Heart Rate and Accelerometer Data Fusion for Activity Assessment of Rescuers during Emergency Interventions

D. Curone, A. Tognetti, E. L. Secco, G. Anania, N. Carbonaro, D. De Rossi, G. Magenes, Member, IEEE

Abstract— The current state of the art in wearable electronics is the integration of very small devices into textile fabrics, the so-called "smart garment". The ProeTEX project is one of many initiatives dedicated to the development of smart garments specifically designed for people who risk their lives in the line of duty such as fire fighters and Civil Protection rescuers. These garments have integrated multi-purpose sensors that monitor their activities while in action. To this aim, we have developed an algorithm that combines both features extracted from the signal of a tri-axial accelerometer and one ECG lead. Microprocessors integrated in the garments detect the Signal Magnitude Area of inertial acceleration, step frequency, trunk inclination, heart rate and heart rate trend in real-time. Given these inputs, a classifier assigns these signals to nine classes differentiating between certain physical activities (walking, running, moving on site), intensities (intense, mild or at rest) and postures (lying down, standing up). Specific classes will be identified as dangerous to the rescuer during operation, such as, “subject motionless lying down” or “subject resting with abnormal heart rate.” Laboratory tests were carried out on seven healthy adult subjects with the collection of over 4.5 hours of data. The results were very positive, achieving an overall classification accuracy of 88.8 percent.

Index Terms—Wearable electronics, sensor fusion, accelerometer, heart rate, smart protective textiles

I. INTRODUCTION

Over the last few years, the progress in microelectronics, material science and telecommunications has allowed for the design of increasingly smaller, inexpensive and low-power consuming devices and sensors that are suitable for integration into portable devices or even sensorized garments. The availability of garments hosting sensors and micro-processors, which record and process environmental and physiological signals for many consecutive hours, have led several research groups to the development of medical-oriented applications aimed at monitoring patients undergoing rehabilitation procedures [1;2] or elderly living in their home environments.

In this context, the European Project ProeTEX (PROtective Electronic TExtiles for emergency operators) [3;4] aims at demonstrating the suitability of wearable technologies to improve the safety, efficiency and coordination of emergency operators such as fire fighters or Civil Protection rescuers. The project foresees the realization of garments (namely a T-shirt, a fireproof jacket and a pair of boots) that host sensors which monitor the environmental variables (external temperature, concentration of toxic gases), the absolute position of the user, and some parameters related to his/her physiological state.

According to the designed data management infrastructure, microprocessors integrated in the garments “locally” process the raw signals recorded by each sensor worn by the user, extracting relevant features. These features are transmitted to the personal computer of a “rescue manager” who monitors the activity of the first line responders from a safe site near the area in which the intervention is taking place [5]. Among the various sensors embedded in the garments, the ProeTEX T-shirt includes a wearable device that detects one ECG lead and locally computes the subject’s heart rate; similarly, a micro-processor extracts features related to the subject’s activity and posture from the signals of a tri-axial accelerometer integrated in the jacket, at collar level.

Since the instrumentation worn by each operator simultaneously records and processes many signals, and the emergency context foresees concurrent monitoring of several users, the project’s major task is the development of algorithms for the real-time detection of possible dangerous conditions of the operators in order to generate feedback and warnings to the rescue manager. These algorithms must be suitable for integration in the “remote monitoring software” described in [5]. For some sensors, a direct comparison with appropriate thresholds allows the generation of alarms related to the monitored variables (for example, the toxic gas concentration in
the air). For other sensors, as in the case of the accelerometer, the interpretation of measured signals is more difficult but can provide important information about the user's status.

Throughout scientific literature, the importance of accelerometers has been established in identifying the activity carried out by a subject, in recognizing the context in which he/she lives or works, and in pointing out possible safety precautions. A very interesting work has investigated indexes which can be useful in order to measure the subject's activity level [6]. Other publications have presented algorithms which allow to detect the subject's posture and the intensity of the movements from the raw signals of a tri-axial accelerometer fixed to the body at waist level, with the sensing axes oriented according to the main body symmetry directions (head-foot, front-back, left-right) [7;8]. By using several activity sensors placed on the chest and limbs, posture and postural sway can be recorded with a high degree of accuracy [9;10]. Furthermore, other works have demonstrated the possibility of extracting the step frequency from these signals, used in order to assess the walking activity [11;12]. All of these confirm that the tri-axial accelerometer is one of the most suitable devices in assessing human activities in an unobtrusive way. Almost all of the reported works have dealt with applications in the rehabilitation or in the elderly surveillance contexts: only recent works [13] have demonstrated the suitability of accelerometer use in the remote monitoring of workers.

