A Real-Time and Self-Calibrating Algorithm Based on Triaxial Accelerometer Signals for the Detection of Human Posture and Activity

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***Abstract*—Assessment of human activity and posture with triaxial accelerometers provides insightful information about the functional ability: classification of human activities in rehabilitation and elderly surveillance contexts has been already proposed in the literature. In the meanwhile, recent technological advances allow developing miniaturized wearable devices, integrated within garments, which may extend this assessment to novel tasks, such as real-time remote surveillance of workers and emergency operators intervening in harsh environments. We present an algorithm for human posture and activity-level detection, based on the real-time processing of the signals produced by one wearable triaxial accelerometer. The algorithm is independent of the sensor orientation with respect to the body. Furthermore, it associates to its outputs a "reliability" value, representing the classification quality, in order to launch reliable alarms only when effective dangerous conditions are detected. The system was tested on a customized device to estimate the computational resources needed for real-time functioning. Results exhibit an overall 96.2% accuracy when classifying both static and dynamic activities.**

***Index Terms*—Activity and posture monitoring, real-time movement classification, triaxial accelerometer, wearable device.**

I. Introduction

Technical progress in microelectronics offers new low-cost, low-weight, and miniaturized devices for wearable instrumentation [1]. Recent advances in technology allow integrating sensors, electronics and wireless transmission modules, into single units to be worn by people during everyday life. These systems monitor parameters related to working activity, health state, or even environmental conditions surrounding the wearer. Therefore, they provide a large amount of biometric and environment-related signals; in this scenario, one challenge considers developing algorithms that synthesize the available data and extract reliable information from them. Implementing smart algorithms on "local" microprocessors, which are directly connected to the sensors, allows transmitting a "reduced" amount of information, with large benefits of efficiency and bit rate drop. To this aim, portable devices were used for functional ability monitoring, rehabilitation, and elderly surveillance, in order to monitor both subject's posture and activity intensity [2], [3]. Many papers on these topics suggested using one [4] or several [5] monoaxial accelerometers placed on the chest and thigh; more recently, triaxial accelerometers (custom-developed by combining three monoaxial sensors [6], [7] or commercial devices [8]–[10]) were also used.

Most of the signal-processing techniques base themselves on updating few activity-related parameters at low frequency (typically, 1 Hz [8], [10]), computed over the raw signals acquired at a higher rate ($10-45$ Hz [5], [8], [10]). Then, sets of thresholds [5], decision trees [8], [11], or fuzzy logic [12], [13] are applied to the extracted parameters in order to classify the activity. Focusing on the movement transducers, a three-axial microelectromechanical systems (MEMS) accelerometer is small and lightweight enough to be easily embedded in a portable device, or even integrated within a garment [14], [15]. In the former case, sensor's orientation may be set to have one sensing axis oriented toward the gravity [7], [10]. On the contrary, the orientation of an accelerometer placed in a garment cannot be set accurately (and it may vary each time a subject wears the garment); few papers face this critical point by looking, for example, at the gravity acceleration as the time-invariant component [16].

Besides rehabilitation and elderly surveillance, wearable accelerometers could assist to monitor workers operating in harsh environments. The European Commission is paying great attention to these applications [17], financing large projects, such as WearIt@Work [18] and ProeTEX [15], [19], [20]; this latter project aims at integrating MEMS accelerometers and other sensors into firefighters and civil protection equipments, in order to monitor physiological, environmental, and activity-related parameters.

Aimed at worker's surveillance applications, this paper deals with the design of an algorithm that analyzes, in real time, the signals produced by one three-axial accelerometer placed on the trunk, in order to classify human activities and posture transitions. With respect to previous works [21], [22], the main peculiarities of this system consider the self-calibration skill of the algorithm and the use of only one accelerometer, thus

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providing results comparable with the ones obtained by other studies, where several sensors were used.

II. Methods

A. Problem Definition and Constraints

In the context of worker's monitoring, this paper deals with the development of a real-time algorithm running on a microcontroller, which identifies activity level and posture of operators "wearing" a triaxial accelerometer. The sensor is placed on the upper trunk, inside a garment (i.e., a jacket). The algorithm does not use any *a priori* information about sensor's orientation. Furthermore, the following constraints were taken into account.

