



Automatic detection of human's falls from heights for airbag deployment via inertial measurements

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ABSTRACT

Workers in different industrial sectors, mainly in the construction and energy areas, face the daily risky situation of falling from the height accidentally, even wearing safety harnesses. To actively protect workers, a safety jacket is proposed. The jacket is equipped with an airbag cushion and an inertial measurement unit, located on the back, to sense the body motion. An algorithm deploys the airbag automatically for falls from heights greater than 1 m, leaving enough time for the airbag to be fully inflated. The proposed algorithm is tested and validated against experimental data collected during real falls performed by a professional stuntman, and during months of daily routine workers' life. Particular attention is devoted to the calibration of the tuning parameters, with the aim of the best trade-off between false positives' minimization, reactivity, and robustness.

1. Introduction

Falls, together with slips and stumbles, are one of the main causes of injuries and fatalities in the workplace, be it in the engineering and construction, electricity and gas, or natural resources sector. In fact, these industries' workers are often required to access platforms and equipment located high above the ground. The US Occupational Safety & Health Administration (OSHA) reports 227,760 non-fatal cases involving falls, slips and trips in 2017 in the United States, [1], and 887 fatalities, [2]. The 2017 Census of Fatal Occupational Injuries statistics reports that falls, slips, and trips fatal events in public and private industry increased by 5% compared to the previous year. Meanwhile, the same Bureau of Labor Statistics of the US OSHA also shows that 66% of workers' falls happen on the same level resulting from slips and trips, and the remaining 34% are falls from a height (ladder, roof, down stairs).

The automatic detection of workers' fall from a height can be approached in two main ways: fall identification after the casualty has taken place and fall detection while the fall is in progress. Several studies have been carried to successfully detect that a person has actually fallen, especially in the context of security and safety of elderly people, see e.g., [25], so that assistance can be provided as soon as possible. Also, considering lone workers, whether it is a fall-related injury or a serious fall incident, emergency response time is critical to

bring needed help directly to the employee. However, to our best knowledge, the recognition of an in-progress-fall is a much more unexplored area of research, although protecting a person while they are falling, and before hitting the ground, could be even more effective to avoid severe physical injuries or death, [6]. In fact, if a fall from a height is detected while it is happening, safety measures could be adopted in order to significantly mitigate the consequences of the impact of the human body with the surface.

The detection of already occurred falls, considering various human activities, not only in the workers' context, can be done with the help of different types of sensors fitted with computing capacity. The two main categories of sensors used for the recognition of human falls are non-wearable (ambient-based and imaging), [29,34] and wearable ones. We do not consider in this paper the presentation of the former types of sensing units since they cannot be adopted for the in-progress-fall detection due to the very short response time needed to properly perform this difficult and critical task. On the other hand, wearable sensors, being attached to the body, ensure a very responsive tracking of the fall event, from the very beginning. Accelerometers and gyroscopes are the most commonly used wearable sensors, often integrated in a so-called Inertial Measurement Unit (IMU), and they have spread consistently in recent years, see [12,24], due to their miniaturization and also to their integration in common smartphones, smartwatches and other personal devices of daily use, [14,15] and [7]. It must be noticed that wearable

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technologies are of course typically used for the continuous and objective monitoring of people movement during normal or particular daily activities, and not only with the aim of recognizing or preventing a fall. Clearly, adding to these monitoring systems the capability of falls' detection, makes it possible to embed automatic e-Call capabilities in case of illness or accident, see [12]. However, the fall from a height recognition task in real time is a case of fall where the entire body (and not only some of its parts) experiences a fall, so that it is essential that the sensors are fixed at one or more important body points where the overall dynamics can be all captured at once.

Although it would be interesting to discuss all main human fall wearable prevention strategies, in order to better focus on the topic of this paper linked to the workers' context, we will here concentrate on the still limited but rapidly developing research on detection of falls from a non negligible height, [8,9].

Most of the active systems to safeguard people, especially elderly people, when falling down and risking serious injuries, are protective vests containing one or more nylon airbags, [26,27]. When the vest-embedded sensors detect an alleged fall, the inflation of the airbags is triggered. Our paper describes a new, IMU-based algorithm able to implement a mobile worker airbag system, considering falls from heights greater than 1 m. The following work brings some innovative contributions with respect to the state of the art:

- (a) As further analyzed later in this contribution, the proposed algorithm covers falling dynamics more complex than the ones detectable with the aforementioned algorithms. This contribution is important because, according to [11], "Although these methods detected falls with high accuracy, they focused on pre-designed falls from a stationary position instead of under moving conditions. Moreover, they targeted elderly people or patients whose motions are not as dynamic as those of construction workers. Therefore, the feasibility of applying these methods to the movements of construction workers is questionable."
- (b) We designed a system with a minimal sensor layout, composed only of a single triaxial acceleration IMU. By reducing the sensors used, we can increase the battery time, which is crucial for adopting such technology. Furthermore, reducing the sensing configuration promotes robustness and reduces cost.
- (c) The proposed algorithm is designed to deploy an airbag, which is a more challenging task than just raise an alert. Needless to say, the falling time is by nature often very short. The key fact, characterizing all airbag safety systems, is that the fall detection has to be completed shortly to ensure enough time to completely inflate the airbag before the contact with the ground occurs. Additionally, contrarily to previous designs (e.g., [27], in which the airbag is placed over a jacket on the back), the airbag is placed inside a traditional vest, which allows to use such technology in the construction field and provides an advanced form of protections for suspended workers.
- (d) Last, but not less important, detection is obtained analyzing the underlying body motion. In general, physics-grounded features better emphasize the safety-related hazards and, ultimately, enable trust in the use of such technology.