Moreover, several recent scientific works have been done on the combination of accelerometer-derived features and information obtained from other sensors (i.e. transducers monitoring physiological parameters) in order to improve the precision of the activity assessment algorithms. The reason for considering the integration of accelerometric signals with physiological signals is that both sources provide only partial information related to the effective subject's activity [14]. Accelerometers can identify a large number of actions, but they are useless in estimating the physical effort required when performing a movement (i.e. they do not distinguish between activities like “walking on a flat surface” or “walking uphill”) [15]. On the other hand, physiological parameters, such as heart rate, gather the physical effort of an activity (following the aforementioned example, the heart rate is higher when a subject “walks uphill” with respect to when he/she “walks on a flat surface”), but they may be influenced by external factors (psychological stress or environmental conditions). Brage and colleagues carried out their activity on the commercial device Actiheart 4 (by Cambridge Neurotechnology, Cambridge, UK) integrating one tri-axial accelerometer plus one heart rate monitor. The authors developed a mathematical model for the energy expenditure estimation based on the device's outputs; then, they validated the model in the laboratory through a direct comparison with a calorimeter's measurements [14;16]. Hewlett Packard developed a PDA which synchronously acquires one ECG lead and accelerometric signals with similar intent [17]. Other authors presented a home care system that identifies the activity performed by the monitored subject, medical events and symptoms [18]. Another work proposed a setup composed by five tri-axial accelerometers and a heart rate monitor in order to recognize 30 different types of activities [19]. Finally, some scientific papers and commercial patents described algorithms for heart rate and accelerometric signal fusion to be implemented into ECG Holter devices [20] or within implanted pacemakers [21]. This latter application evaluates appropriate or inappropriate variations of the heart rhythm by means of an accelerometer placed inside the device.

Many works, dealing with the use of the heart rate for activity assessment, faced the problem of the normalization of this parameter in order to realize algorithms easily adaptable to the physiological signals recorded on different subjects. Actually, the accelerometer data are comparable among different subjects and experiments. The definition of counts/min vs. acceleration was used to measure the activity intensity in commercial devices like the aforementioned Actiheart. Similarly, the use of the Signal Magnitude Area [6;8] index is commonly accepted in scientific literature. On the other hand, the heart rate varies greatly between subjects, which may affect the performance of a classifier using this parameter as input. Mungua Tapia et al. [19] state that using the raw heart rate does not significantly improve the percentage of correct recognition of an activity classifier. Moreover, the heart rate signal has a slower dynamic with respect to the accelerometric signal, especially in transition phases during and after a period of intense physical activity. During these phases, the time constant of the heart rate may greatly vary according to the subject level of fitness [22;23]. Therefore, an algorithms for automatic activity assessment should also take into account this evidence.

In this context, the present work aims at demonstrating the feasibility of an activity classifier based on the analysis of both accelerometer and heart rate derived features to be implemented in wearable instrumentation for emergency monitoring. The main purpose of this classifier is to automatically identify potentially dangerous conditions for the monitored subject over extended periods of time. In addition to easily-detectable conditions, that can be obtained only by analyzing the accelerometer signals (i.e. “resting motionless lying down”), the algorithm should also identify conditions such as “resting with high heart rate” (which is potentially abnormal if not preceded by any physical activity or if sustained for a long period of time after an intense physical activity), which requires a simultaneous analysis of both signals. In order to recognize the potential danger associated to this latter condition (“resting with high heart rate”), the algorithm should be able to identify physically intense activities (such as “running,” “performing stationary intense movements,” etc.) and to differentiate these activities from mild activities (such as “walking,” “moving the trunk and arms,” etc.).

The constraints imposed by the wearable instrumentation heavily influence the design of the algorithm. Since low-power microcontrollers “locally” process the raw accelerometer and ECG signals directly in the garments, the computational complexity of the algorithms for feature extraction must be kept
simple. Concerning the analysis of the accelerometer signals, the microprocessors cannot implement complex analysis in the frequency domain. The present work addresses this issue by extracting only three indexes from these raw signals, indicating specific aspects of subject movement: trunk inclination, movement intensity (which distinguishes between a subject at rest or moving), and step frequency (which determines whether a subject is performing activities on site, walking or running). Similarly, the heart rate monitor processes the raw ECG signal in order to extract the average heart rate in a five-second time window. A simple further analysis quantifies, at each second, the rate of change of this parameter in the last minute of the signal pattern: this index points out the possible changes in the physical effort.

Furthermore, following the results achieved in [7;8] and given the aforementioned constraints, this paper demonstrates the reliability of a classifier which does not require training on a dataset of preliminary recorded signals; it is, rather, based on heuristic rules and scientific findings.

II. MATERIALS AND METHODS

In what follows, a classifier will be presented that can recognize several user states corresponding to important activities of daily living (ADL) in real-time. The classifier processes five input features: operator average heart rate, heart rate variation over the last minute of activity, trunk inclination, movement intensity, and step frequency. All these features derive from the signals (one ECG lead and three output signals of a tri-axial accelerometer fixed to the chest) recorded with wearable instrumentation equivalent to that included in the ProeTEX prototypes. The algorithm foresees processing at two levels:

A. Local processing: two, wearable electronic devices that process in real-time the raw ECG and accelerometric signals; they update the aforementioned features every five seconds and send the data to a remote processing unit in real-time.