1) Algorithm's software is limited by the microcontroller memory size (commonly few kilobytes).
2) The amount of data to be real-time processed on the chip is limited by the device memory too; only few seconds of signals can be processed at each time.
3) The CPU power limits the complexity of the algorithm. Commonly, microcontrollers cannot implement computationally heavy algorithms, such as the fast Fourier transform; simpler routines, based on time-derived features processing, must be preferred [23]. Furthermore, the sampling rate of the analog signals must be considered; too low frequencies induce loss of information, whereas higher rates increase the number of mathematical operations required for data processing. The scientific literature suggests a suitable sampling rate of 50 Hz [8], [10].
4) Slight changes of the power voltage (due to portable batteries discharge) and the environmental temperature may affect sensor's offset and sensitivity. Different studies faced this problem in the past [24], [25]; according to the goal of this study, we suggest an alternative, simple procedure aimed at online updating these variables.
5) According to end-users needs, instead of detecting activities such as "walking," "climbing stairs," or "sitting," the system should provide a general estimation about subject's activity level and posture. Moreover, it is important to detect events, such as falls to the ground and extended periods of inactivity (in particular, if the subject is lying down). Finally, extended periods of intense activity should be detected, too, since they may highlight physical stress conditions.

Given these constraints, the developed algorithm analyzes one-second-wide portions of raw accelerometric signals in "real time" to measure posture and activity intensity. Then, it further processes these parameters, in order to output a "global" label describing the activity. Moreover, the classifier associates a "reliability" value to each output, based on the posture and activity intensity values. Such parameter may be useful in higher level decision-making process.

B. Instrumentation

A portable device for activity monitoring should be made of three main components: sensor (a triaxial accelerometer, in this study), processing unit (a microcontroller), and wireless transmission unit. Concerning the first one, we chose a triaxial MEMS accelerometer, model ADXL330 (by Analog Devices, Inc., USA [26]): it measures accelerations in a range of ± 3 g[1] and it has a sensitivity of about 300 mV/g. Since sensitivity and offset depend on power-supply voltage, these values dynamically change during time because of battery discharge. The sensor detects both gravitational and inertial accelerations: the former is always perceived by the sensor, whereas the latter is induced by subject motion. Sensor's placement roughly depends on the kinds of activities to detect [21]; when precise *a priori* orientation of the sensor is needed, it could be placed in the lower part of the trunk, at waist [10] or lumbar [6] level. In our case, no reference is needed; thus, the sensor is located in the upper part of the trunk, where body rotations and activity intensity are easier to be detected. Hence, this location was chosen when designing the sensors network of ProeTEX garments [15].

An ADUC7027 microcontroller (by Analog Devices, Inc.) has been coupled with the accelerometer. It is a 16-bit/32-bit reduced instruction set computer (RISC) machine with ARM7TDMI-core and up to 41 MIPS peak performance. The device is provided with 8 kB of static RAM (SRAM) and 62 kB of nonvolatile Flash/EE onchip; it has an onchip oscillator and a phase-locked loop (PLL) that generates an internal frequency clock of 41.78 MHz. The core operates at this frequency, or at binary submultiples: in this study, the frequency was set at 1.31 MHz, as a compromise between computing capabilities and current consumption (1 MIPS and 7.2 mA, at 25 °C) [27]. The controller integrates a 16-channels 12-bit analog to digital converter (ADC). The device filters the incoming signals, by means of a first-order low-pass analog filter, at 20 Hz (since frequencies of human movements are lower [28]); then, it digitally samples the signals at 50 Hz. The microcontroller implements the algorithms described in Section II-C, and each second it transmits an output code to a monitoring PC by means of a Bluetooth module (F2M03GLA-S01 by Free2Move, Halmstad, Sweden). A remote software (developed in LabVIEW G language) records data on the PC.

C. Classification Algorithm

1) Signal Conditioning and Calibration: The accelerometer produces three analog signals ($x(t)$, $y(t)$, and $z(t)$), with values ranging between zero and the current power voltage ($v_{ss}(t)$). The classifier processes these four signals, sampled at 50 Hz. According to its datasheet, when the sensor does not measure any acceleration along one sensing axis (due to gravity or subject's activity), it produces a V_0 output

$$V_0 = 0.5 v_{ss}. \quad (1)$$

The sensitivity of each axis (S) is roughly proportional to v_{ss}

$$S \approx 0.1 v_{ss}. \quad (2)$$

Before further processing, a fifth-order digital mean filter is applied to the signals to erase high-frequency-noise components [10]. Then, the voltages are converted into accelerations (x_G, y_G,

