Analysis and development of an automatic eCall algorithm for wearable devices

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***Abstract*— This paper presents an innovative application for the online activation of emergency calls (eCalls) using wearable sensors installed on an instrumented jacket. Such a device allows one to actively monitor the activities performed by the user and to detect possible hazards that lead to loss of consciousness, thus activating the eCall. To do this, a detailed analysis of the measured sensors is carried out, that results to the automatic classification of the human motion. Secondly, the detection of a fall is performed and, in particular, an event associated with a consequent loss of consciousness is monitored and detected. The performance of the proposed approach are analyzed and tested on experimental data collected from several stuntmen simulating different types of falls, and favorably witness the effectiveness of the approach.**

I. INTRODUCTION

In recent years, smart, sensor equipped clothing and wearable technologies have become very popular and the related market is expected to have a three-fold grow in the next few years, [1]. Wearable technology mainly concerns electronic devices, apparel and textiles and represents an emerging promising research area both in the academic and in the industrial field, [2]. The dominant sector will be the increasingly merged healthcare/medical and fitness/wellness areas, which will exceed the advanced infotainment sector in value if not in numbers.

In fact, although consumers generally know wearable devices as the most recent smart-watches and fitness-tracking bands, in medical applications they have been used since the first half of the last century (the first wearable hearing aid device was designed in 1938, [3]). Thanks to electronic miniaturization, wearable medical devices have been widely employed to improve patients' life in many other applications, see [4], [5].

In parallel to the design of new types of wearable devices, thanks to the widespread availability of internet connectivity and the drop of the related costs, the research community has also studied how to use these tools for remote healthcare monitoring, yielding applications such as motion trackers and vital signal measurements, [6]. In the latter, pulse wrist, body temperature, electrocardiogram and blood oxygen can be measured through *ad-hoc* sensors, placed on the human body, [7]. On the other hand, motion tracking algorithms and devices have been designed both to monitor elderly people and subjects with chronic conditions in the home and community settings and to supervise sportsmen during their activities, especially for fall assessment, generally *via* indirect measurements.

Body activity estimation *via* indirect measurements is an interesting problem which has been widely studied in the literature. Accelerometers have been widely accepted as useful and practical sensors for wearable devices to measure and assess physical activity. The work in [8] reviewed the development of wearable accelerometer-based motion detectors for monitoring and assessment of physical activity, including posture and movement classification, estimation of energy expenditure, fall detection and balance control evaluation. Also in [9], an extensive study on the assessment of body movement through accelerometer measurements has been presented. An estimate of human physical activity based on an extended Kalman filter has been proposed in [10], where the authors claim to be able to detect the body posture and to infer the walking speed.

How to estimate body posture has been subject also of many other works related with fall detection algorithms [11], [12]. Due to the high social costs, especially in elderly people, fall detection algorithms have been extensively studied and multiple works have been proposed in the literature. Some algorithms have been designed with static thresholds [13], [14] or more sophisticated machine learning classifiers [15]–[17]. Wearable technologies have been mostly used, though some contributions have been also proposed using data from smartphones [18], [19].

In this paper, an automatic emergency call (eCall) algorithm for a wearable, accelerometer-based device is presented. The goal of the proposed algorithm is to continuously monitor human activity in order to automatically detect all those hazardous situations in which unaccompanied people may be in danger and, at the same time, not able to manually send a rescue call. The algorithm analyzes the human body movement intensity and monitors fall events, assessing whether the person has lost consciousness, which is the situation of interest, in which a person is not able to actively call for help. Characteristic patterns related to the loss of consciousness have been investigated with a minimal sensor layout composed just of a tri-axial accelerometric sensing element. Suitable acceleration-based features have been selected to design a real-time fall detection algorithm, minimizing the number of tests needed to carry out the design phase. The algorithm has been experimentally validated in real situations, thanks to an experimental campaign conducted on a dozen testers wearing the instrumented

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jacket, and has led to the successful detection of the fall unconscious situations.

