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# On-line Classification of Human Activity and Estimation of Walk-Run Speed from Acceleration Data using Support Vector Machines

Andrea Mannini, *Student Member, IEEE,* and Angelo Maria Sabatini, *Senior Member, IEEE*

*Abstract*—**The awareness of the physical activity that human subjects perform, and the quantification of activity strength and duration are important tasks that a wearable sensor system would fulfill to be valuable in several biomedical applications, from health monitoring to physical medicine and rehabilitation. In this work we develop a wearable sensor system that collect data from a single thigh-mounted tri-axial accelerometer; the system performs activity classification (*sit*, *stand*, *cycle*, *walk*, *run*), and speed estimation for *walk* (*run*) labeled data features. These classification/estimation tasks are achieved by cascading two Support Vector Machines (SVM) classifiers. Activity classification accuracy higher than 99% and root mean square errors $E_{RMS}$ = 0.28 km/h for speed estimation are obtained in our preliminary experiments. The developed wearable sensor system provides activity labels and speed point estimates at the pace of two readings per second.**

## I. Introduction

THE interest for data acquisition systems that integrate in-body motion sensors has been rapidly growing in the last few years for several applications, including functional assessment in physical medicine and rehabilitation, health monitoring, and sports training. Recent technological advancements in the field of microelectromechanical systems (MEMS) transducer technology have made it possible to conceive a new generation of wearable sensor systems based on inertial sensors, well suited to the needs and constraints of in-body motion sensing. Ideally, a wearable sensor system should provide long-term monitoring when the user is involved in her activities of daily life (ADLs), outside the setting of specialized motion analysis laboratories. State-of-the-art MEMS accelerometers fit these requirements well, since they are small and lightweight, and can be fastened to the human body without compromising the user's comfort.

Usually, the wealth of data collected by wearable sensor systems is processed with different aims in mind [1]. Traditionally, the estimation of biomechanical parameters is pursued for functional assessment purposes or real-time control of prosthetic/orthotic devices [2]. A recent avenue of research concerns the development of computational methods for automatically classifying human physical activities [3,4]. Although the classification problem has perhaps more to do with research in robotics, artificial intelligence and related fields, the points of contact with research in health care and rehabilitation are numerous. For instance, biomechanical parameters can be interpreted differently depending on the actual activity the user happens to be engaged: think of the problem of assessing the energy expenditure incurred by a subject during ADLs [5]. In this regard, a useful function a wearable sensor system would ideally fulfill consists of joint activity classification and parameter estimation tasks.

One of the most common human physical activities is walking. Estimation of spatial and temporal parameters during walking is very important in the clinical practice. Walking speed is widely considered in healthcare research [6], as a predictor of survival, disability, dementia and falls [7], and in assessing the energy expenditure incurred by human subjects during their daily life activities [7]. Although sometimes overlooked, walking speed is also known to play the role of a confounding variable in many gait analysis reports [8]. Finally, interesting applications where classification of human physical activities and walking speed estimation are intertwined are in devising means for enhancing human-robot interactions and in the development of pedestrian navigation systems [1].

The most common approach for estimating walking speed from accelerometers revolves around the measure of activity counts (ACs), namely the sum of the rectified acceleration signals over epochs of one minute. It is possible to infer a relationship between ACs and walking speed. However, the accuracy of generalized prediction models is known to be moderate [9]. Several research groups propose to use accelerometer data in combination with simple biomechanical models of gait [10]. The main shortcoming of these approaches comes from the limited accuracy of the adopted models, and the need of their subject-dependent calibration. A promising approach consists of using pattern recognition techniques, in order to identify walking events and classify patterns of acceleration signals by activity [11-13]. Mostly, Artificial Neural Networks (ANNs) are used in systems that process accelerometer data in off-line conditions [11-13], although the importance of performing on-line computations is sometimes stressed [12]. Another approach comes from implementing regression techniques, such as the Gaussian Process-based Regression [14].