[1]With symbol g, we intend gravity acceleration, namely $\approx$9.806 m/s^2.

and z_G), measured as multiples of g

$$x_G = \left(\frac{x - V_0}{S_x}\right) \quad y_G = \left(\frac{y - V_0}{S_y}\right) \quad z_G = \left(\frac{z - V_0}{S_z}\right). \tag{3}$$

Equation (2) initializes S, but it does not take into account the random fluctuations of sensitivity caused by environmental parameters, like the temperature; furthermore, v_{ss} changes with time, thus V_0 and S should be periodically calibrated. Several papers faced the problem of dynamically estimating the sensitivity of the accelerometer [25], [29], [30]; all proposed solutions based themselves on the observation that g is the only perceived acceleration, when the sensor does not move. According to sensor's specifications [26], the sensitivities of the three channels are identical and V_0 is given by (1); therefore, the model proposed in [25] can be simplified as follows:

$$\left(\frac{x - V_0}{S}\right)^2 + \left(\frac{y - V_0}{S}\right)^2 + \left(\frac{z - V_0}{S}\right)^2 = 1. \tag{4}$$

Due to (1) and (3), a more reliable value of S, replacing the one provided by (2), is as follows:

$$S = \sqrt{(x - 0.5v_{ss})^2 + (y - 0.5v_{ss})^2 + (z - 0.5v_{ss})^2} \tag{5}$$

S must be calculated only when the device is steady, otherwise (4) is false. In our scenario, a subject cannot be asked to stay motionless for few seconds after wearing the sensorized garment. Therefore, a self-calibrating procedure was foreseen; as soon as the microcontroller is switched on, it calculates rough V_0 and S values, by means of (1) and (2). It uses these values to estimate the accelerations [see (3)], until a new parameters' evaluation is possible. When a period of immobility is detected (see Section II-C3), the routine computes V_0 and S with (1) and (5) and it starts a counter, which is updated every second. When the counter reaches 120 ticks, an "update" flag is turned on; in this condition, as soon as a new immobility period is detected, the routine updates the calibration parameters and reinitializes the counter.

2) Frequency Separation: The frequency separation of gravitational and inertial accelerations allows discrimination between posture-related and activity-related signals [10]. Low-frequency signals (gc_x, gc_y, and gc_z in the following text) approximate the gravitational acceleration, which provides the sensor orientation; high-frequency signals (ic_x, ic_y, and ic_z in the following text) approximate the inertial accelerations (caused by movements). As proposed by Karantonis *et al.* [10], the developed routine extracts the former signal from the calibrated accelerations with a third-order digital elliptical IIR filter (with a cutoff frequency of 0.3 Hz, 0.1 dB passband ripple, and stopband at −100 dB). The difference between original signals and filter's outputs approximate the inertial accelerations.

3) High-Frequency Component Analysis (Activity and Possible Fall Detection; Calibration Parameters Update): An index proportional to the inertial acceleration magnitude (which is independent of the orientation of the sensor) provides a global indicator of the activity intensity. Signal magnitude area (SMA) [6], [10] is an appropriate index, since it shows high correlation with the metabolic energy expenditure [31]. SMA is evaluated every second ($t = 50$ samples) on the inertial signals with the following equation:

$$\mathrm{SMA} = \frac{1}{t}\left(\int_0^t |ic_x|\,dt + \int_0^t |ic_y|\,dt + \int_0^t |ic_z|\,dt\right). \tag{6}$$

The real-time integration is performed by means of simple summations of the ic_x, ic_y, and ic_z values each time a new sample is available and dividing the sum by 50 each second.

SMA is used both to identify activity intensity and possible falls to the ground. Concerning the former outcome, two thresholds were defined based on a database of stereotyped activities (including standing, walking, running, climbing stairs, jumping, and falling on a mattress) performed by ten healthy subjects during preliminary tests: 0.2 g (*low activity threshold* or *lat*) and 0.7 g (*high activity threshold* or *hat*). Every second, the subject is classified as *motionless* (here defined as output A0) if SMA is lower than *lat*. When SMA is between *lat* and *hat*, the class becomes *performing mild activities* (A1). A value higher than *hat* means that the subject is *performing intense activities* (A2). The calibration routine described in Section II-C1 is performed when the subject is in A0 state. Moreover, SMA is used to detect high-energy events, such as falls: a *fall threshold* (*ft*) was set at 2.1 g. The subject is classified in *no fall* class (F0) when SMA is lower than *ft*; otherwise, she/he enters the *possible fall* class (F1). The activity-detection routine is summarized in Fig. 1.

