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An Activity Classifier based on Heart Rate and Accelerometer Data Fusion

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Abstract. The European project ProeTEX realized a novel set of prototypes based on smart garments that integrate sensors for the real-time monitoring of physiological, activity-related and environmental parameters of the emergency operators during their interventions. The availability of these parameters and the emergency scenario suggest the implementation of novel classification methods aimed at detecting dangerous status of the rescuer automatically, and based not only on the classical activity-related signals, rather on a combination of these data with the physiological status of the subject. Here we propose a heart rate and accelerometer data fusion algorithm for the activity classification of rescuers in the emergency context.

Keywords: Wearable electronics, Smart garments, Sensor fusion, Heart rate

1. Introduction

Progress in microelectronics and telecommunications allows for the design of increasingly smaller, cheaper and low-power consuming sensors and devices, to the point that they can be integrated even within garments.

The European Project ProeTEX (Protective Electronic TEXtiles for emergency operators) developed a set of sensorized garments to improve safety, efficiency and coordination of the emergency operators during their interventions [Curone et al., 2010]. ProeTEX produced a wearable prototype that integrates sensors for the real-time monitoring of physiological, environmental and activity-related parameters [Curone et al. 2012], performed by dressing three sensorized garments: a washable T-Shirt directly in contact with the operator's skin, an outer jacket and a pair of boots. The sensors are embedded in the textiles and wired or wirelessly connected to set up a Body Area Network (BAN) surrounding the operator body; the BAN also communicates all sensors' data out of the body to a remote coordinator of the operations [Lanati et al., 2011].

Since the ProeTEX prototype furnishes so many and simultaneous information, and a typical emergency intervention foresee the concurrent monitoring of multiple operators, the project also focused on the development of real-time algorithms for the automatic detection and alerting of dangerous status of the operators. This work deals with a classifier algorithm based on proceesing both activity-related and physiological signals and, precisely, on the analysis of accelerometer and heart rate (HR) derived features acquired with wearable instrumentations and therefore processed with a low computational complexity.

2. Material and Methods

2.1. Signal Processing

Our classifier operates with features extracted from one HR sensor and one 3-axial accelerometer.

The HR sensor is based on a portable electronic unit (by CSEM, Neuchatel, Switzerland) that processes the ECG signals, recorded with 3 commercial electrodes placed on the chest (Red Hot electrodes by 3M), and sampled at 250 Hz: the unit applies a proprietary Pan-Tompkins like algorithm and extracts the HR signal; via Blue-Tooth (IEEE 802.15.1), values are sent to a remote Personal

Computer (PC); since the application is focused on a monitoring (and not diagnostic) task, the HR is updated at 0.2 Hz and each reported value is calculated as the mean HR over the last 5 s.

The second device is based on a stand-alone wireless system (by University of Pavia), equipped with a 3-axial accelerometer (model ADXL330, by Analog Devices) and ZigBee transmission module (IEEE 802.15.4). The raw acceleration data are sampled at 50 Hz and transmitted to the same PC receiving the HR values. Remarkably the sensor is fixed on the chest of the subject without any pre-fixed orientation [Curone et al., 2010b].

Finally, the classifier is implemented on the PC, by using the technical language Matlab® (by The Mathworks Inc.); it uses 5 features that are extracted from the sensors' data and updated every 5 s:

1) *average HR*

2) *HR trend*: the difference between the last available value of the HR and the one produced 1 min before

3) *trunk inclination*: the raw accelerometer signals (a) are a 3D vector [a] made of an inertial [a_i] and gravitational [a_g] components, due to the gravity [g]:

$$\left[a\right] = \left[a_i\right] + \left[a_g\right] \tag{1}$$

Therefore the sensor orientation or trunk inclination coincides with the orientation of the vector [a_g] vs. [g]. During a static condition the [a_i] is null in the Eq. 1, then the inclination is identified as soon as the initial orientation of the sensor is known. On dynamic *conditions* a frequency threshold is needed to separate the static - low frequency - contribution from the dynamic - high frequency - one, namely [a_{lf}] and [a_{hf}] respectively. Therefore it holds:

$$\left[a\right] = \left[a_{lf}\right] + \left[a_{hf}\right] \tag{2}$$

According to the human activities frequency domain, the literature suggests a good threshold around 0.25 ÷ 0.3Hz [Karantonis et al., 2006]. Thus, the inclination is calculated by low-pass filtering the accelerometer signal [a] with an IIR filter (cut-off frequency of 0.3Hz, 0.1dB pass-band ripple and stop-band at 100dB) and computing the angle between this term [a_{lf}] and the initial sensor orientation