In this work we apply machine learning techniques to process acceleration signals. The wearable sensor system developed for this work is capable of on-line human physical activity classification and speed estimation by means of a

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Andrea Mannini is with The BioRobotics Institute, Scuola Superiore Sant'Anna, Pisa, Italy (phone: +39-050-883410; fax: +39-050-883101; e-mail: a.mannini@sssup.it).

Angelo Maria Sabatini is with The BioRobotics Institute, Scuola Superiore Sant'Anna, Pisa, Italy (e-mail: sabatini@sssup.it).

single thigh-mounted tri-axial accelerometer. We intend to classify physical activities in a restricted group of them, which include static postures (*sit* and *stand*) and dynamic activities (*cycle*, *walk* and *run*); locomotion speed is estimated in the case that the classified activity is *walk* or *run*. Both tasks are based on using Support Vector Machines (SVMs). Recently, SVMs have emerged as a powerful technique for general-purpose pattern recognition. They have been indeed applied to classification and regression problems, even in the biomechanical field [15], with very good performance on a range of either binary or multi-class recognition tasks. SVM classifiers are interesting in many regards: first, the optimization criteria are convex, which implies that a global optimal solution exists [17]. Second, many toolboxes exist that allow a fast implementation of these algorithms in a target hardware platform.

## II. Materials and Methods

Six healthy subjects were recruited (age: mean 27.3 ± std 2.0, in years), after being informed on the nature and aims of the experimental procedures. One tri-axial accelerometer (Analog Devices ADXL325), with measuring range ± 5 $g$ (gravity acceleration, $g = 9.81$ m/s$^2$), was fixed on their right thigh in a lateral position, in the middle between hip and knee, with one of the sensitivity axes oriented in the gravity direction. Acceleration data were acquired at the sampling frequency $f_s = 250$ Hz using the ActiNav system, whose development is currently undergoing in our lab [16].

The ActiNav system revolves around an ARMadeus Board (APF27), a state-of-the-art high-performance Single Board Computer (SBC) that runs a real-time Linux-based operating system. The board embodies an ARM9 based Freescale processor, with 128 MB of RAM, 256 MB of FLASH memory, and a 200K-gates Xilinx FPGA. A custom-made PCB is used to arm the APF27 with a 12-bit Successive Approximation Register ADC (AD7490, Analog Devices, Inc.). This converter operates up to 1 MSPS; moreover, due to its 16 analog channels, up to 5 tri-axial analog accelerometers can be integrated in ActiNav. The APF7 board includes four distinct serial interfaces, an RJ45 Ethernet connector, a USB interface and an SPI bus with two free slave select signals; owing to this level of connectivity, several sensor elements are candidate for integration within ActiNav in the future. Since our current research interests are biased toward the development of digital techniques for sensory data processing, the computational performance of the board is of major concern than issues related to power consumption; consequently, no tricks for power management optimization are implemented, and the power consumption is approximately 2 W in the current implementation. The board size is 100×84×16 mm and the weight of the whole system is approximately 170 g.

The subjects were requested to perform five activities, including static postures: *sit*, *stand*, *cycle* (using an exercise bike), *walk* and *run* (on a treadmill). Each trial lasted two minutes; in the case of *walk* and *run* activities, the treadmill speed was varied in the interval between 1.2 and 9.6 km/h (0.6 km/h steps). Each subject was asked to freely choose the speed for the transition from *walk* to *run*. Only the data from the second minute of activity were retained for further processing.

Data were windowed (250 points included within each window, with 50% overlap) and feature vectors were evaluated for each window. Different features of the acceleration signals can be considered: mean, median, variance, peak and range values of windowed data [11]; Pearson's correlation coefficients between different acceleration axes [11]; stride time [11]; biometric data [12]; coefficients of the Fast Fourier Transform (FFT) computed from windowed data [14]. For the purpose of this work, we limited ourselves to compute the mean values of each measurement axis, and the Pearson's correlation coefficients between each pair of them [4,11]. Two cascaded SVM classifiers were used to obtain the activity label and the point estimate of the locomotion speed for feature vectors classified with *walk* or *run* labels [17].

