessing various military physical activities.[3 4 5] Evidently, the combination of BFS with sophisticated analytical methods such as data mining and Machine learning (ML) has provided new insights in the military regarding musculoskeletal injury,[6] post-traumatic stress disorder [7] and interpersonal violence prediction.[8] However, only few studies exist [9 10] in relation to the role of BFS for movement recognition in active military populations and solely characterize Swiss Army recruits using commercially available accelerometers. Physical conditioning training in military varies considerably among countries, even within military alliances such as NATO, metabolic and neuromuscular adaptations can accordingly vary among different armies, with subsequent effects on movement patterns. [11]

The present study represents the preliminary stage of a development process aiming to build and validate BFS and military activity algorithms for specific Army personnel. Therefore, whilst this is original research it is considered as a pilot and feasibility study to inform the development of a subsequent full-scale research on the topic. Apart from producing a bespoke hardware-software deliverable for the specific Armed Forces, this effort intends to share methodologies and protocols in developing activity recognition techniques for military personnel in a cost-effective way.

METHODOLOGY

Subjects

Fifty military personnel (forty one males and nine females) with median and interquartile range (IQR) scores for age of 22 (6.73) years and mean and standard deviation scores for height, mass and body fat percentage of 174.8 ± 6.3 cm, 74.7 ± 9.4 kg and 15.7 ± 5.3 respectively participated in this study. Forty-three subjects were Army cadets and seven subjects were senior Army personnel (First Sergeant, Second Lieutenant, Captain) whilst fourteen of fifty subjects also participated in a trial experiment exploring an optimal location for the sensors. They were all free from injury and accustomed to treadmill gait. All subjects participated voluntarily and gave their written-informed consent as part of procedures that complied fully with relevant laws and with standards of ethical conduct in human research as regulated by the Committee of the Institute.

Experimental procedures

During the investigation for the sensor's optimal location the subjects performed a series of trials on a treadmill (SportsArt 1080HR, San Vittore, Switzerland) at various speeds (4.0 - 10.0 $km \cdot h^{-1}$) with the sensor strapped at three different landmarks (thigh, waist, arm). Statistical analysis (Cronbach's alpha) showed that for the same person performing identical types of exercise, the waist site provided higher consistency and therefore it was considered the most reliable location for data extraction, compared to the arm and the leg landmarks [0.34 (95% CI 0.33-0.35), 0.03 (95% CI 0.03-0.04) and 0.01 (95% CI 0.00-0.02) respectively]. Thereafter, the sensor was placed at the waist along the right mid-axillary line and in parallel with the umbilicus.

During the main experiments subjects performed a series of 1-minute trials involving a) repeated vertical jumps in place, b) walking at 4 $km \cdot h^{-1}$ on the treadmill at a 10% gradient, c) walking at 6 $km \cdot h^{-1}$ on the treadmill on horizontal, and d) running at 10 $km \cdot h^{-1}$ on the treadmill on horizontal. The following features were also used to label the measurements for each participant and the ML classifiers were tasked to infer: <u>Age:</u> Below 30 years (B30)-Above 30 years (A30), <u>Fitness level</u>: Average (A)-Fit (F)-Very fit (VF), <u>Gender</u>: Male (M)-Female (Fe), <u>Type of activity</u>: Walking (W)-Running (R)-Vertical Jumping (J)-Walking uphill (WU). Participants' fitness level was determined based on frequency (exercise sessions per week), training intensity (percentage of maximum oxygen uptake), volume of exercise sessions (exercise duration) as well as physical activity-energy expenditure measurements (via accelerometry) obtained in an earlier study [12] for the same group of cadets.

Instrumentation

For our experiments we developed a custom-made accelerometer sensor which is considered particularly effective in monitoring actions involving repetitive body motions. The sensor was constructed in our laboratory, based on an *Adafruit Feather M0 'Adalogger'* development board. The sensor's technical details are shown in the Appendix. The steps followed on the modelling procedure for the effective classification of the subjects' physical activity were a) data pre-processing, b) model selection and tuning, c) validation and results on unseen data.