A detailed comparison of the current strategy with respect to some of the state of the art algorithms for the construction field is addressed in Table 1. It is worth making some remarks: In the literature, accelerometers are the most used sensors, thanks to their accessibility, reduced costs, and low-energy consumption; pressure sensors, magnetometers, and cameras are less frequent, due to their higher costs and less effective setup. Also, algorithms can be clustered based on their detection type. As remarked, most of the proposed works focused on purely data-driven features, which are usually an ensemble of general statistical features (e.g., mean, standard deviation, peak values). Only a few algorithms, instead, discussed the use of physics-based features

(e.g., body center of pressure velocity), which provide a higher discriminant power. The following work lies in this framework, as the detection of potentially dangerous falls is pursued extracting a physics-based quantity from data collected just with a triaxial accelerometer. As further discussed later in this contribution, the combination of physics-grounded features with an informative sensing unit is central for detecting non-trivial scenarios effectively.

During the experimental campaign, three accelerations are steadily measured on the human body. As later discussed, detecting a fall from a height is particularly challenging because people move prior to the fall (e.g., during their regular work activity) and during the fall itself (e.g., holding onto something for avoid falling). The already challenging detection becomes even more difficult when the sensing layout is reduced to increase the battery life, which is central for ensuring to have an active system in case of need. To this end, the proposed algorithm triggers the airbag deployment only when a suitable acceleration-dependent signal increases its value abnormally during a fall. The algorithm has been experimentally validated, proving the effectiveness of this system in many scenarios in construction. Moreover, to improve robustness, the influence of deliberate jumps from height, or dynamics comparable to accidental ones, are minimized. Some results about the influence of conducting machines or operating high-vibrating tools are also discussed, providing highlights on the limitations of the designed system.

The rest of the paper is organized as follows. Section 2 defines the problem and remarks some of the critical issues related to the algorithm development, and presents the experimental setup used in this work. Further, an analysis of the inertial measurements of four main fall dynamics is discussed in Section 3, providing insights for the algorithm design phase. Then, in Section 4 the proposed detection algorithm is presented. Finally, Section 5 illustrates the algorithm calibration and test phases against experimental data.

2. Problem statement and experimental setup

In this work, the analysis and development of a fall from height detection algorithm is presented. The goal of the proposed algorithm is to detect falls from heights greater than 1 m, a hazardous scenario in which several workers (e.g., construction or line workers) are daily exposed to and not always protected by a safety harness. Furthermore, even when properly equipped, falling workers may float suspended in case the body has gained high kinetic energy during or after the fall, eventually hitting an obstacle before being rescued. Detecting the occurrence of these events and opportunely trigger the deployment of an airbag that could minimize the injuries of these impacts is central.

With respect to some of the algorithms already discussed in the literature about fall recognition or airbag deployment on vehicles, the underlying assumptions of the proposed algorithm make the detection challenging for two main reasons:

- A fall must be detected before the impact, leaving sufficient time for the airbag deployment (up to 0.3s for the cushion full expansion).
- In spite of the short falling time (approximately 0.45s for falls at 1 m), experimental results prove that the person has enough time to try preventing the impact (e.g., maintain the balance or hold onto the closest support), thus increasing the complexity of classifying the sensed motion.

In the current study, the detection algorithm is designed using only measurements recorded by a triaxial IMU placed at the waist, sampling both the accelerations (i.e., a_x , a_y , a_z) and the angular rates (i.e., ω_x , ω_y , ω_z) at 400 Hz. The algorithm is activated only when the jacket is worn and the zipper fastens the garment completely. Once the algorithm triggers the airbag deployment, a cushion is deployed with an expanding gas, protecting both the chest, the abdomen, the back, and the neck, as illustrated in Fig. 1.

Table 1
An overview of the state-of-the-art algorithms for fall detection in construction.

Reference	Method used	Detection type	Features used	Sensor location	Sensor used					Research gap
					Acc.	Gyro.	RFID	Mag	Camera	
[11]	Fall portent detection system with hierarchical threshold-based algorithm	Physics-based	Acceleration norm, vertical acceleration	Head, chest, waist	✓	✓				(b)–(d)
[21]	Activity detection, including slip/trip, using ANN	Data-based	Acceleration norm mean, standard deviation, peak	Pant's pocket	✓					(c), (d)
[16]	Fall Prevention using maximum Lyapunov exponents	Data-based	<i>t</i> -test on maximum Lyapunov Exponents computed on inertial data	Right ankle	✓					(a), (c), (d)
[17]	Construction workers' postural stability assessment	Physics-based	Body center of pressure velocity (COPv) Resultant accelerometer (rAcc)	Waist	✓				✓	(a), (c)
[31]	Near-miss fall detection with one-class support vector machine	Data-based	Inertial quantities mean, standard deviation, max, correlation, spectral entropy, and centroid entropy	Sacrum	✓	✓				(b), (d)
[3]	Construction workers' activity using machine learning	Data-based	Accelerations mean, standard deviation, energy, correlation	Arm	✓	✓				(a)–(d)
[32]	Gait analysis for anomaly detection using Mahalanobis distance	Physics-based	Stride time and distance, horizontal velocity, maximum foot clearance, stance ratio, swing ratio	Right ankle	✓	✓				(a)–(c)
[23]	Fall prone vs healthy construction workers assessment	Physics-based	Center-of-pressure velocity, acceleration norm, maximum Lyapunov Exponent	Lower back Right ankle	✓	✓			✓	(b)–(d)
[33]	Near-miss fall detection with one-class support vector machine	Data-based	Inertial mean, standard deviation, correlation	Sacrum	✓	✓				(b)–(d)
[5]	Near-miss fall detection with one-class support vector machine	Data-based	Inertial mean, standard deviation, peak values correlation, spectral entropy, spectral centroid	Waist	✓	✓	✓			(b)–(d)
[30]	Real-time tracking system of near-miss accidents for construction workers	Data-based	N/A	N/A			✓			(a)–(d)
[10]	Computer vision anomaly detection	Data-based	Automatically extracted through CNN	N/A				✓		(a)–(d)
[19]	Safety helmet wearing classification	Data-based	Extracted with FFT	Head	✓					(a)–(d)
[4]	Real-time detection and classification of loss of balance	Data-based	Mean pressure, variance, max, min, range standard deviation, kurtosis spectral energy, entropy	Foot					✓	(c)–(d)
[28]	Static balance monitoring tool for proactive tracking of construction workers	Data-based	Center of pressure's total path length, acceleration norm	N/A					✓	(a)–(d)
[22]	Identify falling events through floor vibration using semi-supervised support vector machines	Data-based	Acceleration peak, energy, correlation	N/A	✓					(a), (c), (d)
[18]	Identify safety hazards through human bodily responses to external environment	Data-based	Acceleration norm (mean, median, max, min, standard deviation), relative acceleration norm (mean, standard deviation, Shapiro-Wilk statistic, correlation)	Waist	✓					(c)