The aim of an SVM classifier is to find an optimally separating hyperplane in the feature space. This hyperplane is obtained by maximizing the margin between data of different classes. A kernel-based transformation maps data to a higher dimensional space, in which the hyperplane is contructed. Since the optimization problem is shown to be convex, no local minima of the error function are reached during the training phase [15, 17].

Suppose a training set of instance-label pairs is available for a binary classification problem:

$$\{\mathbf{x}_i, y_i\}_{i=1,\ldots,L} \tag{1}$$

Assume that **w,** $b$ are the hyperplane parameters; the optimization problem solved by SVM classifiers is then:

$$\min_{\mathbf{w},b,\xi}\left\{\frac{1}{2}\mathbf{w}^T\mathbf{w} + C\sum_{i=1}^{L}\xi_i\right\} \tag{2}$$

subject to the following set of constraints:

$$y_i\left(\mathbf{w}^T\phi(\mathbf{x}_i) + b\right) \geq 1 - \xi_i \tag{3}$$

where $C$ is a regularization coefficient and $\xi_i$, called slack variables, are purposefully introduced to deal with non linearly separable feature vectors. The function $\phi(x_i)$ is the nonlinear feature mapping function that is related to the kernel function:

$$K(\mathbf{x}_i, \mathbf{x}_j) = \phi(\mathbf{x}_i)^T\phi(\mathbf{x}_j) \tag{4}$$

A widely used kernel function is the Radial Basis Function (RBF):

$$K(\mathbf{x}_i, \mathbf{x}_j) = \exp\left(-\gamma\left\|\mathbf{x}_i - \mathbf{x}_j\right\|^2\right), \gamma > 0 \tag{5}$$

The hyperparameters $\gamma$ and $C$ can be optimized in the course of a cross-validation study. The training set is then processed according to the optimal values of these parameters, in order to define the classifier model for testing.

SVM classifiers were implemented using the LibSVM package, which is available either in C or MATLAB programming languages [18]. The extension to the multi-class problem of interest in this paper was achieved by adopting a "one-against-one" approach: if we assume the existence of $K$ classes, $K(K-1)/2$ binary classifiers were trained on data from all pairs of different classes out of the $K$ classes and a voting strategy was then applied for labeling purposes.

The classification/estimation process was structured over two distinct classification levels. The first-level SVM classifier was devised to perform the activity classification. The second-level SVM classifier assigned a specific speed class to the feature vectors that were labeled *walk* or *run* by the first-level SVM classifier, Fig. 1. Finally, we attempted to refine point estimate of the speed by cascading a logistic regression classifier to the second-level SVM classifier. Given $M$ speed classes, the goal of the logistic classifier is to estimate the *a posteriori* probability for each class given the feature vector $\mathbf{x}$ presented to the classifier:

$$P(y=i\mid \mathbf{x}) \qquad i=1,\ldots,K \tag{6}$$

The speed estimate was then obtained by taking the weighted average of the speeds for each class considered in the classifier development (Bayesian soft assignment rule):

$$v' = P(y=i\mid \mathbf{x})\cdot v(y=i) \tag{7}$$

where probabilities from (6) are the weights.

From an implementation viewpoint, after that the ActiNav system collected acceleration data, SVM classifiers were trained and validated externally on a remote host running Mathworks MATLAB (R2008a) and the LibSVM toolbox [16, 18], as shown in Fig. 2. The validation procedure was conducted using three different approaches: a validation based on the training of classifiers for each subject [7, 13], aka individual training, an $N$-fold cross validation ($N$ = 5) and the leave-1-out validation. See [19] for further details on these different validation approaches.