4) movement intensity: it depends on the inertial component [a_i] (i.e. the effective body acceleration). According to [Karantonis et al., 2006], a Signal Magnitude Area (*SMA*) can be defined as a good estimation of the subject movement intensity: it is the sum integral of the 3 inertial acceleration magnitudes over a temporal window t, and normalized by its length t (with t = 5s):

$$SMA = \frac{1}{t}\left[\int_0^t \left|a_{ix}\right| dt + \int_0^t \left|a_{iy}\right| dt + \int_0^t \left|a_{iz}\right| dt\right] \tag{3}$$

5) step frequency: since the sensor orientation is well known (point *3*), then the step frequency is computed on the vertical component of the [a_i] only. Firstly, all peaks along the vertical direction are detected, then step candidates are searched among the peaks, by assuming a quite regular cadence of the human walking and running. Precisely, two expected Time Distance (*TD*) are used: a walking (*WTD*) and running (*RTD*) time distance, respectively. WTD and RTD are initialized and dynamically updated with the average nine *TD*s of consecutive walking (or running steps): according to a tolerance parameter (*TOL*), set to 25%, each time the routine detects a local peak, and the *SMA* points out a mild activity (i.e. possible walking activity), and the distance between the peak and the last recorder one fits into the range $WDT \cdot (1 \pm TOL)$, then the peak is accounted as a 'detected walking step'; similarly, when the SMA points out intense movements (i.e. possible running activity), the following control is performed to identify a 'running step': $RDT \cdot (1 \pm TOL)$. Every 5 s all the walking and running *TD*s are stored inside a temporary vector (*TV*) and the step frequency is calculated as the reciprocal of its mean distance.

2.2. Activity Classification

Every 5 s the algorithm extracts the five aforementioned features from the ECG and accelerometer signals. Then the routine processes these 5 inputs in order to classify the subject activities into one of the following 9 classes:

a. *upright standing*
b. *moving trunk or arms*
c. *walking*
d. *intense walking (climbing stairs or walking by carrying heavy objects)*
e. *running*

f. stationary intense movements
g. resting after intense movements
h. motionless lying down
i. moving lying down

***Table 1**: normalized coordinates of each class centroids.*

class	***normalized***				
	SMA	***incl.***	***step freq.***	***HR***	***HR trend***
a. upright standing	0	1	0	0	0.5
b. moving trunk, arms	0.2	1	0	0	0.5
c. walking	0.2	1	0.375	0	0.5
d. intense walking	0.2 0.2	1 1	0.375 0.375	0.7 0.7	1 0.5
e. running	0.5 0.5	1 1	0.625 0.625	0.7 0.7	1 0.5
f. stationary intense movements	0.2 0.2	1 1	0 0	0.7 0.7	1 0.5
g. resting after intense movements	0 0	1 1	0 0	0.7 0.7	0.5 0
h. motionless lying down	0	0	0	0	0.5
i. moving lying down	0.2	0	0	0	0.5

These classes represent a spectrum of relevant activities of an emergency operator, like performing a fire-fighting activity on site, rescuing a victim and carrying him/her out form a building, moving lying down on a restricted route; other classes represents a typical set of dangerous conditions to be extremely detected when the operator is immersed in harsh and smoky environments.

The class assignment is performed by detecting a minimum Euclidean distance between the five dimensional set of features [*SMA, trunk inclination, step frequency, HR, HR trend*] and nine reference points or 'centroids' representing the classes. Remarkably, the centroids' coordinates are heuristically fixed and no training procedure is required, nevertheless the algorithm's performance strongly depends on this *centroids' positioning*. A *data normalization* procedure is also needed to assign an equivalent weight to all the features when the Euclidean distance is computed: hence, a range of expected values for each feature need to be determined and linearly scaled in a [0,1] interval:

- according to [Karantonis et al., 2006] and [Bouten et al., 1997], *SMA* shows low inter-subject variability and typically ranges between *0* (no activity) and *2 g* (very intense activity)
- *inclination* (i.e. the cosine of the trunk orientation vs. the vertical axis), ranges between *1* and *0* (upright and lying down posture, respectively)
- *step frequency* of humans varies from 'no walking' to 'fast running', namely from *0* steps/s to *4* steps/s [Ito et al., 2006]
- unlike the accelerometer features, the HR-derived parameters are highly subject-dependent; therefore smarter normalization procedures are needed: the algorithm normalizes the *HR* by using the widely accepted HR Reserve model [Karvonen et al., 1957], that sets the HR boundaries at the maximum (HR_{max}) and resting values (HR_{rest}), respectively; since it is unpractical to perform a direct measurements of these values, the algorithm asks for the HR_{rest} and age only, and approximates the HR_{max} with the formula: $HR_{max} = 205.8 - 0.685 \cdot \text{age}$.
- finally, according to the HR Recovery model [Shetler et al., 2001], *HR trend* feature is normalized on a range of ±12 bpm.