The paper is organized as follows: in section II the specific problem and the hidden patterns to mine are defined, while providing a description of the experimental set-up. Triggering patterns are analyzed in section III and the minimal number of features needed to characterize them are illustrated in detail. Section IV describes the designed fall detection algorithm and shows its performance on experimental data. Conclusions and final remarks are depicted in section V.

II. PROBLEM STATEMENT AND EXPERIMENTAL SETUP

The algorithm proposed in this work aims at detecting all the emergency scenarios in which a person may not be able to directly issue an emergency. These events are strictly linked with the loss of consciousness. Among all the possible circumstances associated with this status, in order to make the algorithm robust, two main patterns have been considered:

- *Movements intensity variation*: loss of consciousness implies a loss of muscle strength and tone, which reduce the movements capability [20]. In this situation, the person may not move from few seconds up to several minutes or, in the worst case, may not spontaneously recover without external help (*e.g.*, during an heart attack). Moreover, due to the loss of muscle strength, it is impossible to stand on the legs, forcing the person to cower. In brief, the pattern is completely characterized by a sudden variation of movement intensity followed by a prolonged lack of movements in an unusual position;
- *Falling*: this second scenario extends the previous one for all the events where the person was not moving before losing consciousness. In fact, although most of the falls are due to stumbles against an obstacle, a person may fall because of faint, an event that may occur even when the person was standing still not moving. While in case of stumbling the person is necessarily moving (and may lose consciousness only after hitting the ground), in case of faint a person loses consciousness before falling.

The aforementioned patters have been investigated by means of a tri-axial inertial measurement unit (IMU) embedded in the jacket of Fig. 1. The IMU samples at 500 Hz and is located at the lumbar area. The location of the sensor unit was chosen according to previous studies showing that the waist is one of the most sensitive locations to represent the body as a whole [9], [21].

III. FEATURES SELECTION

As described in the previous section, two main patterns are monitored to detect the lack of responsiveness. A preliminary test phase has been conducted in order to mine these patterns. In this section, the results of this exploratory step are presented.

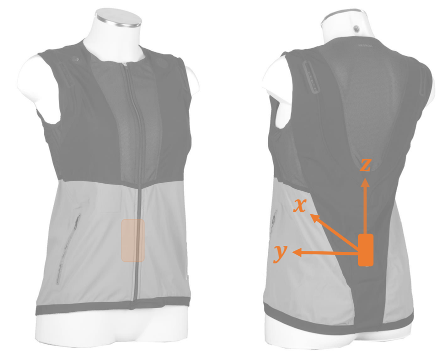

Fig. 1. The jacket used during tests.

Movements intensity

The experimental setup used in the tests consists of three accelerometers. Analyzing the three accelerometers signals separately might be unnecessarily complicated for estimating a signature of the body movement intensity. A single inclusive signal can be the acceleration norm $\|a\|$

$$\|a\| = \sqrt{a_x^2 + a_y^2 + a_z^2} \tag{1}$$

which represents, in a single signal, the intensity of all the acceleration signals together.

The acceleration norm has been analyzed for different types of motions, from more intense (*e.g.*, a run) to less intense (*e.g.*, a very slow walk), where the motion is performed almost quasi-statically. Tests in which the tester performed slower motions than *very slow walk* have been excluded from this analysis because they are considered not representative of a real case scenario with the person moving naturally. However, few tests have been performed with the tester standing still and they are included in the classification baseline.