As an additional measure intended to assess the accuracy in the estimation of *walk* and *run* speed, the validation study was repeated using, for training purposes, a dataset including data from speeds varying between 1.2 km/h to 9.6 km/h in steps of 1.2 km/h (1.2 km/h-step dataset). Once the validated SVM classifiers were uploaded to the ActiNav processor, the system was capable of computing data features and delivering the labels of the classified activities and, possibly, the point estimate of *walk* (*run*) speed to the host computer at the pace of two readings per second.

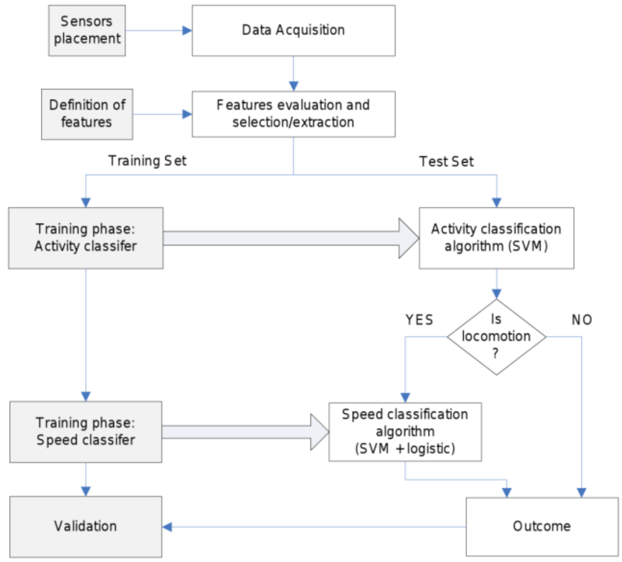


Fig. 1. Block diagram showing the two-level classification process.

## III. Results and Discussion

The validation results in terms of classification accuracy for the training sets with speed steps of 0.6 km/h and 1.2 km/h are reported in Table I. Activity classification is highly accurate for every validation approach and for both datasets. The reduction in the number of classes, in the case of the 1.2 km/h-step dataset, allows better classification accuracy, because of the wider margin existing in the feature space. The speed classifiers tested on subjects never seen during training (leave-1-out method) are dramatically less accurate than classifiers trained and validated according to the other methods considered in this paper, see also Fig. 3.

In the case of individual training, the root mean square

TABLE I
Classification Accuracy, %

| Validation method | Activity | Speed |
|---|---|---|
| **0.6 km/h-step dataset** | | |
| Individual training | 99.6 | 86.7 |
| 5-fold cross validation | 99.7 | 81.2 |
| Leave-1-out validation | 95.2 | 21.0 |
| **1.2 km/h-step dataset** | | |
| Individual training | 99.5 | 95.9 |
| 5-fold cross validation | 99.7 | 95.1 |
| Leave-1-out validation | 92.4 | 38.8 |

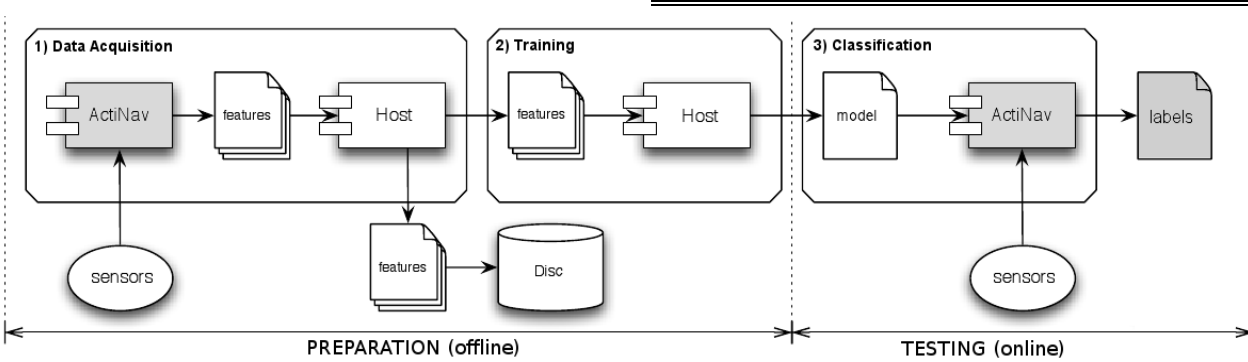


Fig. 2. Task organization during the different phases of data acquisition, training and test.