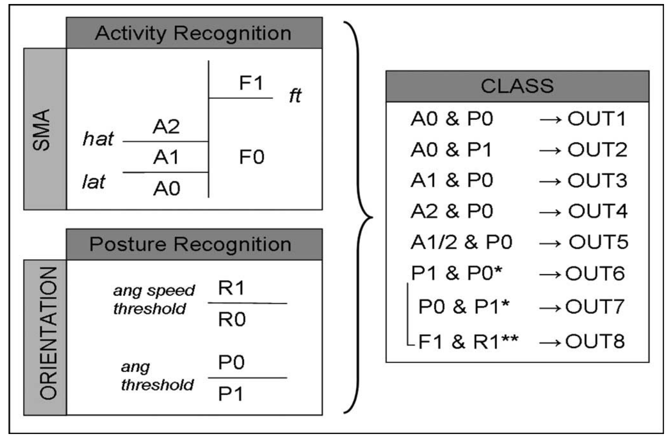

Fig. 1. Based on the combination of SMA, orientation, and angular speed, (left panel) activity levels and postures are determined and (right panel) combined using rules to obtain the classification. (*) OUT6: subject is lying down (P1), while 1 s before was upright (P0), *vice versa* for OUT7—subject is upright (P0) and was laying down (P1) 1 s before. (**) Every time OUT6 is produced, a further analysis is performed to detect a possible fall (OUT8): if output of "possible fall classifier" in 1 of the last 3 s is F1 and output of "rotational speed classifier" is R1 in the same interval (high body rotational speed), then the subject enters this condition.

4) Low-Frequency Component Analysis (Posture Detection): The use of low-frequency accelerations to assess posture has been discussed in [7], where a Kalman-filter-based algorithm is applied to estimate inclination and rotational speed of the body with high accuracy. Since the application described here requires lower precision (body inclination is used only to discriminate between upright or lying down postures), we designed a simpler routine. The primal idea is borrowed from [16], describing a method to detect the vertical acceleration, given the raw signals

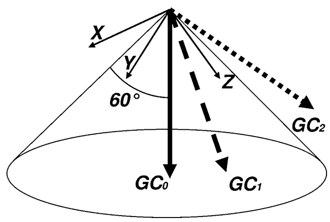

Fig. 2. Evaluation of the subject posture independent of the sensor orientation. *X*, *Y*, and *Z* are the orthogonal axes of the sensor. GC_0: initial detected gravity vector. GC_1 and GC_2: gravity vectors detected at time 1 and 2, respectively.

of a random-oriented triaxial accelerometer. In the system described in this study, a software routine computes the orientation by processing the average low-frequency accelerations (namely GC_x, GC_y, and GC_z), which were evaluated on 1 s time windows, of the gc_x, gc_y, and gc_z signals, respectively. GC_x, GC_y, and GC_z return an estimation of the mean gravity components in the orthogonal reference system of the accelerometer. When the subject moves, the sensor modifies its orientation, thus, the perceived gravity components also change: a large change with respect to the initial values proves a change of posture.

The first step of this routine foresees the detection of the initial sensor's orientation toward the gravity (GC_{x0}, GC_{y0}, and GC_{z0} in the following text). This orientation represents the initial posture of the subject. Once again, the application context does not allow asking a rescuer to wear the sensorized garment and stay in a stereotyped posture for few seconds waiting for the calibration. Thus, the routine automatically measures the initial orientation when it detects the first period of inactivity (see Section II-C3). Moreover, we made the hypothesis that the subject is standing when dressing the garment (since the sensor is placed inside a jacket, it is likely that he wears it when standing, or sitting with erected trunk).

Once estimated, GC_{x0}, GC_{y0}, and GC_{z0} are compared to GC_x, GC_y, and GC_z, respectively, in time: a fast way to perform this comparison consists of computing, at each second *i*, the scalar product between the initial gravity vector ($\boldsymbol{GC}_0$) and the current gravity vector ($\boldsymbol{GC}_i$) [16]. Then, according to the definition of scalar product, a simple division by the product of the two vectors' magnitudes returns the cosine of the angle between the two vectors $\cos(\alpha_{0,i})$. Given this parameter, two posture classes can be identified, due to a threshold set at 0.5 (cosine of 60°) [10]: *standing* (output P0, if $\cos(\alpha_{0,i}) \geq 0.5$) and *lying down* (P1, if $\cos(\alpha_{0,i}) < 0.5$). This procedure does not catch the *direction* of the postural change (i.e., if the subject has tilted-up forward, backward, or on one side); rather, it allows detecting only postural *orientation changes*. In short, it is possible to imagine a cone centered in the initial gravity vector, with semiangle vertex of 60° (see Fig. 2): if, at time *i*, the gravity vector belongs to the cone, then the subject is classified as *standing* ($\boldsymbol{GC}_1$ in Fig. 2); if the vector goes out of the cone, then the subject is classified as *lying down* ($\boldsymbol{GC}_2$).