The different types of motions have been analyzed both in time and frequency domain. In time domain, as shown in Fig. 2, the acceleration norm of the most intense movements is characterized by two factors: its variation range and the pattern periodicity. In fact, during a run, the acceleration norm can reach peaks of 80 $\mathrm{m/s^2}$, while in the very slow walks it does not exceed 11 $\mathrm{m/s^2}$ (which is, roughly speaking, less than 1 $\mathrm{m/s^2}$ more than gravity). Moreover, in the same time window, the motion yielded 14 cycles during the run, but only 4 during the slowest walk. As expected, the pattern frequency is lower in slower movements. In conclusion, the movement analysis in the time domain shows that more intense movements are characterized by an increase of the pace associated with stronger impacts on the ground at each step. The differences in the movement intensity levels are evident also in the frequency domain. Indeed, the fundamental frequency grows in more intense movements (*e.g.*, for the tester analyzed, it is 2.796 Hz for running, 1.98 Hz for the fast walk and 0.754 Hz for the slowest walk - comparable results have been obtained for the other testers) as well as the associated magnitude. Furthermore, more

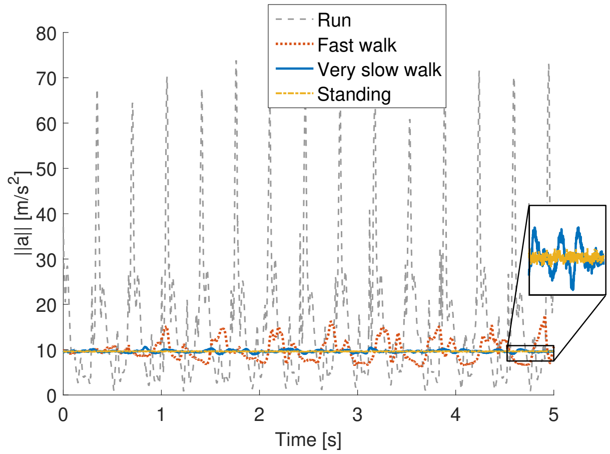

Fig. 2. A few seconds of the acceleration norm analyzed at different levels of intensity. The pattern frequency and the acceleration norm range are higher for more intense movements.

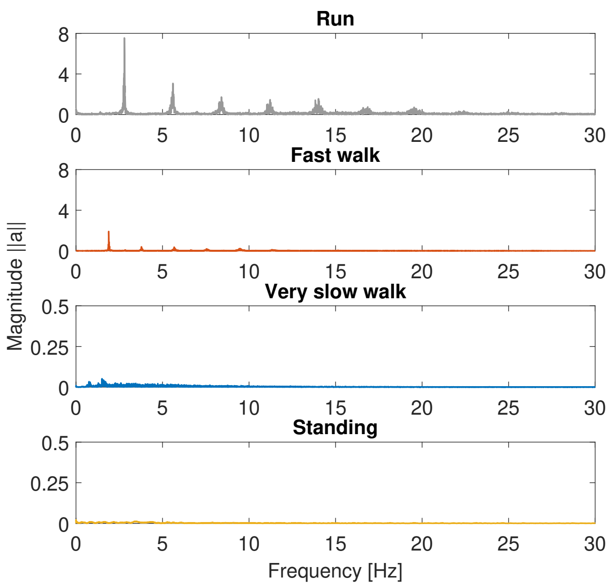

Fig. 3. The spectra of the acceleration norm is analyzed at different levels of intensity. The scale of the magnitude of *very slow walk* and *standing* have been adapted in order to make more visible the main harmonics components.

intense movements show more high frequency harmonics that are multiples of the fundamental one than in case of less intense movements. As depicted in Fig. 3, in *run* the first 7 harmonics are larger than the baseline, while in *very slow walk* only the first two can be appreciated. The analysis in the frequency domain shows that the information associated with the different motions is confined in the $0.7-25$ Hz bandwidth. By filtering the acceleration norm with a band-pass filter, the most informative harmonics are retained. Besides, using a band-pass filter, the mean value, which could be possibly biased by sensors drifts and high frequency noise components, is filtered out, thus making the system robust with respect to the most common sensors' errors.