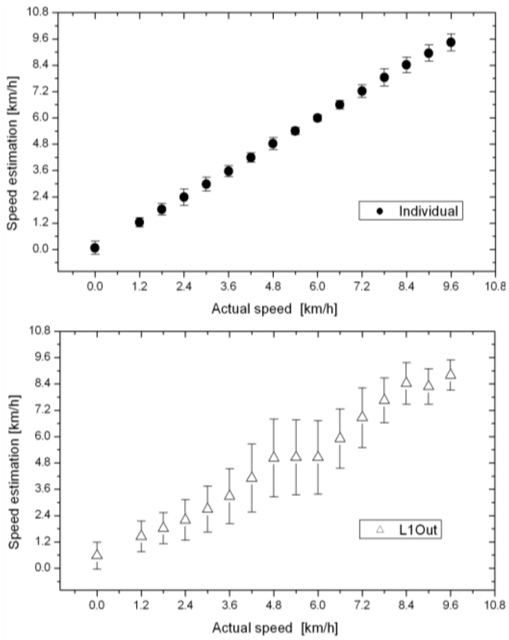


Fig. 3. Speed estimation according to two different validation methods (mean ± std)

TABLE II
WALK-RUN SPEED ESTIMATION ACCURACY, $E_{RMS}$ [KM/H]

| Training set | Test set | SVM | SVM + Logistic |
|---|---|---|---|
| [1.2:0.6:9.6] km/h | [1.2:0.6:9.6] km/h | 0.30 | 0.28 |
| [1.2:1.2:9.6] km/h | [1.8:1.2:9.0] km/h | 0.89 | 0.70 |

error ($E_{RMS}$) between the actual and the estimated speed turns out to be $E_{RMS}$ = 0.3 km/h, see Table II. When the classifier is validated using the 1.2 km/h-step training set, and tested using the intermediate speeds, we obtain $E_{RMS}$ = 0.89 km/h. The reduction in performance can be partly compensated by adopting the soft-assignement strategy implemented by the logistic classifier on top of the second-level SVM classifier: $E_{RMS}$ = 0.70 km/h.

The estimation accuracy of systems similar to ActiNav are comparable. However, it must be pointed out that these systems are principally limited to *walk* activity [11], or they may produce an estimate of *walk* (*run*) speed by a previously available estimate of *walk* (*run*) distance, which is not pursued, or attempted, in our system. [12]. In [14] the $E_{RMS}$ turns out to be significantly lower than our results indicate; however, it must be considered that in their approach, on-line processing is not of interest since 10 s-long data windows are submitted to frequency-domain analysis in order to estimate a single speed value.

## IV. CONCLUSIONS

The ActiNav system developed in this paper is capable of fulfilling its classification/estimation tasks using only one tri-axial accelerometer; feature extraction and two-stage SVM classification are performed in on-line conditions, and the system sends two activity labels and speed point estimates each per second to the host computer. The system performance, in terms of accuracy of either activity classification or speed estimation, are comparable, or slightly better, than competing state-of-the-art systems.

Currently, our research activity concentrates on tricks to extend the range of measured speeds accommodated by the system. In particular, we intend to deal with two problems: first, the transition from stand to walk (very low speed conditions), which may be critical for the classifiers; second, the problem of accelerometer saturation, which may arise at the highest tested speeds with the present configuration.

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