B. Remote processing: the remote station processes the features in order to classify the operator state.

A. Local signal processing

Heart Rate (HR): a portable electronic unit designed by the Centre Suisse d'Electronique et de Microtechnique SA, partner in the ProeTEX project, processes the ECG signal recorded with commercial electrodes (Red Hot electrodes by 3M). The unit samples the raw signals at 250 Hz; it applies a proprietary algorithm and sends via Bluetooth® the resulting HR to the global processing unit. The module updates the heart rate at 0.2 Hz; each output value represents the average heart rate in the last five seconds. The designers of this device chose such an update frequency taking into account the purpose of the ProeTEX project (worker monitoring, not diagnostics) and considering the reduced quality of the ECG signal recorded with textile electrodes with respect to the signal recorded with standard clinic electrodes.

The heart rate trend is evaluated as the difference between the last available heart rate value and the one produced one minute (12 samples) before, and it represents the rate of change of the physiological parameter.

Accelerometer pre-processing: the activity device consists of a wireless module (PAM, produced by ADATEC srl, Italy) based on a tri-axial accelerometer (model ADXL330, by Analog Devices) and a low power microprocessor. This latter device (model MSP430F149, by Texas Instruments) performs the A/D conversion with a sampling frequency of 50 Hz and real-time processes the raw signals. The whole module (5 × 3 × 1.5 cm) is placed on the back of the upper part of the trunk.

The processing algorithm, implemented on the microprocessor, produces three of the five inputs of the classifier (activity intensity, trunk inclination and step frequency).

The accelerometer measures the acceleration and the local gravity. Considering a calibrated tri-axial accelerometer (i.e. offset and sensitivity are compensated and the output is expressed in unit of g), the accelerometer signal (y) contains two factors: one is due to the gravity vector (g) and the other depends on the system inertial acceleration (a), both of them expressed in the accelerometer reference frame [10]:

\[
y = a - g
g \begin{pmatrix} y_1 \\ y_2 \\ y_3 \end{pmatrix} = \begin{pmatrix} a_1 \\ a_2 \\ a_3 \end{pmatrix} - \begin{pmatrix} g_1 \\ g_2 \\ g_3 \end{pmatrix}
\]

The inclination vector (z) is defined as the vertical unit vector expressed in the accelerometer coordinate frame [10]. In static conditions, only the factor due to gravity is present and the inclination of the accelerometer with respect to the vertical is known. In dynamic conditions, the raw accelerometer signal does not provide a reliable estimation of the inclination, since the inertial acceleration is added to the gravity factor. This estimation error increases as the subject’s movements become faster (e.g., running, jumping).

Trunk Inclination: the accelerometer module performs an on-line estimation of the trunk inclination. Scientific work on ADL monitoring proposes the detection of the trunk inclination by low-pass filtering the accelerometer signal with very low cut-off frequencies [8;24;25], ranging from 0.25 to 0.35 Hz. Since the delay of a low-pass filtering process is not acceptable for the ProeTEX frame (e.g. the delay has to be very short to generate sudden alarms), we designed a custom algorithm based on a Kalman filter [26] in order to estimate the inclination vector z. This technique was presented in a recent work [13] reporting an algorithm for the fall detection to be implemented in the ProeTEX prototypes. Moreover, the real-time inclination estimation gives reliable values even during intense activities with a short time delay (to the order of 0.3 seconds) [13]. The algorithm carries out an initial calibration phase as soon as it detects that the subject is in a standing posture for at least two seconds. The system uses the data recorded in these two seconds in order to align the system with respect to the vertical of the fixed frame (0 degrees: the subject is standing; 90 degrees the
subject is lying on the floor), and to make the inclination measurement independent from the knowledge of the initial accelerometer orientation inside the garment. In order to have a compact and practical representation of \( \mathbf{z} \), intrinsically containing information on the two Euler’s angles [27], the algorithm extracts a unique parameter, namely the cosine of the angle between \( \mathbf{z} \) and the vertical unit vector in the fixed reference frame:
\[
\cos(\theta) = \mathbf{z} \cdot \mathbf{Z}
\]
where \( \theta \) is defined as the trunk inclination and \( \mathbf{Z} \) is the vertical unit vector \((0, 0, 1)^T\).