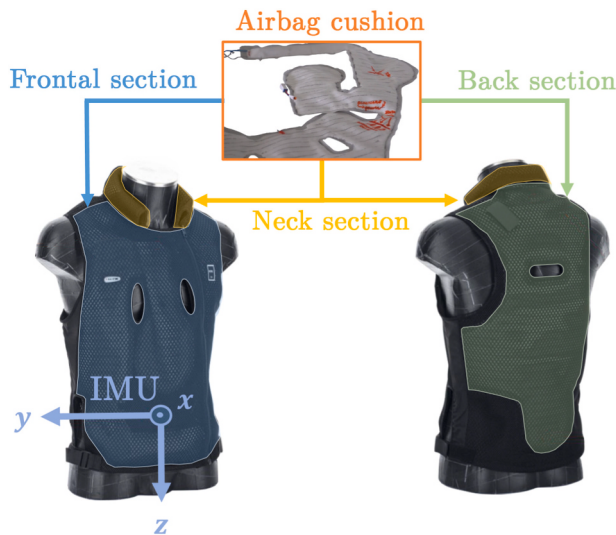


Fig. 1. The jacket used during the experimental campaign. The sections protected by the airbag cushion are highlighted. An IMU, located at the waist whose axes are aligned as illustrated, is used to sense the motion of the body.

To design and validate the algorithm, an experimental campaign was conducted: A professional stuntman performed twenty real falls, spanning different types of accidents from different heights. Additionally, the daily use of the jacket was also monitored on nineteen workers, leading to more than 500 h of recordings during a test session lasted two months. In the former case, falls were also monitored with a high-rate camera, while in the latter workers themselves recorded their daily activities with written notes.

3. Experimental setting and preliminary data analysis

Before introducing the detection logic, a preliminary analysis of some of the most representative fall dynamics is discussed. The focus of this section is to investigate the behavior of the inertial signals and get insights for the algorithm design phase.

In Fig. 2, four main types of fall dynamics are shown. All the recordings begin with the stuntman standing on the aerial work platform (AWP) ready to fall off, and end 1 s after the first impact to the ground (or on the life saving cushion).

Fig. 2a represents what can be considered the *nominal* falling pattern: In the first 0.75 s, the stunt performer moves one leg out of the AWP; the positive pitch rate (i.e., ω_y) denotes a rotation of the trunk that aims to lift the body upwards. Then, to remove the second foot from the platform, the person performs a leap, clearly visible on the z-axis as the measured acceleration exceeds gravity (its nominal value when standing at steady state). When the effect of the jump is vanished, the sensed acceleration on the vertical axis lies in a small range around zero, meaning that the person is free falling. Prior to the impact, the fall is slightly slowed down when the tip of the feet touches the ground, increasing the value of the vertical acceleration more than the range spanned during the fall. At the contact, the vertical and longitudinal reactions of the ground are sensed by the device, showing significant variations of both accelerations and angular rates. This pattern can be considered representing a *nominal* scenario because the stuntman remains vertical during the entire dynamics, thus minimizing the sequence of possible movements before the impact. As illustrated next, this is an ideal scenario and any different fall dynamics is a combination of this pattern with extra motions (e.g., body rotations, limbs movements or reactions).

The second scenario analyzed in Fig. 2b is similar to the previous one, but with one substantial difference in the falling dynamics. In fact, the vertical acceleration does not show any peak larger than the steady

state value, meaning that the stuntman does not jump to remove the supporting foot from the AWP. Besides, the vertical acceleration moves to zero slowly because, as the performer does not jump off the aerial support, the fall is slowed down by the reaction force of the sustaining leg. For this reason, the person is not free falling as in the previous case. Furthermore, it is worth noticing that the lateral acceleration (a_y) and yaw rate (ω_z) are non-negligible in this case. Indeed, the stuntman rotates his trunk during the motion as he does not face the direction of the fall in this example. However, this is a special condition that cannot be used to generalize the falling pattern.

Instead, Fig. 2c shows an event in which the stuntman falls forward, simulating a slip while walking. This results into a non-negligible longitudinal (a_x) and vertical acceleration, in addition to a significant pitch rate. The body rotates during the fall, but since no additional movements are recorded, the accelerations are almost zero.

The final example (Fig. 2d) well illustrates the effect of the oscillations induced by any extra body movement at high-frequency. In this case, the stuntman tries to hold onto anything available to avoid the tumble, an instinctive reaction when losing equilibrium. As illustrated, both the accelerations and the angular rates are influenced by these high-frequency components, making the pattern apparently different than that of the previous cases. However, it is important to remark that the slow-varying trend of the vertical acceleration is comparable to the *nominal* case, gradually moving from gravity to zero.

From the observation of these examples, the preliminary analysis gives some insights for the detection algorithm design:

- During the fall, gravity is the principal force experienced, influencing the macroscopic motion, accelerating the body towards the ground. Any other force affects the falling dynamics less significantly.
- Gravity acts as a slow-varying force, which needs to be separated from the possible high-frequency components due to additional movements.
- Differently from some of other detection algorithms, when the person starts falling not standing on the hitting surface, the body attitude does not necessarily change and the person might fall on their own feet. Thus, the gyroscopes' information content is minimal and their use negligible for this application.
- Although z is the main axis during a vertical fall, all three accelerations need to be monitored to account for any rotation of the body during the fall.