A similar procedure allows estimation of trunk's rotation speed. At time *i*, the scalar product between the current orientation vector ($\boldsymbol{GC}_i$) and the orientation vector referred to the previous second ($\boldsymbol{GC}_{i\ -1}$), divided by the product of the two vectors' magnitudes, measures the cosine of the angle described by the trunk between time $i-1$ and time *i*, here defined as $\cos(\alpha_{i\ -1,i})$. Since the time interval is 1 s, this value is equivalent to the cosine of the average rotation speed in the last second (expressed in degrees per second). High angular speed identifies rapid changes of trunk's orientation (i.e., events, such as falls to the ground). Therefore, a threshold on $\cos(\alpha_{i\ -1,i})$ can be set to a reasonable value of 0.71 (cosine of 45°): a value of $\cos(\alpha_{i\ -1,i})$ higher than this threshold (average speed lower than 45°/s) means *low body rotation speed* (output R0), whereas a value lower then the threshold implies *high body rotation speed* (R1).

5) Global Classification: Each second, a routine combines the aforementioned outputs by means of logic rules and returns a code pointing out an activity class. Two main groups of activities were considered: *steady* movements (activities that can be performed for long times) and *posture transitions* (from *standing* to *lying down* and *vice versa*). The routine classifies the former ones as OUT1 (*upright standing*), OUT2 (*motionless lying down*), OUT3 (*upright mild activity*), OUT4 (*upright intense activity*), and OUT5 (*active lying down*). A further analysis detects *posture transitions* as OUT6 (*upright to lying down*), OUT7 (*lying down to upright*), and OUT8 (*fall to the ground*). The right panel of Fig. 1 reports the classification strategy.

6) Reliability Parameter Evaluation: Each second, the global classifier clusters the activity in one of the eight aforementioned outputs. Anyway, such a classification scheme does not guarantee the reliability of the classification. Thus, each output is coupled with a reliability value, ranging between 0 (unreliable output) and 1 (highly reliable detection). The computation of this value is based on the Euclidean distance between each index and the class thresholds. Precisely, the algorithm calculates the reliability of the partial classifications Q_{A}, Q_{F}, Q_{P}, and Q_R (associated to the outputs A, F, P, and R, respectively), with the following formula:

$$Q = \min\left(\frac{1, |v - th|}{d}\right) \tag{7}$$

where *v* is the current value of the variable [SMA, $\cos(\alpha_0, i)$, or $\cos(\alpha_{i-1,i})$], *th* is the threshold used to classify the value into one of the classes (A, F, P, or R), and *d* is the size of the uncertainty region. When the distance between value and threshold is higher than *d*, the classification is certain (*Q* equal to 1); otherwise, the lower is the distance between *v* and *th*, the higher is the classification uncertainty (the lower is *Q*). Fig. 3 reports the reliability functions associated to the four partial classifiers outputs. Finally, partial reliabilities are combined using the same rules described in the previous paragraph with fuzzy logic instead of Boolean operators (the minimum between two values substitutes the logic "AND" operator and the maximum between two values substitutes the logic "OR").

III. Experimental Trials and Results

A. Experimental Setup

A session of trials was realized to assess the performance of the classifier. Six healthy adult subjects (22 to 37 years old) were asked to execute two sequences of 36 predefined activities each,