To capture the body movement intensity, we propose to extract the mean absolute value from the filtered accelera-

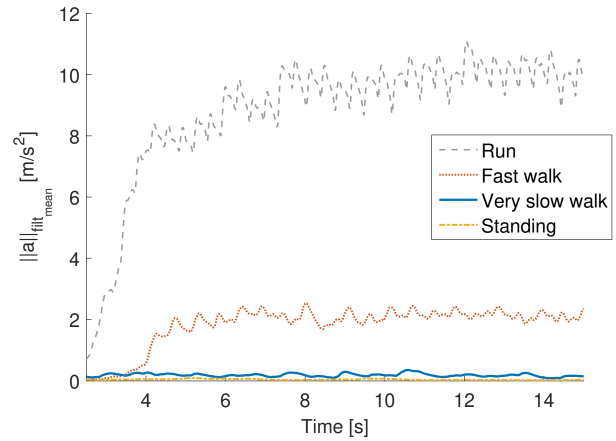

Fig. 4. The mean absolute value of the filtered acceleration norm is evaluated for different levels of motion intensity. In *very slow walks*, the signal oscillates around 0.2 $\mathrm{m/s^2}$, while it is one order greater in *fast walk*, fifty times in *run*. In case of *standing*, the signal is not flat on zero (though never exceeds 0.1 m/s^2) because of the low-intense spontaneous movements.

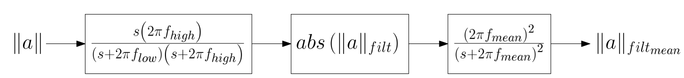

Fig. 5. The filtering chain proposed to extract a feature $\|a\|_{filt_{mean}}$ of the movement intensity. In the first block, the band-pass filter is tuned with $f_{low} = 0.7$ Hz and $f_{high} = 25$ Hz. In the second block, the absolute value of the filtered signal is obtained. The final block is a low-pass filter (cut-off frequency $f_{mean} = 1$ Hz) estimating the signal mean value $\|a\|_{filt_{mean}}$.

tion norm $\|a\|_{filt}$ with a second-order low-pass filter. The obtained feature $\|a\|_{filt_{mean}}$ can be used as a signature of the movement intensity. In Fig. 4, the results for different type of motions are shown: in all the three cases, the signal $\|a\|_{filt_{mean}}$ settles to increasing levels according to the motion intensity. As the *very-slow walk* is the slowest type of motion considered acceptable, a static threshold between its minimum value and *standing* is enough for discriminating whether the person is moving or not. A sensitivity analysis of the second-order low-pass filter cut-off frequency f_{mean} has been conducted and the best trade-off between signal smoothness and settling time has been found for $f_{mean} = 1$ Hz. In Fig. 5, the filtering steps performed to obtain the feature from the acceleration norm are summarized.

Falling

In the literature, several fall detection algorithms have been presented [22], [23]. One of the main differences between the proposed algorithm and many of the algorithms already present in the literature is related to the sensor layout employed. As illustrated in Section II, our experimental set-up is equipped of a three-axial accelerometer sensor (as proposed in [11], [16]), with no additional sensors like gyroscopes (as in [14]) or more sophisticated ones, like acoustic sensors [24], a magnetic compass [25] or cameras [26], [27].

The proposed fall detection algorithm has been inspired by some threshold-based algorithms as [12], [28]. One of the main difficulties in the development of threshold-based algorithms is the tuning phase. A conservative tuning

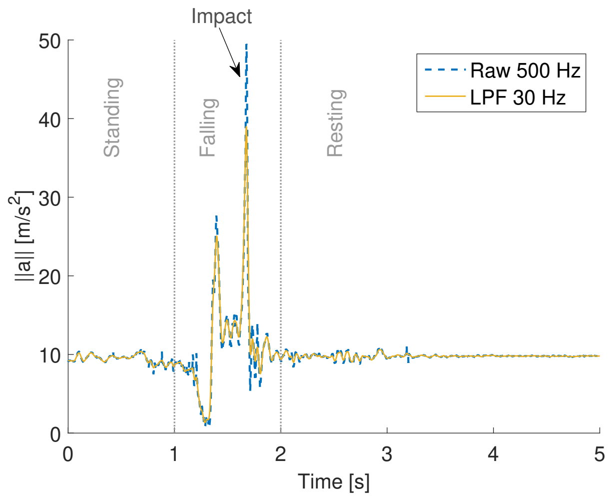

Fig. 6. The acceleration norm $\|a\|$ during a fall. The dashed line represents the raw data sampled at 500 Hz, whereas, the solid line is the acceleration norm filtered with a second-order low-pass filter with cut-off frequency of 30 Hz. This is one of the falling events recorded during the experimental campaign.