**Activity Intensity:** the routine measures the activity intensity by means of the Signal Magnitude Area (SMA) index computed on the inertial acceleration components detected with the sensor. By definition, the SMA is equal to the sum of the axis acceleration magnitude summations over a time window and normalized by its window length [6]. The following equation reports the SMA discrete form:
\[
\text{SMA}(k) = \frac{1}{N} \left( \sum_{N-k}^{N} |a_1| + \sum_{N-k}^{N} |a_2| + \sum_{N-k}^{N} |a_3| \right)
\]
where \( N \) is the window extent (250 samples, in this case) and \((a_1, a_2, a_3)\) are the three components of the inertial acceleration estimated by the accelerometer signal. At each time, the last available SMA value can be used to know if the subject is resting, performing mild activities or intense activities. Considering the gravity component \( g \) as a slowly varying one, the inertial component \( a \) can be approximated with the output of a IIR high-pass digital filter with a cut-off frequency of 0.3 Hz applied to the \( y \) components. The idea of using the SMA as a measure of the movement intensity and the SMA computation technique was borrowed by [8].

**Step Frequency:** the analysis of the inertial acceleration allows for quantifying the subject’s step frequency [28:29]. In particular, [28] demonstrated that the analysis of the only vertical component of the inertial acceleration, \( a_y \), improves the performance of a step detector. This component is the projection of \( a \) along the vertical, which can be identified by knowing the inclination vector \( \mathbf{z} \). Therefore, the algorithm evaluates the instantaneous vertical inertial acceleration vector module \((|a_y|)\) by means of the following formula, and taking into account that \(|\mathbf{z}| = 1\):
\[
|a_y| = |a| \cdot \cos(\alpha) = a \cdot z
\]
where \( \alpha \) represents the angle between the inertial and the gravitational acceleration vectors. The \(|a_y|\) signal is then real-time processed in order to detect the peaks corresponding to possible steps.

Among all peaks identified in the signal, the routine chooses the step candidates by using heuristic rules that take into account the regularity of the step sequence during walking or running. A subject keeps different step rates during walking and running, but the two activities may be easily recognized in terms of movement intensities (by means of the current SMA value). For this reason, the algorithm uses two “expected time-distance (TD)” values: a “walking time-distance” (WTD) to identify the step candidates when a subject performs mild activities, and a “running time-distance” (RTD) to identify the step candidates when a subject performs intense activities. Moreover, the actual step frequency may vary depending on the ground and context; therefore, WTD and RTD are not fixed, but updated routinely on-line by taking into account the last available distances between the recognized steps. Regarding the walking activity, a vector (WDD) records the last nine detected time distances between consecutive walking steps; then, WTD is computed as the mean of the values in WDD. The routine uses a further tolerance parameter (TOL), set to 25% for both the walking and running activities. Each time the routine detects a local peak, if the SMA points out mild activity and the distance between the peak and the last recorded step fits into the range:
\[
\text{WDT} \cdot (1 \pm \text{TOL})
\]
then the peak is accounted as a “detected walking step.” A similar routine, applied when the SMA reveals intense movements, detects the running steps. In both cases, the measured time distance is stored in a temporary vector (TV), initialized at the beginning of each 5 second time period. At the end of the period, the routine produces a step frequency output as the reciprocal of the mean distance between the detected steps recorded in TV.

**B. Remote processing and activity classification**

Once the local modules compute the five described features from the raw ECG and the accelerometric signals, a classifier (implemented in the ProeTEX remote monitoring software [5]) processes them in order to classify the activity performed by the subject, in one of the following classes:

- **a. upright standing**;
- **b. moving trunk or arms**;
- **c. walking**;
- **d. intense walking (e.g. climbing stairs or walking carrying heavy objects)**;
- **e. running**;
- **f. stationary intense movements (e.g. lifting a weight)**;
- **g. resting after intense movements**;
- **h. motionless lying down**;
- **i. moving lying down**;

The algorithm identifies each “standard activity” by means of arrays with five ordered values (SMA, inclination, step frequency, Heart Rate, HR trend). Each array defines a point in a 5D parameter space, here called “centroid,” whose coordinates may be set for activity recognition by means of heuristic rules and knowledge available in the scientific literature. Each time the accelerometer module and the heart rate monitor produce a new sample (an array of the five
activity-related indexes, quantifying the activity done in the last five seconds), the classifier assigns it to the class of the nearest centroid, according to the Euclidean metrics.

Many existing activity classification systems [19;30] generally use classification techniques which need optimization and training phases. This would be impractical in the described application where the system must be used “as is” without a training procedure for the emergency operators. For this reason, the algorithm performance depends on the right normalization of the data and on the correct placement of the initial centroids only. The next paragraphs describe these two important issues.

Data Normalization: according to their definition, the activity-related indexes vary in different ranges of values. A normalization procedure of the five indexes is therefore required in order to assign the same weight to all variables when computing the Euclidean distance between each experimental finding and the standard centroids. The ranges of variability of each feature are defined given heuristics and scientific literature findings. Once these ranges are defined, the variables are linearly scaled in the interval [0,1] with respect to their minimum and maximum expected values.