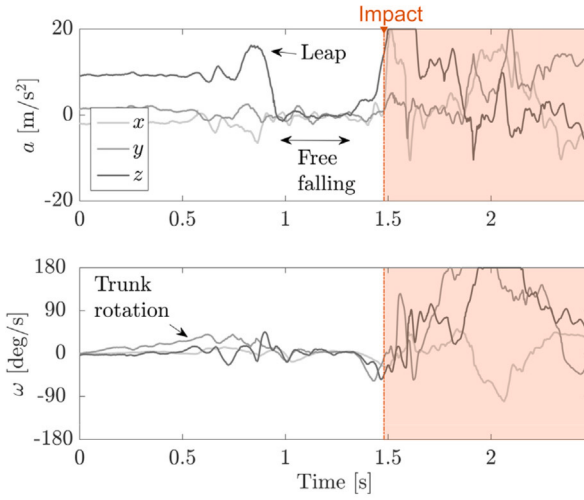
4. Detection algorithm

Based on the above considerations, in this section the proposed algorithm to automatically detect falls is presented and analyzed. As illustrated in Fig. 3, the algorithm is structured in five subsequent blocks. First, measured accelerations are filtered from the high-frequency components not related to the fall dynamics. Then, projection of gravity on the triaxial acceleration vector is removed. In this stage, the projection angles are computed, which are used in a subsequent stage for improving detection robustness. Zero-mean accelerations are integrated with a non-distorted integrator, which computes a non-diverging estimate of the body velocity for each axis. The norm of the triaxial velocity vector is computed as a signature of the overall body velocity, which is used for deploying the airbag when the body is accelerated to an unsafe velocity.

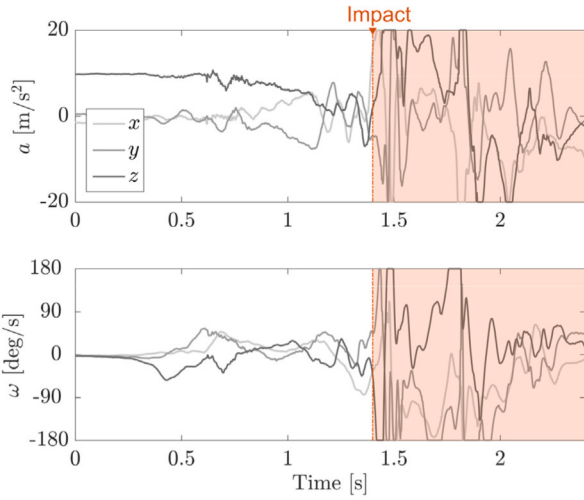
It is worth to remark that the only input of the algorithm is the triaxial acceleration/angular rates vector, measured through the IMU; output of the algorithm is the trigger for the airbag deployment.

4.1. Filtering

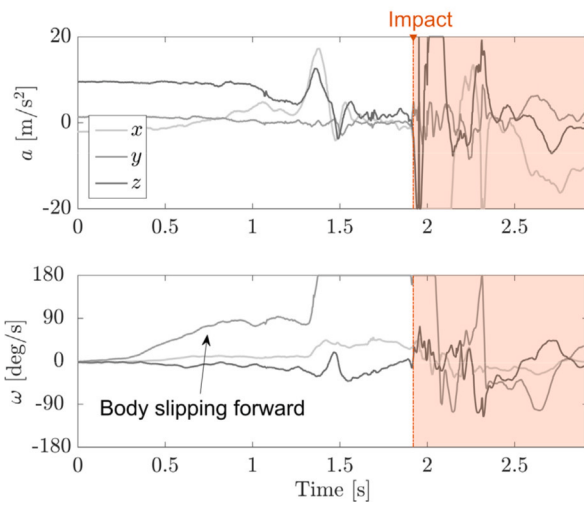
In Section 3, we remarked that the sensed falling dynamics is influenced by two main components: gravity, acting as a constant force,



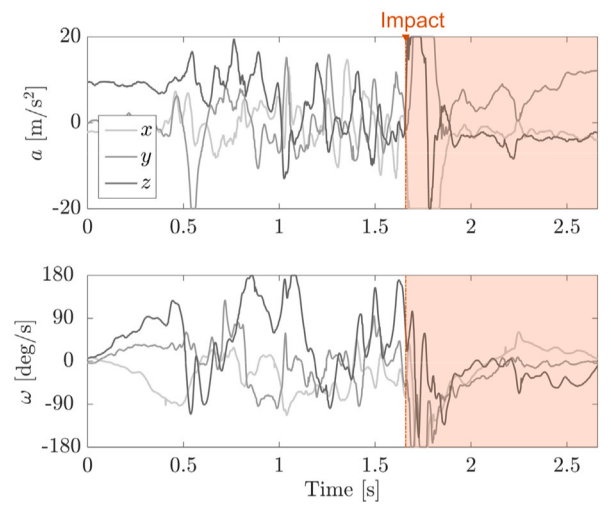
(a) Nominal fall, numbered 7 in Table 2. Fall height: 1 m.



(b) Slow-dynamics fall, numbered 5 in Table 2. Fall height: 1 m.



(c) Fall with a significant rotation that leads the person to a different attitude, numbered 6 in Table 2. Fall height: 1 m.



(d) Fall in which the person moves significantly while falling, numbered 13 in Table 2. Fall height: 2 m.

Fig. 2. An overview of accelerations and angular rates for the four main falling dynamics.