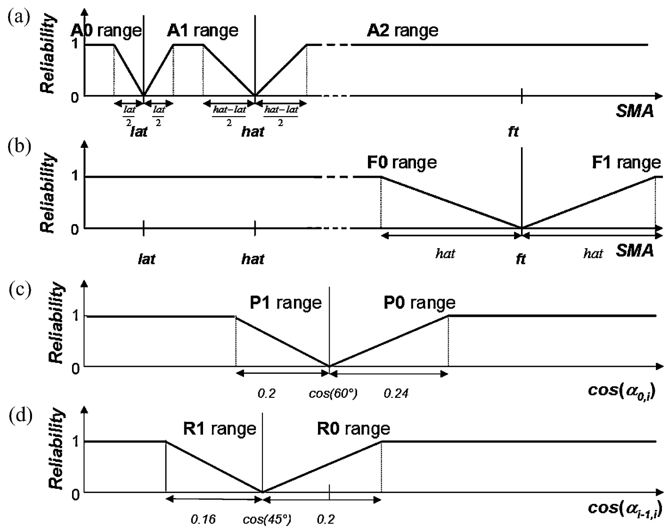

Fig. 3. Reliability functions associated to the four partial classifiers. (a) Activity-level classifier (A outputs). (b) Possible fall classifier (F outputs). (c) Posture classifier (P outputs). (d) Body rotational speed classifier (R outputs).

involving both steady activities and posture transitions. The experiments were carried out in a gym, where the subjects were free to move in a seminatural way. The *steady activities* required during the trials (and the respective *correct class*) were: upright standing and sitting down (*upright standing*); walking (*upright mild activity*); running and jumping (*upright intense activity*); bending over to pick up objects from the ground, moving trunk and arms without walking, and climbing wall bars (*upright mild or intense activity*); staying motionless when lying down (*motionless lying down*) and moving when lying down (*active lying down*). The performed *posture transitions* were: falling to the ground (*fall to the ground*), standing to lying down (*upright to lying down*), and getting up from ground (*lying down to upright*).[2] A test driver verbally asked the subject to perform the activities, with "generic" requests, like "please, start running," "now walk," etc. He did not provide any further instruction. Beginning and end times of each activity were manually annotated (therefore, a ± 1 s precision at the beginning and end of each activity were taken into account when comparing the output of the classifier with the expected one). All subjects were asked to execute steady activities for at least 20 s. The trials lasted about 7 min each. Therefore, more than 94 min of signals were analyzed (corresponding to 5688 samples), including 336 steady actions (5373 samples) and 96 postural transitions (315 samples). Since one of the features to be tested was the autocalibration routine, one of the two sequences started with an activity (walking) phase.

[2] *Bending over, moving trunk*, *and climbing wall bars* cannot be *a priori* classified as mild or intense activities, since subjects were free to perform slow or fast actions. *Moving when lying down* considers subjects moving their trunk as they preferred (i.e., from supine to prone) or moving limbs. *Fall to ground* means that subjects dropped on a mattress after standing or doing intense activities (running or jumping); falls on mattress are supposed to be less intense than real falls (both in terms of activity level and rotational speed); thus, good detection of falls with this protocol implies a better detection of the real ones.

TABLE I
PERCENTAGES OF SAMPLES OF EACH PERFORMED ACTIVITY AS CLASSIFIED IN EACH OUTPUT CLASS

Activity\Class	1	2	3	4	5	% Right
Upright standing	*93.4*	4.9	1.3	0.0	0.4	*93.4*
Sitting down	*90.6*	6.0	3.4	0.0	0.0	*90.6*
Mov. trunk and arms	4.4	0.0	*60.3*	*35.3*	0.0	*95.6*
Picking up objects	2.4	0.0	*39.5*	*57.8*	0.3	*97.3*
Climbing wall bars	1.8	0.0	*90.8*	*3.2*	4.2	*94.0*
Jumping	0.0	0.3	0.4	*99.3*	0.0	*99.3*
Walking	0.1	0.0	*99.9*	0.0	0.0	*99.9*
Running	0.0	0.0	2.4	*97.6*	0.0	*97.6*
Resting lying down	3.3	*95.7*	0.0	0.0	0.9	*95.7*
Moving lying down	0.0	4.3	0.0	0.2	*95.5*	*95.5*

1—upright standing, 2—motionless lying down, 3—upright mild activity, 4—upright intense activity, and 5—active lying down. Italic fonts mean correct classifications.

TABLE II
PERCENTAGES OF POSTURE TRANSITIONS AS CLASSIFIED BY THE DEVELOPED ALGORITHM

Activity\Class	6	7	8	other
6.Standing to Lying down	*83.3*	0.0	16.7	0
7.Getting up from the ground	0.0	*97.9*	0.0	2.1
8.Fall to the ground	8.3	0.0	*87.5*	4.2

Italic fonts mean correct classifications.