Concerning the activity intensity, [8] suggested thresholds for distinguishing among inactivity (SMA close to zero g), mild and intense activities. We chose a maximum SMA value of 2 g that could be reached during very intense activities such as falling to the ground. Furthermore, [6] demonstrated the low inter-subject variability of this index, at least when considering adult healthy subjects, as in our case.

Since the trunk inclination represents the cosine of the angle between the trunk and the vertical direction, the boundary conditions can be set at 1 and 0 (representing the upright and lying down postures, respectively).

The step frequency variable ranges between zero steps per second and a reasonable value of four steps per second (reached during very fast running [31]).

Unlike the accelerometer-derived features, the definition of a sound range for the heart rate-derived features is much more critical: the heart rate dynamics is highly subject-dependent and hard to define. Several works on automatic activity detection pointed out the difficulty of using this parameter because of its large inter-subject variability [19;30]. For this reason, the developed classifier normalizes the heart rate using the widely accepted Heart Rate Reserve (HRR) model [32]. This model sets boundaries of a subject’s normal heart rate with the maximum heart rate (experimentally evaluated with specific programs or assessed before by means of statistical formulas) and the resting heart rate (which mainly depends on the fitness level of the subject and could widely vary, between 50 and 90 beats per minute). Several studies have demonstrated the linear relationship between the activity intensity measured with the HRR model and the amount of oxygen consumed by the individuals [33]. The use of the HRR model requires to measure both a subject’s maximum and minimum heart rate. Since in our context an experimental evaluation of the actual maximum heart rate of each operator is not possible, the algorithm approximates it by means of a statistical formula that takes into account the variability of the parameter according to the subject’s age. More specifically, it uses the model proposed by [34] (HRmax = 205.8 – 0.685 · age), which was demonstrated to be the most reliable model for estimating the maximum heart rate of healthy adults [35]. Some scientific studies [14;16] have proposed measuring the minimum heart rate (HRrest) as an average of the lowest heart rates during 24-hour recordings. Since a similar evaluation is not possible in our case, the classifier uses the self-measured heart rate (averaged in one-minute time windows) when the subject has just woken up as an estimator of HRrest. The monitoring software associates the two calibration parameters (age and resting heart rate) to each user/prototype, and it uses them each time a subject is monitored.

Finally, the algorithm normalizes the HR trend feature considering a range of ±12 beats per minute, according to the Heart Rate Recovery model [36].

Static Classifier: once 5D parameter space boundaries are established, the algorithm identifies thirteen centroids, representing the nine aforementioned “standard activities” according to the following rules:
- two centroids describe classes d., e., f. and g.: while a subject performs intense physical activities or rests after an intense one, the heart rate shows a transitory dynamic (increasing or decreasing) followed by a steady-state phase. The two centroids capture these different phases.
- one centroid describes each of the remaining phases, characterized by a stable heart rate.

Moreover, the following findings represent the sources for the choice of the centroid location. Table I summarizes the centroid coordinates in the normalized features space:
- SMA is used in order to discriminate the activity intensities: the thresholds proposed by [8] identify three “average values,” representing inactivity (0), mild activities (0.2) and intense activities (0.5).
- Inclination enables to distinguish between activities carried out when the subject is lying down (0) and when he/she is standing up (1);
- Step frequency allows for discriminating among activities carried out without deambulation (0 step/second) while walking and running (average values of 1.5 steps/second and 2.5 steps/second are set, respectively, according to the average experimental findings of [44]);
- Heart rate allows for differentiating between resting or mild activities (in which the heart rate should be near its resting value, namely the 0 normalized value) and intense physical activities (characterized by a higher heart rate, set at 0.7-HRR, as the average of the “target heart rate” for intense physical activities).

- HR trend value of 0.5 identifies a stable heart rate; a normalized value of 1 (corresponding to +12 beats in the last minute) identifies activities in which the heart rate is increasing; a normalized value of 0 (corresponding to -12 beats in the last minute) identifies recovery after intense activities.

III. System Validation

A. Experimental setup

A session of trials was organized in order to evaluate the accuracy of the classifier. During the acquisitions, seven healthy male subjects performed a sequence of activities including all nine classes to identify. The subjects had an average age of 31.7 years (with a standard deviation of 3.7 years, in a range of 27-38); the self-measured average resting heart rate was 62.1 bpm (standard deviation 9.5 bpm, range 50-75) – see Table II.

Each subject performed the following sequence of activities: upright standing, walking, upright standing, climbing stairs, upright standing, running, upright standing (after intense activity), moving trunk and arms without walking, lying down motionless, moving the body when lying down, upright standing, knee bending (lifting the whole body weight), upright standing (after intense activity). The sequence of resting phases and intense physical activities allowed the subject’s heart rate to return to resting values before starting each new activity, thus avoiding possible biases in the results. During the acquisitions, an experimenter verbally communicated to the subject when to start performing each activity without any further request.