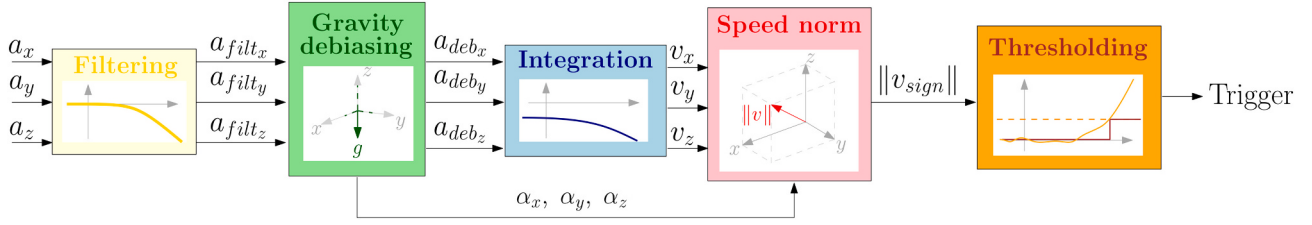
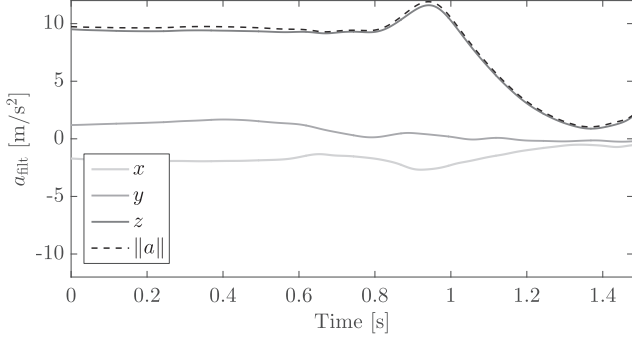
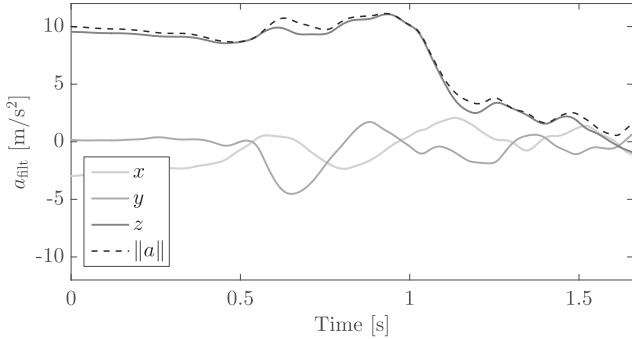


Fig. 3. An overview of the algorithm flow chart.



(a) Nominal fall – same example of Figure 2a – numbered 7 in Table 2.



(b) Fall in which the person moves significantly while falling – same example of Figure 2d – numbered 13 in Table 2.

Fig. 4. An overview of the filtered acceleration signals. In both examples, the high-frequency components induced by the small body movements are filtered out, making the falling pattern easier to detect.

and some possible body movements generating other forces at higher frequencies. As the goal of the proposed algorithm is not to track all the movements of the body (including the micro ones), these high-frequencies components can be filtered out. To this end, all three accelerations are filtered with a linear, second-order, low-pass filter $F(s)$ such that

$$F(s) = \frac{(2\pi f_{LPF})^2}{(s + 2\pi f_{LPF})^2}, \quad (1)$$

in which f_{LPF} is the cut-off frequency, a tuning parameter of the overall algorithm.

In Fig. 4, the filtered signals of two falls analyzed in the previous section are shown as examples. The filtered accelerations of the pre-impact *nominal* dynamics are shown in Fig. 4a. As expected, the minimal movements previously captured do not influence the signals anymore. Indeed, this is even more evident in Fig. 4b compared to its raw counterpart (Fig. 2d): The sequence of movements aiming to interrupt the fall, which heavily influence the original signals, are almost entirely removed, making the pattern now comparable to the nominal

one.

Once the signals are filtered, gravity is one of the main (if not the only) force acting on the person. To prove that, the acceleration norm is computed as

$$\|a(t)\| = \sqrt{a_{filt_x}^2(t) + a_{filt_y}^2(t) + a_{filt_z}^2(t)}, \quad (2)$$

in which a_{filt_i} , with $i = \{x, y, z\}$, are the filtered accelerations. As shown in Fig. 4, the norm only slightly differs from the vertical acceleration, as it is affected by gravity.

4.2. Gravity debiasing

Assuming that a falling person experiences a free-fall and does not perform any additional movements, the inertial forces match the gravity, and the accelerometers yield to a zero output measure. When the body has not reached the free-fall condition yet, the measured accelerations are still (at least partially) subject to the effect of gravity. Besides, during the fall, the body may change orientation with respect to the nominal upright condition, meaning that gravity can influence more than one axis based on the body attitude. For this reason, acceleration measurements need to be debiased from the effect of gravity, considering its projection on each of the acceleration vector.

As already proved, the acceleration norm approximates gravity at low frequency. Thus, it is possible to create three new signals, denoted with a_{deb_i} , $i = \{x, y, z\}$, such that

$$a_{deb_i}(t) = a_{filt_i}(t) - g \frac{a_{filt_i}(t)}{\|a(t)\|}, \quad (3)$$

where $\|a\|$ is the acceleration norm computed as in Eq. (2), g is gravity, and a_i is the projection of component i on the acceleration norm.

These new signals represent the measured accelerations debiased from the projection of gravity on the three axes through the product $g \frac{a_{filt_i}}{\|a\|}$: When the person is standing stationary, the signals are approximately zero, while they take after values when the subject is actually moving (e.g., during a jump or a fall).

It is worth to remark that, even during a vertical fall, the body might not be perfectly aligned with respect to gravity. For this reason, more than one signal might be different from zero, based on the falling posture.

4.3. Integration

Injuries reported after falls from height depend on multiple factors [13]. Among them, the principal are:

- landing position;
- neuromuscular reflexes;
- composition of the impact surface;
- falling height.