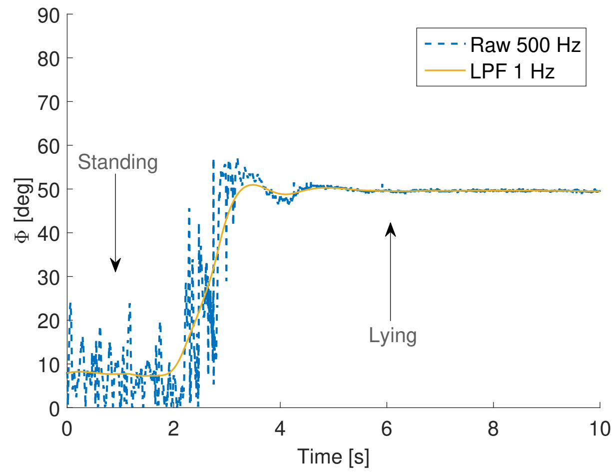

Fig. 7. The posture angle analyzed during a fall. The dashed line represents the posture evaluated with raw data. The solid is the posture angle filtered at 1 Hz with a second order low-pass filter. This event is part of the experimental campaign conducted.

may generate too many false positive, whilst an incautious threshold may cause unacceptable misdetections. To ensure the identification of all the falls while minimizing the false positive, a different approach is proposed in this work.

Assuming the person not initially moving, a standard fall is characterized by three zones (Fig. 6): in *standing* the person is assumed standing still; when the person starts *falling*, the acceleration norm tends to zero (a free-fall phase) and then reaches a peak at the impact (or multiple peaks in case of a multi-impact fall); after the impact, in *resting*, the person is supposed not to move for some seconds. Non-standard falls differ from the standard one mainly in the free-fall phase, the most sensitive to the specific falling dynamics.

To detect this pattern, the fall detection algorithm is triggered when the acceleration norm exceeds a static threshold and then the person lies without moving for a predefined time window. This can be done using raw signals (sampled at 500 Hz) or after undersampling, so to ensure a lower energy consumption. Since the acceleration norm shows an impulsive profile at the impact, the sampling frequency cannot be reduced indiscriminately because of the filtering process needed to remove aliasing correctly. A too strong filtering action can smooth the wave excessively, making it impossible to detect the impact. In this work, a good trade-off has been found filtering the signal at 30 Hz, thus downsampling the signal up to 60 Hz.

Posture angle

As mentioned in Section II, a person is not able to stand when unconscious after a collapse. No matter which the falling dynamics is, the final attitude of the body is usually horizontal or, more precisely, not perfectly vertical. The same condition is verified when the person slowly cowers. Both the movement intensity variation and the detection of a fall need an additional feature to trigger the eCall robustly.

As discussed also in [29], a feature describing the body posture can be derived by inertial measurements. The so-called posture angle, defined as the angle between the upper part of the body and the vertical axis defined by gravity, can be evaluated as

$$\Phi = \text{acos}\left(\frac{|a_z|}{\|a\|}\right), \tag{2}$$

where $|a_z|$ is the absolute value of the vertical acceleration (making the posture angle insensitive to the bending direction). Posture angle is a quasi-static approximation; this means that, during transients, the obtained value may not be representative of the real one.

The posture angle signal, obtained from accelerometer measurements, is usually very noisy. Noise is filtered with a low-pass filter with 1 Hz bandwidth. As the change of posture has a relatively slow dynamics and because of the quasi-static approximation, the filtered signal well represents the trend of the raw one (Fig. 7).