Each activity lasted for a period between 2 and 5 minutes. Each of the seven sessions had an average length of 2757 seconds, resulting in a total of 5 hours 21 minutes of data, corresponding to 3860 classifiable samples. The experimenter manually recorded the beginning and ending time of each activity; therefore, the two former and two latter samples of each activity were discarded in order to avoid misclassifications due to a wrong labelling. Furthermore, 72 samples (2.21% of the total amount) were discarded because they showed clear artefacts (spikes) of the heart rate signal due to temporary losses of the contact between the ECG electrodes and the subject’s skin. At the end of this selection, we evaluated the classifier on 3281 samples (4 hours 36 minutes of signals).

Concerning the data analysis and given the adopted classification principle, it is possible to consider different classifiers having inputs of accelerometer-derived features, physiological features, or all five features. The following paragraph reports the results obtained with these three classifier configurations in terms of global accuracy and confusion matrix between the different classes.

B. Results

First, it is possible to evaluate the performance of a classifier whose inputs are the only three features extracted from the raw accelerometer signals: namely, SMA, trunk inclination, and step frequency. Considering the nature of these inputs and according to the centroid locations reported in Table I, classes defined by identical accelerometer information content but different levels of physical effort can not be distinguished by this classifier. This is the case of classes like “moving trunk and arms” and “stationary intense movements”, or classes like “walking” and “intense walking”, or even “upright standing” and “upright standing (after intense activity)”. For this reason, the classifier only identifies the following six classes: “standing” (including the classes a. and g. as defined in Section II.B), “performing on the spot activities” (including classes b. and f.), “walking” (including

<table>
<thead>
<tr>
<th>TABLE II</th>
<th>SUBJECTS DETAILS</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sub.</td>
<td>Age (years)</td>
</tr>
<tr>
<td>1</td>
<td>33</td>
</tr>
<tr>
<td>2</td>
<td>27</td>
</tr>
<tr>
<td>3</td>
<td>38</td>
</tr>
<tr>
<td>4</td>
<td>34</td>
</tr>
<tr>
<td>5</td>
<td>29</td>
</tr>
<tr>
<td>6</td>
<td>30</td>
</tr>
<tr>
<td>7</td>
<td>44</td>
</tr>
<tr>
<td>All</td>
<td>31.7</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>TABLE III</th>
<th>CONFUSION MATRIX REPORTING THE RESULTS OBTAINED WITH THE CLASSIFIER BASED ON THE ACCELEROMETER DERIVED FEATURES (SMA, TRUNK INCLINATION, STEP FREQUENCY)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Activity</td>
<td>a</td>
</tr>
<tr>
<td>Upright standing (a.)</td>
<td>98.73</td>
</tr>
<tr>
<td>On the spot movements (b.)</td>
<td>-</td>
</tr>
<tr>
<td>Walking (c.)</td>
<td>0.25</td>
</tr>
<tr>
<td>Running (d.)</td>
<td>-</td>
</tr>
<tr>
<td>Motionless lying down (e.)</td>
<td>-</td>
</tr>
<tr>
<td>Motionless lying down (f.)</td>
<td>-</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>TABLE IV</th>
<th>CONFUSION MATRIX REPORTING THE RESULTS OBTAINED WITH THE CLASSIFIER BASED ON THE HEART RATE DERIVED FEATURES (AVERAGE HEART RATE, HEART RATE TREND)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Activity</td>
<td>a</td>
</tr>
<tr>
<td>Mild activities (a. b. c. h. l.)</td>
<td>92.19</td>
</tr>
<tr>
<td>Intense activities (d. e. f.)</td>
<td>7.31</td>
</tr>
<tr>
<td>Recovery (g.)</td>
<td>-</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>TABLE V</th>
<th>CONFUSION MATRIX REPORTING THE RESULTS OBTAINED WITH THE 5 DIMENSIONS CLASSIFIER (THREE ACCELEROMETER DERIVED FEATURES – SMA, TRUNK INCLINATION, STEP FREQUENCY – AND TWO HEART RATE DERIVED FEATURES – AVERAGE HEART RATE AND HEART RATE TREND)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Activity</td>
<td>a</td>
</tr>
<tr>
<td>a. Upright standing</td>
<td>98.95</td>
</tr>
<tr>
<td>b. Moving trunk or arms</td>
<td>1.98</td>
</tr>
<tr>
<td>c. Walking</td>
<td>-</td>
</tr>
<tr>
<td>d. Intense walking</td>
<td>-</td>
</tr>
<tr>
<td>e. Running</td>
<td>-</td>
</tr>
<tr>
<td>f. Stationary intense movements</td>
<td>2.52</td>
</tr>
<tr>
<td>g. Resting after intense movements</td>
<td>6.42</td>
</tr>
<tr>
<td>h. Motionless lying down</td>
<td>0.25</td>
</tr>
<tr>
<td>i. Motionless lying down</td>
<td>-</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>TABLE VI</th>
<th>AVERAGE HEART RATE AND TRENDS REPORTED WITH THE RESULTS OBTAINED WITH THE 5 DIMENSIONS CLASSIFIER (THREE ACCELEROMETER DERIVED FEATURES – SMA, TRUNK INCLINATION, STEP FREQUENCY – AND TWO HEART RATE DERIVED FEATURES – AVERAGE HEART RATE AND HEART RATE TREND)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Activity</td>
<td>a</td>
</tr>
<tr>
<td>a. Upright standing</td>
<td>80.59</td>
</tr>
<tr>
<td>b. Moving trunk or arms</td>
<td>1.88</td>
</tr>
<tr>
<td>c. Walking</td>
<td>-</td>
</tr>
<tr>
<td>d. Intense walking</td>
<td>-</td>
</tr>
<tr>
<td>e. Running</td>
<td>-</td>
</tr>
<tr>
<td>f. Stationary intense movements</td>
<td>2.52</td>
</tr>
<tr>
<td>g. Resting after intense movements</td>
<td>6.42</td>
</tr>
<tr>
<td>h. Motionless lying down</td>
<td>0.25</td>
</tr>
<tr>
<td>i. Motionless lying down</td>
<td>-</td>
</tr>
</tbody>
</table>
classes $c.$ and $d.$), “running”, “motionless lying down” and “moving lying down”. Table III reports a confusion matrix summarizing the results obtained by applying the classifier to the aforementioned signal dataset. Each column of the table refers to an activity carried out by the subjects; each cell of the column reports the percentage of samples as the algorithm classified them. Percentages highlighted in bold characters point out the correctly identified samples. Globally, the algorithm correctly classifies 3194 samples out of 3281 (97.35 %).