The first two are out of the control of the detection algorithm and may be hardly used for detecting the fall. Not even the composition of the impact surface (which is where the airbag plays the difference in

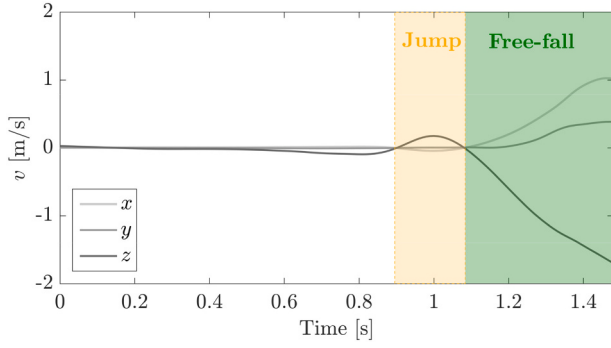


Fig. 5. Computed speed for each axis. Highlighted the jump, in which only the vertical axis is involved, and free-fall phases, where all the axes are different from zero.

reducing the consequences of a trauma) can be used for recognizing the fall.

On the contrary, the falling height determines the speed during the fall. The longer the falling time, the greater the final speed, the higher the likelihood of being subject to severe injuries [20]. Hence, computing the speed is paramount to decide whether the airbag needs to be deployed or not.

Speed can be computed integrating the debiased acceleration computed according to Eq. (3). To this end, an integrator $I(s)$ is combined with a high-pass filter $H(s)$ in order to avoid any drift due to low-frequency components. The non-distorted integrator $G(s)$ turns out to be a non-unitary low-pass filter, as in

$$G(s) = H(s)I(s) = \frac{s}{s + 2\pi f_{HPF}} \frac{1}{s} = \frac{1}{s + 2\pi f_{HPF}}, \quad (4)$$

with f_{HPF} left as a tuning parameter.

For each axis, an approximated velocity component v is obtained, as shown in the example in Fig. 5. Not surprisingly, in this example the prevalent speed is the vertical one, reaching -1.48 m/s at the impact. However, it should be stressed that the obtained velocities are only an approximation of the real ones and that can only be used as a feature for the considered problem and not as an accurate estimate of the actual speed.

4.4. Speed norm

The computed velocities can be used to grade the level of risk associated to a fall. Triggering the algorithm by analyzing three axes separately might be unnecessarily complicated, thus a distinctive signature of the body speed is needed.

However, at this stage, the three components may also reflect forces not acting in the same direction of gravity. Take, for instance, the jump phase: Gravity (pointing downwards) acts in the opposite direction of

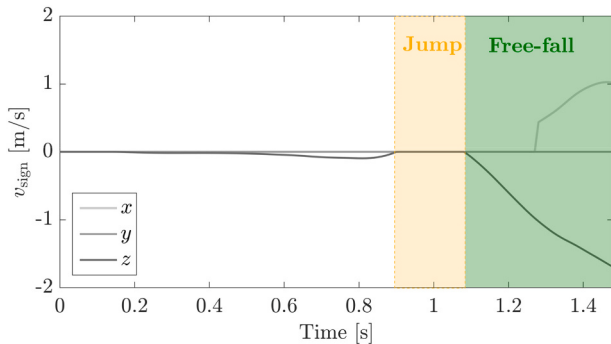


Fig. 6. Velocities pointing at the direction of gravity. The algorithm forces the axes not active to zero.

Table 2

List of all the fall events performed by the stuntman.

Test #	Fall height [m]	Safety harness	Final position	Description
1–2	1	No	Standing	Slipping forward
3	1	No	Standing	Slipping backward
4	1	No	Standing	Slipping laterally
5	1	No	Prone	Tumbling forward
6	1	No	Supine	Tumbling backward
7	1	No	Prone	Somersault forward
8	1	Yes	Standing	Tumbling forward
9	1	Yes	Prone	Somersault forward
10	1	Yes	Supine	Tumbling backward
11	1	Yes	Supine	Tumbling laterally
12	2	Yes	Supine	Tumbling laterally
13–15	2	Yes	Standing	Tumbling forward
16–17	2	Yes	Supine	Tumbling backward
18–20	2	Yes	Standing	Tumbling forward

(shock absorber)

the leap (forward upwards). Ignoring this condition might trigger the algorithm unnecessarily. To account for these issues, only the velocity components in agreement with the direction of gravity are considered, yielding the final signal v_{sign_i} , which is obtained as

$$v_{\text{sign}_i}(t) = \begin{cases} v_i(t) & \text{sgn}(v_i) \neq \text{sgn}(\alpha_i) \\ 0 & \text{sgn}(v_i) = \text{sgn}(\alpha_i) \end{cases}, \quad (5)$$

in which $i = \{x, y, z\}$ and sgn is the signum function.

As illustrated in the example of Fig. 6, the condition in Eq. (5) forces the speed to be null during the jump, leaving the estimated speed of the active axes (i.e., the axes partially influenced by gravity) unaltered during the free fall.

It is now possible to compute the norm of the signed speeds in Eq. (5) as

$$\|v_{\text{sign}}(t)\| = \sqrt{v_{\text{sign}_x}^2(t) + v_{\text{sign}_y}^2(t) + v_{\text{sign}_z}^2(t)}, \quad (6)$$

with $\|v_{\text{sign}}(t)\|$ representing in a single signal the estimated overall body speed, and thus being the needed fall signature.