In both the situations where the unconsciousness is detected because of a variation of the motion intensity or a fall, the person is considered unconscious based on the final posture. This is another critical trade-off. To properly tune this threshold, several experiments have been conducted simulating falls and loss of consciousness events, using data measured with thirteen persons acting as stuntmen. In the general case, the person can be said to be lying if the posture angle is larger than 35 deg. This means that, in this work, all the special cases in which the person is unconscious in an almost-vertical position (*i.e.*, with a posture angle smaller than 35 deg) are intentionally not triggered in order to reduce the number of possible false positives.

IV. eCALL ALGORITHM

In the previous section, the patterns of unconsciousness have been mined and some specific features have been selected. In this section, the rule-based eCall algorithm is

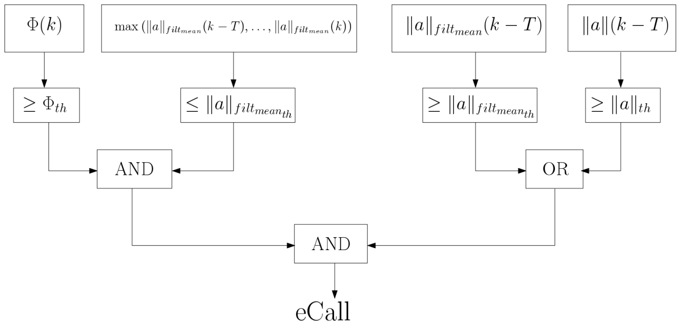

Fig. 8. The eCall algorithm.

defined and experimental results are shown to prove its effectiveness.

Algorithm design

An emergency call must be triggered when the person is thought to be unconscious. Based on the mined patterns, this condition is verified when:

- *the person is resting*: the person is assumed to be unconscious when she/he lies horizontally and has not made any movements in the last few seconds. Lying horizontally is verified by checking if the posture angle is larger than the threshold Φ_{th}. Motion is detected by means of the movements signature $\|a\|_{filt_{mean}}$ over a time window of length T: the person is assumed not moving only if the signal never exceeds the threshold $\|a\|_{filt_{mean_{th}}}$;
- *the person fell or was in motion*: according to the analyzed patterns, prior to unresponsiveness, the person is expected to either fall or be moving. Falls are detected based on a threshold on the acceleration norm, while the person is considered moving based on the same threshold used for checking whether the person is resting or not.

The rule-based algorithm is implemented following the structure of Fig 8 with parameters listed in Table I. The left-hand side corresponds to checking whether the person is resting, while on the right the condition on the prior state is analyzed. When both the two branches are verified, the system will alert the person and, if no actions are taken, the emergency system is automatically called.

Experimental results

The proposed algorithm has been experimentally calibrated and validated in real case scenarios, with more than 80 emergency and daily-life situations with a dozen testers. The algorithm has proved to correctly detect all the emergency events, with no false eCalls when tested against daily-life scenarios. Here, the results of two events of the experimental campaign are presented.

In Fig. 9, the tester simulated a fall from a standing still condition. The algorithm detected the fall and the following prolonged resting condition, which is detected as soon as the fall dynamics was completed. As no movements have been detected in the time window analysis, the algorithm triggered the firecall correctly.

Parameter	Value	Measurement unit
Time window T	20	[s]
Posture angle threshold Φ_{th}	35	[deg]
Impact threshold $\|a\|_{th}$	20	$[m/s^2]$
Moving threshold $\|a\|_{filt_{mean_{th}}}$	0.1	$[m/s^2]$

TABLE I

ECALL TRIGGERING SPECIFICATIONS.

In Fig. 10, the tester simulated a sudden illness event during a run. Before cowering, the tester slowed down the pace, smoothly lying on the ground. As expected, since the motion was very intense when running, the posture angle is saturated to the maximum value, making its value not reliable. Also the *impact* flag is influenced by the high value of the peaks reached by the acceleration norm during the run. To remove this undesired effect, $\|a\|_{th}$ could be raised to a higher value, though possible misdetections may happen in case of not-too-strong impacts. However, it is important to notice that the system is not influenced by this flag. In fact, because of the movements of the person when cowering, the person is detected resting only one second later than the impact. The eCall is then triggered robustly without the influence of the erroneous fall detection.