Thanks to the normalization, 13 centroids are defined (see the Table 1): the *d*, *e*, *f* and *g* classes need 2 centroids capturing the increasing/decreasing HR dynamic followed by a steady-state phase when the subjects perform intense physical activities, or they rest after this phase; the other classes (*a*, *b*, *c*, *h*, *i*) need one centroid only, thanks to the HR stability. Three SMA values represent the inactivity, mild activities and intense activity (0, 0.2 and 0.5 respectively), whereas inclination enables to distinguish between lying down (0) and standing up (1) posture; the step frequency boundaries are set at 0, 0.375 and 0.625 (i.e. the normalization of 0, 1.5, 2.5 steps/s: no deambulation, walking and running, respectively); finally, the HR supports the discrimination between resting or mild activities (i.e. HR to be near the HR_{rest}, i.e. 0 normalized value) and intense activities (i.e. a higher HR, set as $0.7 \cdot HR_{max}$, as the average of the 'target HR' for intense physical activities). A HR trend value of 0.5 identifies a stable HR, whereas values of 1 and 0 refer to a HR increasing of +12bpm and a HR recovery of –12bpm in the last minute respectively.

***Table 2**: confusion matrix of the 4-inputs classifier, based on the vector of features [SMA, inclination, step frequency, HR].*

class	actual activity (% of samples)								
	a	***b***	***c***	***d***	***e***	***f***	***g***	***h***	***i***
a	**91.57**	*5.17*	-	-	-	-	*30.88*	.	.
b	*1.89*	**89.22**	*0.26*	-	-	*23.45*	*0.85*	*0.46*	-
c	-	*0.43*	**98.96**	*12.79*	*0.51*	*0.28*	*0.28*	*0.91*	-
d	-	-	*0.78*	**83.89**	-	*0.28*	*5.38*	-	-
e	-	-	-	-	**99.49**	-	-	-	-
f	*0.13*	*1.29*	-	*3.32*	-	**75.71**	*3.68*	-	*0.61*
g	*6.16*	*3.02*	-	-	-	*0.28*	**58.92**	-	-
h	*0.25*	-	-	-	-	-	-	**95.43**	*2.44*
i	-	*0.86*	-	-	-	-	-	*3.20*	**96.95**

***Table 3:** confusion matrix of the 5-inputs classifier, based on the vector of features [SMA, inclination, step frequency, HR, HR trend].*

class	actual activity (% of samples)								
	a	***b***	***c***	***d***	***e***	***f***	***g***	***h***	***i***
a	**88.93**	*5.17*	-	-	-	-	*11.05*	.	.
b	*1.89*	**86.21**	*0.26*	-	-	*18.93*	*0.57*	*0.46*	-
c	-	*0.43*	**94.52**	*7.67*	*0.26*	*0.28*	*0.28*	*0.91*	-
d	-	-	*5.22*	**89.00**	-	*0.28*	*5.38*	-	-
e	-	-	-	-	**99.23**	-	-	-	-
f	*2.52*	*3.02*	-	*3.32*	-	**79.66**	*7.08*	*0.46*	*4.88*
g	*6.42*	*4.31*	-	-	*0.51*	*0.85*	**75.64**	-	-
h	*0.25*	-	-	-	-	-	-	**94.98**	*2.44*
i	-	*0.86*	-	-	-	-	-	*3.20*	**92.68**

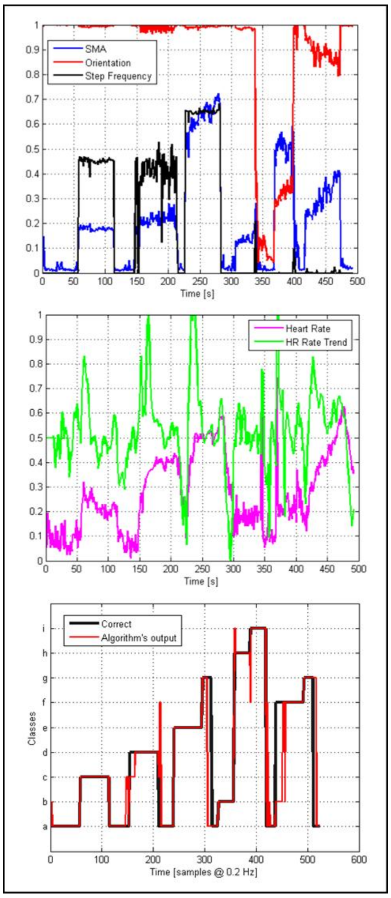

***Figure 1** (right column): time patterns of the normalized SMA, trunk inclination and step frequency (top panel), HR and HR trend (middle panel) during one experiment; output of the classifier vs. the actual activity of the subject (bottom panel).*