Considering the two heart rate parameters only as inputs, the classifier distinguishes among three types of behaviors: mild activities (average normalized heart rate close to 0, heart rate trend close to 0.5), intense physical activities (high heart rate with increasing or stable trend) and recovery after intense activities periods (high heart rate and decreasing trend). Considering the definitions provided in Section II.B, the first category includes classes $a.$, $b.$, $c.$, $h.$, $i.$; the second category is constituted by classes $d.$, $e.$, $f.$; the latter coincides with class $g.$ Actually, the reduction of the class number depends on the exclusion of the accelerometer information; some of the classes characterized by different accelerometer features (such as, for example, “running” or “performing stationary intense movements”) have the same behavior (and therefore coordinates) in terms of heart rate derived features (see Table I). Table IV reports the confusion matrix that summarizes the results obtained with this classifier. Globally, the algorithm correctly recognizes 2824 samples (86.07 %). Despite the global results, the accuracy in recognizing the “recovery” class is unacceptable since the algorithm misclassified more than 60 % of the samples in this category.

Finally, the confusion matrix reported in Table V summarizes the performance of the classifier that uses both accelerometric and physiological features. That algorithm correctly classifies 2913 samples (88.8 % of the total) also having better performance within the “recovery” class. Concerning this classifier, Fig. 1 reports the time trend of the normalized activity-related indexes recorded during an acquisition session performed by one subject. The graphs reported in Fig. 2 show the distribution of the experimental findings in the 5D normalized space belonging to the same sequence of activities. The results of this trial are representative of the other sessions.

IV. DISCUSSION

The first classifier uses as input three features extracted from the raw signals of a tri-axial accelerometer fixed to the subject’s trunk. These three features directly quantify the main characteristics of the activity: posture, movement intensity and deambulation. The routines used to extract the features from the accelerometer signals work in real-time on a low power micro-controller directly connected to the sensor. In particular, a routine that analyzes the accelerometric signal in the time domain quantifies the step frequency. Past studies have proposed to detect this parameter by transmitting the raw accelerometric signal to a remote PC where a more resource-consuming analysis in the frequency domain [8] is implemented. However, this is not applicable in our scenario. Furthermore, the detection of the three features is independent of the sensor’s orientation. The algorithms do not require that one sensing axis of the accelerometer is aligned with the head-foot direction, as is required, for example, by the algorithm proposed in [8]. This latter requirement is fundamental in many wearable applications, as in the case of ProcTEX prototypes: in fact, when integrating an accelerometer directly into garments, it is quite impossible to set a fine orientation of the sensor. Moreover, the orientation of the sensor may slightly vary each time a subject wears the garment. The results reported in Table III demonstrate how a simple classifier, which does not require any preliminary training
procedure, detects the current activity with high accuracy. In fact, it misclassifies only 87 samples over 3281. In particular, it recognizes the “motionless lying down” class, representing a major target of the classifier for project’s purposes, in 95.43% of the samples.