V. CONCLUDING REMARKS

In this paper, an automatic eCall algorithm for fall detection with a sensor equipped wearable device has been illustrated. The robust monitoring of the unconsciousness situations can be achieved recognizing a sudden variation in motion intensity and falling events. In the paper, the experimental calibration of all the thresholds is analyzed and finally the proposed algorithm is validated in real case scenarios with more than 80 emergency and daily-life situations simulated with a dozen volunteer testers.

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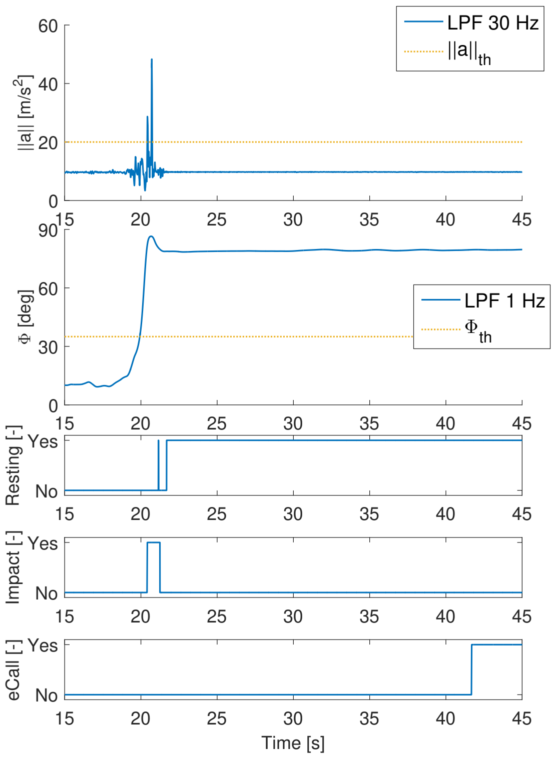

Fig. 9. Experimental validation of the eCall algorithm during a fall. In this case, the person was not moving and collapsed when she/he lost consciousness. The tester begins the resting phase at the first variation of signal *Resting*, but this condition is robustly detected only few instances later, resulting in a signal spike.

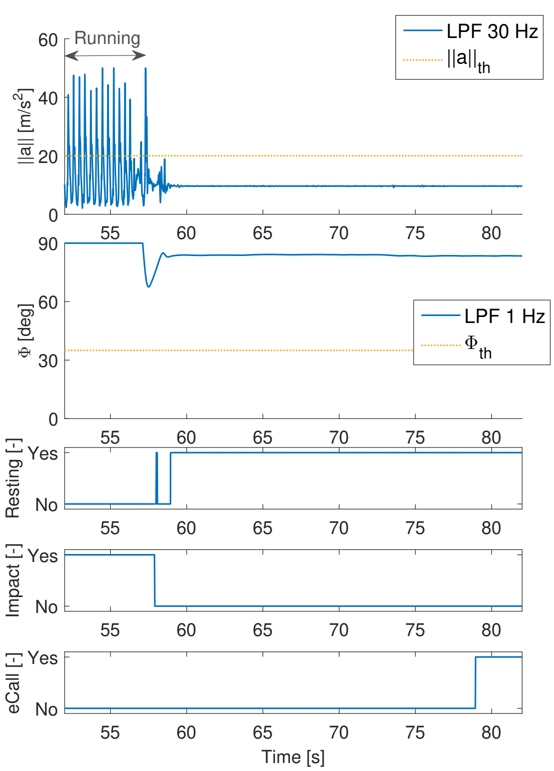

Fig. 10. Experimental validation of the eCall algorithm due to a sudden change of the movement intensity. During this experiment, the tester simulated a sudden illness while running. This is one of the falling events recorded during the experimental campaign.

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