4.5. Thresholding

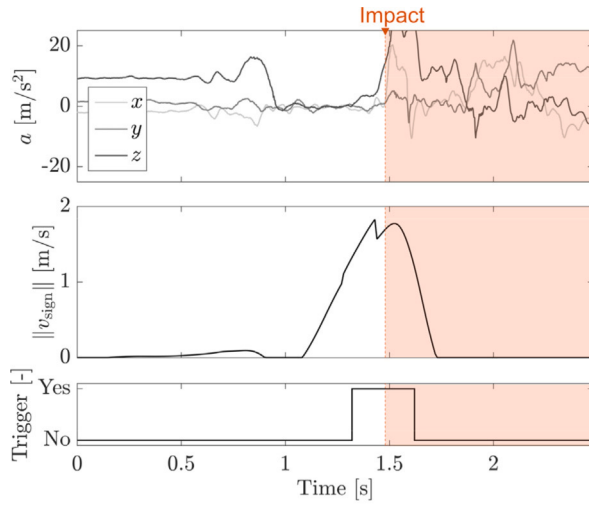
The algorithm triggers the airbag deployment when the instant body speed estimated in Eq. (6) exceeds a suitable threshold $\|v_{\text{sign}}\|_{th}$, or

$$\text{Trigger}(t) = \begin{cases} \text{Yes} & \|v_{\text{sign}}(t)\| \geq \|v_{\text{sign}}\|_{th} \\ \text{No} & \|v_{\text{sign}}(t)\| < \|v_{\text{sign}}\|_{th} \end{cases}. \quad (7)$$

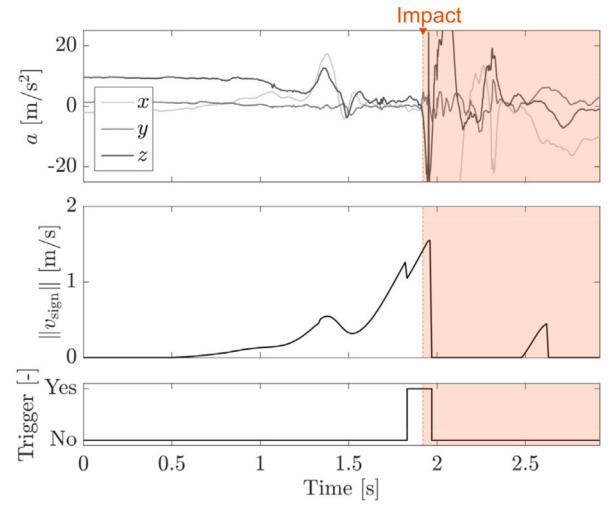
Prior to analyzing the experimental results, it is worth pointing out the key factor of the proposed algorithm. By estimating a signature of the body velocity, we are now capable of triggering any anomalous event in which the body is accelerated to an unsafe velocity. This detail is crucial: The airbag is not only deployed to protect a person during a fall but also during any unsafe event whose dynamics accelerates the body like in a fall. For this reason, tuning parameter $\|v_{\text{sign}}\|_{th}$ is central to provide protection, while minimizing the number of incorrect activations.

5. Results

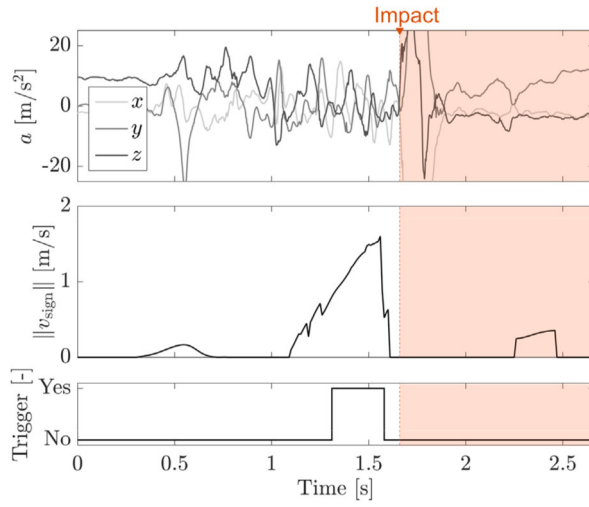
The proposed algorithm is tested against data collected during an experimental campaign, which includes both real falls performed by a professional stuntman (at different heights), as listed in Table 2. More than 500 h of recordings on twenty workers, in which no falls were reported, are used to validate the algorithm during regular working days (both at height and not). Since the workers covered a vast variety of interventions and tasks, this second set of data can be considered a



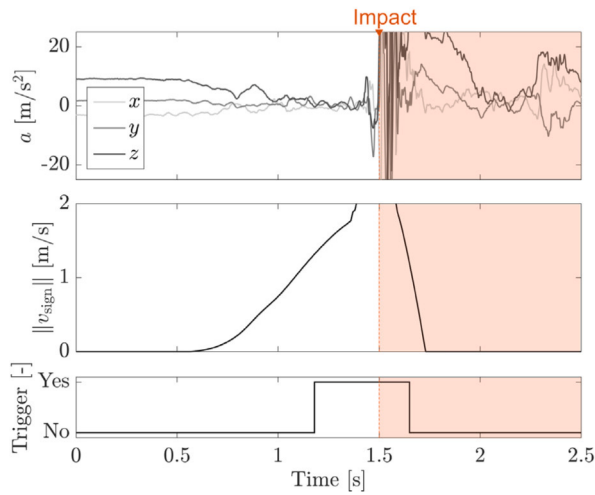
(a) Nominal fall, numbered 7 in Table 2. Fall height: 1 m.



(b) Fall with a significant rotation that leads the person to a different attitude, numbered 6 in Table 2. Fall height: 1 m.



(c) Fall in which the person moves significantly while falling, numbered 13 in Table 2. Fall height: 2 m.



(d) Fall in which the harness is equipped with a shock absorber, numbered 19 in Table 2. Fall height: 2 m.

**Fig. 7.** An overview of detection results against some of the real falls.

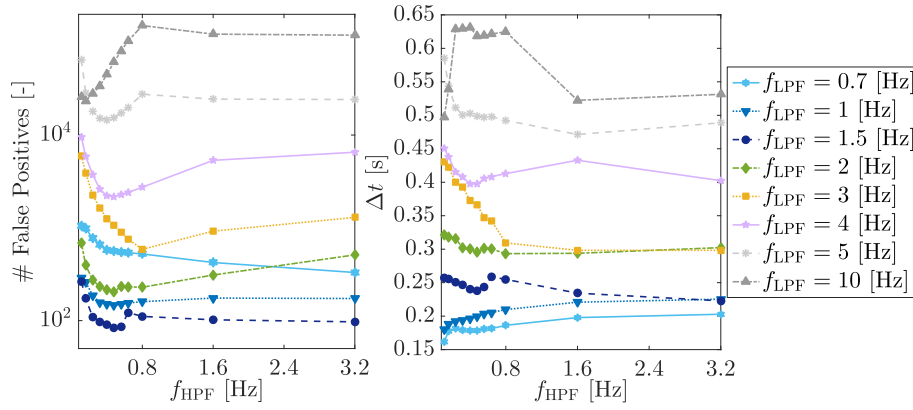


Fig. 8. Sensitivity analysis of f_{LPF} and f_{HPF} in terms of number of false positives (on the left) and detection time Δt (on the right). The minimum number of false positives is obtained for $f_{LPF} = 1.5$ Hz and $f_{HPF} = 0.5$ Hz, leading to an average detection time of 0.2378 s.