Data pre-processing

The input to the modelling phase consisted of 11 features representing the accelerometer and gyroscope measurements. The sensor was characterised by six degrees of freedom (6-DOF), representing the total number of ways an object can move in three-dimensional space, with three translational and three rotational motions. All 6-DOF were centred around three axes comprised of two horizontal axes, and one vertical axis, commonly referred to by X, Y, and Z and they are required to meet the industry standard definition of "Full Motion". Every pair of lines listed the rotational velocity components in the first line, and the linear acceleration components in the second. The x, y, and z axes were specified on the Inertia Movement Unit board. The units for yaw · pitch · roll expressed in $deg \cdot s^{-1}$ and for acceleration in $m \cdot s^{-2}$, without the gravity component (which the Inertia Movement Unit board itself removes during its own onboard processing). It should be noted that the Inertia Movement Unit board outputs the yaw · pitch · roll values in $rad \cdot s^{-1}$, which we convert to $deg \cdot s^{-1}$ in our own code before writing them to the logfile. The dataset was enriched with the subjects' physical characteristics (gender, age, fitness level) and type of activity (walk, run, vertical jump and walk uphill). By placing the sensor on the subjects' waist, 15183 measurements were collected with sensor data (acceleration and gyroscope values) being polled every 100 ms.

Our research's primary goal was to infer the subjects' activity type by leveraging machine learning classification methods on accelerometer data. To this end, the collected data prior to be fed into the machine learning models were cleaned from outliers and pre-processed to extract features that characterize 10-second rolling windows. Rolling time windows are a popular statistical method for time series that provides rolling subsamples of the original full sample, which are generally more stable and with lower variability compared to the individual measurements. [13] Due to this high variability between consecutive accelerometer values, the mean, variance, median, 1st and 3rd quantile of the initial measurements, were extracted instead of using the exact measurements for the creation of the time windows. For a 6-DOF accelerometer, this translates to 6 x 5 = 30 input features.

Model selection

In ML classification methods, a training set is provided to the learning algorithm, in which the data are labeled and classified correctly. Then the algorithm generates a classification model that learns the patterns involved in the data and can automatically classify future situations. The trained models are usually tested on unseen data (test set) to ensure that they have not just overfit on the training dataset. Having more accurate classification technique ensures that lesser misclassifications (e.g. a subject's walk being classified as run) will occur on the test set. Therefore, the selection of a suitable modelling method is of paramount importance in solving such problems. Since all classification algorithms may behave differently depending on the type and characteristics of the underlying data, a comparison between the most common classifiers was applied, to select the most suitable algorithm for recognizing physical activity or other subject's physical characteristic from the accelerometer. The algorithms used were a) Random Forest (RF), b) K-Nearest Neighbor (KNN), c) Kernel Support vector machines (KSVM), d) Multilayer Perceptron 2-hidden-layers (MLP2HL), and e) Gradient Boosted Trees (GBT). These five state-of-the-art supervised learning algorithms were considered the most appropriate for this particular task.[14] Following data cleaning, data from a set of 36 subjects were used for training (n=27) and validating (n=9) the algorithms to select the most suitable one for our activity recognition task (Table 1).

The model development was performed using the Scikit-learn machine learning library, [15] a Python module integrating a wide range of state-of-the-art algorithms for medium-scale supervised learning (mapping an input to a target based on example input-target pairs) and unsupervised learning (discovering undetected patterns in a data set with no pre-existing labels) problems. Due to the relatively limited training data size (n=27) and the large number of models' hyperparameters, a grid search cross-validation procedure (GridSearchCV) was leveraged to perform an exhaustive search over a set of specified values for each estimator. This method aimed at finding the best combination based on the best k-fold cross-validation (k=10) score obtained by using k-1 of the folds as training data and validating the resulting model on the remaining part of the data.

RESULTS

Table 1 presents a comparison of the accuracy between the five popular classifiers. The metric used is classification accuracy which is defined as the fraction of correct model predictions divided by the total number of predictions and is considered the most popular metric for evaluating classification models.[16]

Table 1. Accuracy values across the selected classifiers

Model	**Train accuracy %**	**Validation accuracy %**
RF	98.5	92.9
KNN	95.2	93.0
KSVM	81.5	81.7
MLP2HL	85.8	84.5
GBT	100	90.3

RF: Random Forest; KNN: K-Nearest Neighbor;

KSVM: Kernel Support vector machines;