B. Results

The accuracy of the classifier in detecting the five aforementioned *steady activities* was assessed with a second-by-second comparison of its output with the expected class, derived from manual annotations of beginning and ending time of each activity. Given the scarce precision of the synchronization imposed by the manual annotation, the first and last second of each activity were not taken into account in the comparison. Thus, the validation procedure was carried out on 4365 samples. Table I reports the confusion matrix that summarizes results, in terms of percentage of samples belonging to each steady activity as classified by the algorithm. Globally, it assigns, to the expected "steady-activity" class, 96.20% of the samples (4199 over 4365).

The algorithm detects and classifies the *posture transitions* applying a flag to the sample in which the transition is identified; for this reason, a second-by-second comparison with the expected class is not possible. Thus, we considered a correct detection when the right OUT6–OUT8 flag is generated in one of the seconds manually accounted as belonging to the posture transition activity. Table II summarizes these results. Besides confusion between falls and other upright to lying down transitions, one fall and the subsequent "getting up from ground" movement were not recognized as posture transitions (they happened at the beginning of an acquisition, before the first immobility phase, and thus, before the autocalibration routine could be applied to the signals). Moreover, two misclassifications ("upright to lying down" and subsequent "lying down to upright" transitions) happened during one "climbing wall bars" activity, due to the fact that a subject bended its trunk more than the 60° threshold, which is used to distinguish between upright and lying down postures.

Fig. 4 summarizes the achieved results concerning the "reliability" value associated to each steady activity sample, in terms of average and standard deviation evaluated over all the samples correctly and wrongly classified in the five classes.

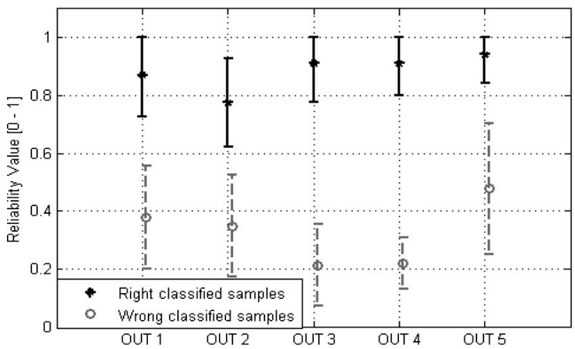

Fig. 4. Reliability of the correct- and wrong-classified samples for each expected classifier output: mean value $\pm$ standard deviation.

TABLE III
CONFUSION MATRIX SUMMARIZING THE PERFORMANCE OF THE POSTURE CLASSIFIER

Posture\Class	A	B
A. Upright	*99.5*	0.5
B. Lying down	1.6	*98.4*

Italic fonts mean correct classifications.

Finally, concerning the hardware, the algorithm runs on the microcontroller with memory occupation of less than 10 kB; the interrupt routine requires 15 ms and it consumes 7.2 mA (with the processor working at 1.31 MHz) for sampling and processing. Further hardware and firmware optimization will be discussed in future works, since this paper wants to focus only on algorithmic aspects of the system.

IV. DISCUSSION

The results reported in Section III summarize the performance of the algorithm in classifying the activities carried out by six adult subjects during the validation tests; this section reports a more in-depth analysis of the results concerning *steady activities* and *posture transitions*.

The confusion matrix in Table I shows, as for all activities, the percentage of correct detections is over 90%, ranging from 90.6% of samples belonging to the "sitting down" activity, correctly accounted as "*upright standing*," to the 99.9% of samples belonging to the "walking" activity, correctly classified as "*upright mild activity*." Moreover, the amount of correct classifications in 10 trials over 12 is higher than 94%; just in two trials, the classification errors raised to 9.7% and 12.1%, respectively, concentrated in the first activities, before the automatic calibration of the sensor could take place.