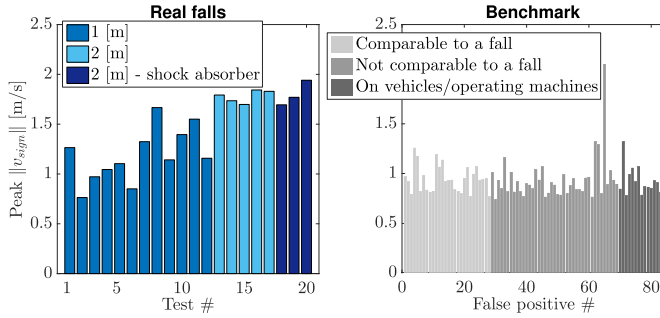


Fig. 9. Analysis of the peak speed $\|v_{sign}\|$ achieved during the real falls (on the left) and during the benchmark tests (on the right). Detect all the falls from 1 m increases the likelihood of triggering the airbag unnecessarily, which drops for a higher $\|v_{sign}\|$. As highlighted, multiples are the causes of possible false positives.

good benchmark for the implementation of the algorithm on the target control unit. Results of the former are shown in Fig. 7: As illustrated, the algorithm is able to detect that the person is falling prior to the impact, even when the harness used during tests is equipped with a shock absorber, which might slow down the fall.

The present results have been obtained after an intensive calibration of the tuning parameters f_{LPF} , f_{HPF} , and $\|v_{sign}\|_{th}$. The first two were chosen based on the results of a sensitivity analysis. As depicted in Fig. 8, we evaluated the number of false positives generated against the regular work data and the average detection time Δt prior to the impact, assuming to trigger the same set of real fall tests. Given a parametrization, this second index quantitatively grades how conservative/reactive the algorithm is, providing valuable insights on the calibration choice.

Results show that for high values of f_{LPF} , the filtering action smooths less the effect of secondary movements, making the algorithm sensitive (high number of false positives) and reactive (triggering time significantly high). Instead, for a too low cut-off frequency ($f_{LPF} < 1$ Hz), the filter smooths the signals excessively, making the detection slow, generating a significant amount of false positives.

For small values of f_{HPF} , the number of false triggers globally increases (except for $f_{LPF} = 20$ Hz) as more slow components are retained during the integration process. On the contrary, the performance trend for $f_{HPF} \geq 8$ Hz is not comparable for different values of f_{LPF} , but it is generally worse than the optimal value in the range $0.32 \leq f_{HPF} \leq 0.56$ Hz. However, the algorithm affects the detection time less significantly than f_{LPF} , excluding the trends obtained for $f_{LPF} = 3$ Hz and $f_{LPF} = 5$ Hz, in which it is difficult to explain such a wide range. A good trade-off is found for $f_{LPF} = 1.5$ Hz and $f_{HPF} = 0.5$ Hz.

Given that filters tuning, an analysis of the optimal $\|v_{sign}\|_{th}$ is assessed in Fig. 9, showing the peak $\|v_{sign}\|$ for both the real falls (prior to the impact) and for the benchmark data. The analysis shows that, aiming to detect all the falls would generate a significant number of false positives. In fact, by analyzing the dynamics incorrectly triggered, workers at height may also be exposed to intense vibrations (marked as *not comparable to a fall* in the same figure), or they might intentionally jump from heights comparable to the target one (e.g., from vehicles (generally trucks), operating machines at heights, or high steps), leading to similar dynamics than what analyzed in this investigation.

The algorithm is made robust by choosing $\|v_{sign}\|_{th} = 1.3$ m/s. This choice comes at the cost of not triggering some of the falls at the lowest heights, but with a significant reduction in the number of false positives (with this parametrization, only three false triggers are generated).

Considering the main challenging goals of this investigation (see Section 2), it is worth to make two additional remarks:

- Tuning parameters f_{LPF} and f_{HPF} need to be jointly calibrated to provide a prompt calibration that cuts the detection time. This is only possible when the most informative harmonics are retained, and high-frequency components not related to the fall are filtered out. In this experimental campaign, we analyzed how the calibration affects the detection performance.
- Threshold $\|v_{sign}\|_{th}$ plays a key role in the algorithm robustness. In fact, a lower threshold value allows to detect any fall, even the ones at 1 m, but with a significant number of false positives. Instead, a higher value of $\|v_{sign}\|_{th}$ reduces the number of false positives, at the cost of not being able to detect the less harmful falls from the lowest height.

6. Final remarks

This work presented an innovative algorithm for the detection of accidental falls from height, which triggers a the deployment of protective airbag. Specifically, the detection is based on a sequence of signal manipulation stages, aiming to extract the slow-varying dynamics related to the effect of gravity. Tested against experimental data, the proposed approach proved to be capable to detect falls from heights greater than 1 m, and be robust against the use of the regular use of the jacket. The month-long tests remarked that the algorithm cannot be active while operating with highly-intense vibration machines, causing undesired activations. For these applications, we believe that further investigations are required, since a general guideline on how to calibrate the tuning parameters is not available. In any case, despite the use of the system is rather straightforward and non-certified skills are required, we believe that properly trained workers could avoid triggering the airbag due to its incorrect use.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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