MLP2HL: Multilayer Perceptron 2-hidden-layers;

GBT: Gradient Boosted Trees

Although all models performed similarly well, RF and KNN presented higher accuracy on the validation set. RF was also characterized by flexibility and general robustness on high-dimensional data and therefore it was selected as the optimal classifier. On a later stage it was further fine-tuned on a 10-fold cross-validation to perform activity recognition on unseen measurements. The use of a fine-tuned version of our RF classifier predicted the activity of nine subjects (test set) which were not included in the training set. As indicated below, this procedure was able to infer the activity type by assigning the correct label to most of the individual measurements of the test set. The metric used to evaluate our classifier was overall classification accuracy which represented *Correct classifications/All measurements.* For each trial, a 100% correct prediction would involve each data sample being classified as the actual type of activity, e.g. for 100% WU accuracy, all test data samples should be classified as uphill walking. Analytical accuracy values are shown in Table 2.

Table 2. Accuracy values for various subjects in each type of activity

	Predicted characteristics – correct classifications (% correct)			
True characteristics	**Walk**	**Run**	**Jump**	**Walk Uphill**
M-F-B30-WU	0 (0%)	15 (1.4%)	70 (6.4%)	1011 (92.2%)
M-F-B30-J	15 (1.9%)	8 (1.0%)	718 (88.3%)	72 (1.9%)
Fe-F-B30-W	328 (65.0%)	111 (22.0%)	3 (0.6%)	63 (12.5%)
M-VF-B30-J	0 (0%)	13 (2.1%)	572 (94.1%)	23 (3.8%)
M-VF-B30-R	0 (0%)	456 (99.4%)	0 (0%)	3 (0.7%)
Fe-VF-B30-WU	1 (0.1%)	7 (0.6%)	53 (4.3%)	1173 (95.1%)
Fe-VF-B30-WU	2 (0.2%)	1 (0.1%)	93 (9.6%)	878 (90.1%)
M-F-B30-W	791 (89.5%)	0 (0%)	0 (0%)	93 (10.6%)
M-F-A30-J	2 (0.3%)	529 (73.8%)	162 (22.6%)	24 (3.4%)
Overall Accuracy (*Correct classifications /All measurements*)	**6089/7290 (83.6%)**			

M: Male; Fe: Female; A: Active; F: Fit; VF: Very fit; B30: Below 30 years old; A30: Above 30 years old;   *W: Walk; R: Run; J: Jump; WU: Walk uphill*

Analytical accuracy values for gender showed overall classification accuracy values of *5446/7777 (70.0%)* (Figure 1).