A correct classification implies that both subject *posture* and *activity level* are correctly identified. In order to quantify the performance of the posture-detection algorithm, we considered two groups of activities: one including the activities carried out with the subject standing (independently of movements' intensity) and one including the activities with the subject lying down. Results are presented for the posture in a two row—two-column confusion matrix in Table III. Only 0.5% of the samples (17 over 3413) with the subject standing were confused for lying down activities; at the same time, a lying down subject was confused for upright subject in 1.6% of the samples (15 over 952) only. A similar analysis can be applied to the activity-intensity detection by considering only activities belonging to a single SMA range (partial classes A0, A1, or A2) and splitting them in three classes (namely, motionless upright or lying down in a first group, walking in a second group, and jumping or running in a third one): Table IV shows that 94.9%, 99.9%, and 98.2% of samples are correctly classified in terms of activity intensity in the three aforementioned group respectively. These results are somehow comparable with the outcomes of [21]; in this paper, the authors analyzed user-annotated data collected in free-living conditions (aspects which can affect and reduce the performance of the classifier) and were able to recognize 20 different daily activities, by analyzing the signals of five worn triaxial accelerometers (thus, with a system more complex than the one described in this paper). Moreover, the authors discarded all signals fragments belonging to the first 10 s at the beginning of each activity. If data given in [21] are grouped in terms of activity intensity (which can be presumed by a description of the movements to recognize), their classifier correctly identifies 95.7% of the samples belonging to the "*standing still*" class and 95.0% of the samples to the "*lying down*" class. Moreover, it correctly distinguishes between inactivity and mild activity in 98.7% of the samples.

TABLE IV
CONFUSION MATRIX SUMMARIZING THE PERFORMANCE OF THE ACTIVITY INTENSITY CLASSIFIER

Act\Class	A	B	C
A. Inactive	*94.9*	4.0	1.1
B. Mild	0.1	*99.9*	0.0
C. Intense	0.1	1.7	*98.2*

Italic fonts mean correct classifications.

Our algorithm's accuracy is comparable with the one of the classifiers described in a recent paper [32], producing 97% of correct classification for the "*lying down*" status, 98% for the "*sitting*," and 81% for "*standing*." Furthermore, they recognize "walking" as a "*mild activity*" in 89% of the samples. This study foresees processing of the signals detected with two oriented, hip- and wrist-mounted, triaxial accelerometers [32]. The authors tested several classifiers, based on minimum-distance principle, *k*-nearest neighbor, and support vector machines, using both time- and frequency-domain features as inputs. They concluded that using one accelerometer, fixed to the hip, and one simple linear classifier are enough to achieve good classification accuracy, if the signal features are appropriately selected. These conclusions perfectly match our experimental setup and the basic idea of the developed algorithm. Besides this, the features used by the classifier presented here do not require any *a priori* knowledge about sensor's orientation. Similar results and conclusions are reported in another recent work [33], in which several classifiers were tested for more than 68 h on raw accelerometric data, recorded both in supervised and unsupervised conditions (out-of-laboratory settings, with user's self-annotating their activities).

Results reported in Section III show that the developed classifier recognized 94 *posture transitions* over 96; the two errors-concerned activities carried out before the autocalibration procedure could occur, at the beginning of an acquisition. A key aspect that should be furthermore explored is the distinction between falls to the ground and other upright to lying down transitions. Nonetheless, the classifier is currently able to capture 87.5% of the falls and 83.3% of the other upright to lying down transitions: these outcomes are comparable with the algorithm described in [10] (using a triaxial accelerometer, whose axes are oriented according to the body symmetry axes; therefore, recognizing posture changes by analyzing only one acceleration component): this classifier detects 74.1% of the upright to lying down transitions and 100% of the falls to the ground preceded, as in our case, both by resting and intense activities.

Our system can be further compared with the one developed by Karantonis *et al.* [10] in terms of hardware: the algorithm presented here works on a microcontroller with a clock frequency of 1.31 MHz (against the 4.31 MHz frequency of the processor used for that application) and similar power consumption.

Finally, results reported in Fig. 4 point out that using a simple routine based on the comparison of the partial outputs of the classifier with fixed thresholds could be useful in order to associate a "reliability" value to each output (which is substantially lower in case of wrong detections, since in these conditions at least one partial output of the system is closer to the threshold separating the classes); the appropriate use of this value should be taken into account in future research.

V. Conclusion

This paper presents a human activity classifier, based on the real-time analysis of the signals detected with a triaxial accelerometer fixed to the trunk. Low-level routines, suitable for implementation on a low-power microcontroller, process the raw accelerometric signals in order to extract simple features, which are directly related to the posture and activity intensity. Features extraction is independent of sensor's orientation with respect to the body. These features are exploited by a global classifier, which detects both steady activities (activities that can be executed for long time) and posture transitions. Preliminary tests, carried out on six subjects in a gym demonstrated that the algorithm recognizes all activities with an accuracy higher than 90%. Once designed a stable release of the routine, important future developments will consider the hardware improvement and optimization of the device (suitable for integration in a jacket, containing sensor and microcontroller) in which the algorithm is implemented.

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