Despite of the quality of these results, this classifier does not distinguish among activities characterized by different levels of physical effort. Several scientific works have demonstrated the relationship between the physical effort and physiological signals like heart rate [33]. Therefore, we have decided to exploit the same principle adopted in the accelerometric signals classifier, that is, to develop a classifier based on the heart rate signal only, recorded with a wearable device included in the ProETEX prototype. The device processes one ECG lead and extracts in real-time the average heart rate in a time window of five seconds. This update frequency is sufficient to monitor the heart rate of workers performing everyday activities. The heart rate trend is evaluated as the difference between the last available heart rate value and the one produced one minute before. This feature is useful for identifying an increase or decrease of the physical effort. The development of a classifier based on heart rate derived features only has three major limitations. First, the wide inter-subject variability of this parameter (which depends on the subject’s age and fitness level [32]) affects the performance of the classifier; several past studies have pointed out the issues related to the use of the heart rate, if not opportunistically normalized to remove (or, at least, to reduce) its variability among subjects [19;30]. Second, the response of the heart rate to changes in physical effort shows slow dynamics, which is also influenced by the subject’s physical training level [36]. Third, a classifier based only on physiological inputs does not permit to identify the performed activity with the desired precision and therefore to understand the subject’s real condition: indeed, a stable and high heart rate may be normal if a subject is running, but it represents a potential threat for the same subject if he/she has been resting for a long time. Even the environmental factors or the psychological state can influence the heart rate, besides the activity intensity [14]. The classifier presented here responds to the two former considerations by implementing a normalization procedure - according to the widely accepted Heart Rate Reserve model [32] - and by introducing the “heart rate trend” parameter, which improves the performance while detecting the initial phases of the intense physical activities (characterized by an increasing heart rate). Nevertheless, the results reported in Table IV show that the accuracy of such a classifier is suboptimal, in particular with respect to the recognition of the “recovery” class.

The third aforementioned consideration is of great importance given the emergency monitoring goal: it leads to the design of a classifier that “fuses” accelerometric and physiological signals for increasing the number of identifiable classes with respect to an accelerometric signal-based classifier. Particularly, the addition of the heart rate features discriminates between activities that differ in terms of required physical effort only (for example “walking on a flat surface” vs. “walking uphill”). Furthermore, it detects the “resting with high heart rate” condition. This state is safe if maintained for few seconds at the end of an intense physical activity, but it points out possible dangers if maintained for too long [36] or if not preceded by an intense physical activity. In this case, the high heart rate may be caused by physical stress or dangerous environmental conditions, like the presence of toxic gases, high temperature or smoke. Table V shows the results of this classifier. The accuracy of the algorithm in detecting the different classes ranges from 75.64% of “resting with high heart rate” to 99.23% of “running”. The major misclassification occurs between classes identified by the same accelerometric centroid coordinates but characterized by different levels of the physical effort (Table I). The algorithm misclassifies 18.93% of the samples belonging to the “stationary intense movements” class into the “moving trunk and arms” class; similarly, it detects as “upright standing” the 11.05% of the samples belonging to the “resting after intense physical activity” class (see the values in italic format of Table V).

Recent work on activity classification using both the accelerometric and heart rate signals highlighted that the different dynamic response of these two variables does not allow for the correct identification of the initial phases of physically intense activities [30]. On the other hand, even if the accelerometer is useful in recognizing several postures and activities, it is not suitable for measuring the physical effort related to the movements [15]. The results obtained with the developed classifier prove that the combination of the accelerometer-derived features with the heart rate allows to accurately detect the rescue worker’s physical activities.

V. CONCLUSION

This paper presented a real-time activity classification algorithm based on signals recorded with two wearable devices: a triaxial accelerometer fixed on the trunk and a portable heart rate monitor. The former produces three features related to the subject’s posture, movement intensity and deambulation. The latter produces the current heart rate and a parameter indicating whether the heart rate is increasing, decreasing or if it is stable in the last minute. The purpose of the classifier is to detect potentially dangerous conditions for the subject wearing the instrumentation by combining features derived from the two signals. We tested the routine on a dataset of more than 4.5 hours of data recorded on seven healthy adult subjects performing activities in laboratory conditions. The tests demonstrated that the combination of heart rate and accelerometric signals allows for detection with an adequate accuracy of physical conditions that are not identifiable by exploiting only accelerometric features.

The achieved results represent only a preliminary assessment of the algorithm that will be extensively tested (in a more realistic scenario) during “field” trials involving professional fire fighters in simulated operative interventions.

Moreover, a possible improvement for the algorithm foresees
routines for adaptation of the centroid coordinates. A ProTEcX system worn for long time by the same subject records many accelerometer-related and physiological data. These data contain useful information about the subject’s physical and physiological characteristics, which can be used in order to adapt the centroid location, and, in turn, improving the accuracy of the classifier.

VI. REFERENCES