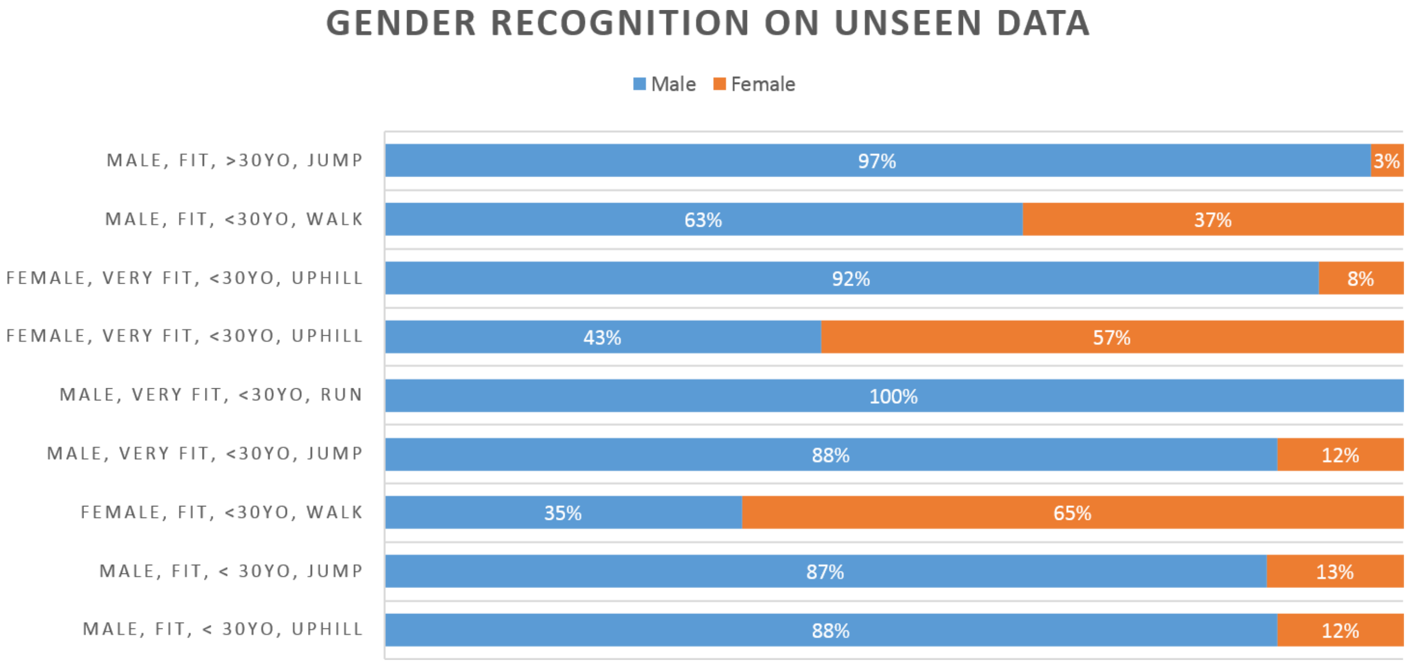

Figure 1 Accuracy values for various subjects in each gender

Analytical accuracy values for fitness level are shown in Table 3 with an overall accuracy of 62.2%.

Table 3. Accuracy values for various subjects in each fitness level

	Predicted Fitness Characteristics		
True Characteristics	**Average**	**Fit**	**Very Fit**
Male, Fit, < 30yo, Uphill	16 (1.5%)	880 (80.3%)	200 (18.3%)
Male, Fit, < 30yo, Jump	1 (0.1%)	637 (78.4%)	175 (21.5%)
Female, Fit, <30yo, Walk	9 (1.8%)	488 (96.8%)	7 (1.4%)
Male, Very Fit, <30yo, Jump	0 (0%)	579 (95.2%)	29 (4.8%)
Male, Very Fit, <30yo, Run	0 (0%)	0 (0%)	459 (100%)
Female, Very Fit, <30yo, Uphill	0 (0%)	733 (59.4%)	501 (40.6%)
Female, Very Fit, <30yo, Uphill	0 (0%)	226 (23.2%)	748 (76.8%)
Male, Fit, <30yo, Walk	0 (0%)	167 (18.9%)	717 (81.1%)
Male, Fit, >30yo, Jump	0 (0%)	632 (86.8%)	96 (13.2%)
Overall Accuracy (*Correct classifications /All measurements*)	**4541/7300 (62.2%)**		
YO: years old			

DISCUSSION

The results showed that factual prediction of various dynamic activities can be achieved with high sensitivity using a custom-made sensor and a specific ML model. In particular, the RF algorithm generated superior classification of characteristics in a variety of movements against a range of popular classifiers. The study offers unique contribution to the existing literature in several ways. First, the employment of a custom-made sensor alongside a validated ML algorithm demonstrates the capacity to design and deploy low-cost and easy-to-use BFS systems without interacting with the commercial sector, something that allows direct access and handling of the raw data, so the whole pipeline is transparent and customisable, whereas commercial devices generally keep the details of data processing a secret.

Second, our protocol was focused not only on applying a popular ML method for the prediction problems, but to validate the optimal ML algorithm from a range of established available algorithms. Third, this pilot experiment recruited an authentic Army population group instead of pathological,[17] healthy non-athletic [18] or professionally athletic [19] populations, which extensively used in activity recognition studies.

Whilst the focus of this first experimental stage was to conduct a feasibility trial of our bespoke technique, these early findings compared well with previous data. Although our algorithm prediction accuracy (83.6%) was slightly lower compared to the average 86% obtained for civilians performing similar activities, [20] our data provides confidence for the subsequent stages of investigations, considering that our product is in the development stage whereas the comparative data are derived from fully validated systems. Furthermore, it must be emphasized that direct comparisons with previous research could be problematic, since many confounding factors such as sensor placement, exercise protocol, algorithm selection, data volume, sensor hardware, may affect algorithm performance.