2.3. Experimental Setup

A whole session of experiments was carried out to evaluate the algorithm performance: 7 healthy male subjects (31.7 ± 3.7 years old; HR_{rest}= 61.4 ± 9.9 bpm) performed the following sequence of activities (on parentheses the correct class assignments are reported): upright standing (*a*); walking (*c*); upright standing (*a*); lifting stairs (*d*); upright standing (*a*); running (*e*); upright standing, after intense activity (*g*); moving trunk & arms, without walking (*b*); motionless lying down (*h*); moving the body, when lying down on the ground (*i*); upright standing (*a*); knees bending, lifting the whole body (*f*); upright standing, after intense activity (*g*). Clearly this is a semi-naturalistic protocol, but it well represents a realistic scenario of activities as they may be performed during a real intervention; moreover, this rotation of resting phases and intense physical activities allowed the subject's HR to return to his HR_{rest} before starting the next activity, thus avoiding possible biases and also allowing the typical recovery periods observed during a real operation. During the experiments each activity was verbally communicated and lasted for periods between 2 and 5 min; 1st and last samples of each activity were excluded from the classification to avoid errors due to a wrong labeling; on the whole, a total amount of 3332 samples (4h 29 min) were analyzed and classified.

3. Results

A typical time-pattern of the inputs and outputs of the classifier, during one experiment, is reported in Fig. 1. The classifier performances are also reported by means a two confusion matrix (Table 2 and 3), where:

- each column of the table refers to one class of the actual activity, as it has been performed by the subjects (par. 2.2)

- each row reports the class in which the data are classified, according to the effective output of the algorithm
- each diagonal value represents the percentage of the correctly classified samples (in bold style), whereas the non-diagonal values refer to the percentage of the misclassified samples (in italic style)

To examine the effective influence of using two HR-derived features (namely the HR and HR trend) vs. the performance of the algorithm, two classifiers, based on a different set-up of inputs, were tested on the same data: the first classifier used 4 inputs only, namely the SMA, trunk inclination, step frequency and HR, whereas the second one used a 5-dimensional inputs (SMA, trunk inclination, step frequency, HR and the HR trend). Clearly, in the first case, the classifier did not use all the 13 centrodis of the Table 1, since the couples (that describe the intense physical activities and the recovery phase) were differing in terms of the unused 'HR trend' dimension. Table 2 and 3 report the performance of the 4-inputs and 5-inputs classifiers, respectively.

4. Discussion and Conclusion

The 5-inputs and 4-inputs classifiers correctly identify 2983 and 2819 samples out of 3281 (89.55% and 85.91% respectively): using the *HR trend* feature improves the performance of 3.64 % with respect to the use of the *HR* feature only. According to the Table 2 and 3, the two routines show the best and worst results while recognizing the *running* (*e*) and *resting after intense movements* (*g*) classes, respectively, even if the 5-inputs algorithm confuses 30.88% of this latter class in the *upright standing* one (*a*) and 23.45% of the *stationary intense movements* class (*f*) in the *moving trunk or arms* one (*b*); similarly 12.79% of the samples of the *intense walking* class (*d*) are confused in the *walking* one (*c*). On the other side, the 4-inputs classifier tries to combine a fast response of the accelerometer-derived signals (which rapidly change as soon as the subject modifies his activity) with a relatively slower-response of the physiological signals (which slowly change their dynamics - see also the middle panel of Fig. 1). On the contrary, introducing the *HR trend* (i.e. the 5-inputs classifier) improves the identifications of those classes that are characterized by a higher HR, with a small reduction of the performance in the detection of the classes with a lower HR only (compare the difference of performance, 16.72%, between the identification of the (g) class, *resting after intense movements*).

The advantage of a classification algorithm that fuses the data coming out from different sources, is an improvement of the classification precision: 9 different activities can be clearly distinguished, taking into account not only some movement-related parameters (here represented by *SMA, inclination* and *step frequency*), but also the physical effort of the subject (represented by the *HR and HR trend*). While the first triplet of parameters is quite insensitive with respect to the age, sex, fitness level and characteristics of the subject [Bouten et al., 1997], the use of physiological signals causes some drawbacks related to their inter-subjects variability [Karvonene et al., 1957; Sheltrer et al., 2001], which have been partially solved by the proposed normalization procedure of all the parameters. To this aim, it is important to notice that novel self-adapting routines may be conceived: the system may be worn for a long time by the same subject, and the acquired data may be used to personalize and tune the class centroids, according to the fitness level of each subject.

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