Analytically and like previously demonstrated [21] the findings of the present study showed initially that the placement of BFS on the waist, compared to arm and thigh, was characterized by higher consistency. Further, the data revealed moderate differences among the five algorithms tested, but the RF algorithm was superior not only in the training phase, where information was known, but also in the validation phase where characteristics were unknown. The average accuracy of the RF algorithm (96.0%) was comparable to the data of other investigators [22 23] who achieved 99% accuracy using the same algorithm. Lower accuracy values (86-94%) have been related with the use of other algorithms (KNN, SVM) when similar dynamic activities were performed in a laboratory. [21] However, as the recognition rate of each algorithm is a mean value across all activities used in a specific study, there is a possibility that the inclusion of completely different movement within each study affects critically the algorithm's performance.[18 24] As such, Dutta et al. [25] reported significantly higher algorithm accuracy (90%-100%) for stationary activities such as lying, sitting, standing compared to dynamic such as treadmill-hard surface uphill-downhill, walking or running (20%-80%). The algorithm used in the present validation phase demonstrated, on average, lower recognition rate and large range of values for jumping (mean value 68%) compared to walking uphill (mean value 92%) (Table 2). Uphill walking reflects a daily stimulus imposed on the infantry population of this study who predominately march on rough terrains with gradient as part of their occupational training and service. As recently demonstrated [12] such exposure to prolonged aerobic overloading results in neuromechanical modifications in the lower extremities of infantry soldiers compared to civilian populations of similar age. These modifications enhance the ability to perform occupation-specific and routine locomotion tasks at a lower muscle mechanical and neural cost, resulting in a movement characterized by lower amplitude of dynamic muscle actions in the triceps surae complex. Whether this unique mechanical behaviour has a relationship with the way our sensor and ML techniques detect gait remains unknown but as this study's sample came from the same military population as for that study[12] it is worth noting the strength of the present study to include authentic military samples already conditioned to routine military activities.

The algorithm's capacity to recognize accurately gender and fitness level was reduced compared to activity recognition, with males though more accurately recognized than females (77% vs. 23%). Accordingly, participants characterized as ''fit'' were more accurately recognized (60%) compared to ''average'' (0.5%) and ''very fit'' (40%). Gender differences may reflect the inclusion of three female datasets (out of nine) in the algorithm testing procedure, so the supervised learning protocol was not fully balanced with regards to gender input. However, the criteria used (frequency, intensity and time of exercise sessions) for categorizing fitness levels may have determined from the outset the outcome of the algorithm in predicting this classification as the group was very homogeneous in terms of the training regimen followed given the need for all cadets to achieve very similar standards. A future classification based on performance measures should allow the algorithm to predict better different fitness categories.

Further stages of our algorithm development include the validation of the refined ML technique on a larger range of military activities by also including special groups (e.g. parachutists). Eventually, we aspire to combine activity data with physiological variables to predict phenomena relating to the onset of fatigue and performance decline. Data acquisition and processing on a such large scale will enable commanders to remotely control their operations and avoid using commercial fitness tracking systems, hence, preventing the leak of sensitive training/mission information.

There were limitations to this study; first, the inclusion of a small number of senior army personnel may have affected the generalizability of the findings. However, all participants lived in the same residential training camp and had the same daily exercise and diet opportunities. Second, although the activities used represented most of the prevalent everyday activities in the Army (running, walking uphill, jumping, walking) logistical issues prevented us from capturing these activities outside the laboratory. Nevertheless, the characteristics (running-walking speed and gradient) of the present exercise activities were similar with those used in most military physical conditioning programs. Finally, we used a single and not multiple BFS (5-17 sensors kit) which is usually used and can achieve a significant increase in the recognition accuracy by combining two sensors from different locations. [21]

CONCLUSIONS

The findings of this pilot study are encouraging and provide a solid platform for developing a reliable activity recognition technique for military personnel in a cost-effective way. We demonstrated that a low-cost and easy-to-use BFS prototype alongside with a validated algorithm can accurately predict the type of movement and to a lesser extent gender and level of fitness, in an active infantry military group. Our findings support the investment of BFS in military settings which should be preferred instead of smartwatches and phones due to their superiority in terms of autonomy, data protection, size, and body coverage.

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