Man down situation detection using an in-ear inertial platform

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Abstract—Man down situations (MDS) are a health or life threatening situations occurring largely in high-risk industrial workplaces. MDS automatic detection is crucial for workers safety especially in isolated working conditions. However, many existing solutions suffer of multiple false alarms and long response times, reducing the confidence in this technology and its deployment in the industry. This project aims to improve this technology by providing a global MDS definition according to a combination of three observable critical states based on characterization of body movement and orientation data from inertial measurements (accelerometer and gyroscope): the worker falls (F), worker immobility (I), the worker is down on the ground (D). The MDS detection strategy was established based on the detection of at least two distinct states, such as F-I, F-D or I-D, over a certain period of time. This strategy was tested using a large public database, revealing a significant reduction of the false alarms rate to 1.1%, reaching up to 99% accuracy. The proposed detection strategy was also incorporated into a digital earpiece, designed to address hearing protection issues, and validated according to an in vivo test procedure based on simulations of industrial workers normal activities and critical states.

Index Terms—industrial wearables, man down, fall detection, occupational health and safety, lone worker, inertial sensors, data fusion

I. INTRODUCTION

Certain areas of industrial workplaces, like mining, forestry, construction and fire-fighting, are known as precarious and dangerous, involving numerous physical and mechanical hazards, as well as lone-work situations, that is, they are places where accidents and morbidity are more frequent. Labour laws require employers and industries to ensure employee protection by adopting preventive measures, appropriate safety equipment and occupational health and safety training. However, any given workplace will never be totally safe from accidents especially for a lone worker and high-risk workers. In this context, portable devices alerting a control center when an emergency is detected should be worn with main advantage to call help when worker is unable to do it on his own, either due to loss of consciousness or an incapacitating injury. These systems are therefore essential in ensuring occupational health and safety in the workplace, and their reliability is just as critical. Current market solutions do not meet industry requirements in terms of reliability, robustness and ease of use since they are plagued by relatively high false-alarm rates, overly long response times and poor ergonomics. The device may hinder the comfort of heavily equipped workers when it must be worn on the belt or chest, and some solution algorithm may take several tens of seconds or even minutes before the emergency alert is triggered. These flaws result in additional costs for employers, loss of confidence in the technology and lesser deployment of this technology in the industry.

According to the IRSST, falls from heights, from same level or from slips constitute the greatest causes of occupational injuries, responsible for more than 21% during 2010-2012 [1]. Compensation paid for victims of injuries in case of falls from heights are larger than the average and constitute a significant risk of decreased productivity and quality of life [2]. Many existing devices are designed to detect fall, but most researches, 327 studies conducted up until 2013 [3], and developments has aimed towards the elderly-care market since the elderly are vulnerable and most prone to fall. Several solutions use subject post-fall disability state, mostly characterized by immobility or down position state, to limit detection errors whenever the device fails to detect a fall occurrence, making it a very important aspect that should be included in a robust fall detection solution [3]. Moreover, the post-fall disability state duration is a direct factor of fall severity, weakness of the victims and mortality rate [3].

The EERS-CRSNG Industrial Research Chair in In-Ear Technologies (CRITIAS), who has developed a unique technology designed to protect industrial workers from noise-induced hearing loss, kickoffs this project to integrate a man down detection solution into a digital earpiece prototype by incorporating an inertial platform and addressing both issues with a single and simple solution. While some consumer MDS detection devices have recently been developed for elders using hearing-aid devices [5], there has been very few scientific studies on MDS detection usage in workplace. Moreover, MDS definition is not consistent through studies, distinguishing types of emergencies such as falls, dangerous substance exposure, health problems (stroke, incidents, heart attacks) or loss of consciousness [6], which some lead to more complex solutions, as vital signs monitoring (respiration,
heart rate and galvanic skin response sensors) and several environmental hazards detection (gas, chemicals, noise).

Without state-of-the-art scientific definition of man down situations, this project seeks a global and simple detection solution based on characterization of motion and orientation tracking using an in-ear inertial platform, for all emergencies faced by workers, where nature and causes of danger are innumerable, diverse and hard to predict considering all variables like workplace, work tasks, workers health, physiognomy, etc. The detection strategy and digital earpiece solution implementation will be validated using test scenarios inspired by typical activities performed by targeted workers.

II. MATERIAL AND METHODS

A. Motion and orientation tracking

The earpiece prototype used a STMicroelectronics LSM6DS3 inertial measurement unit (IMU), which has a 3-axis accelerometer, for linear acceleration measurements and a 3-axis gyroscope, for rotational speed measurements \( \omega = [\omega_x, \omega_y, \omega_z]^T \). Inertial sensors are affected by numerous measurement errors such as constant error sources due to cross axis coupling, scaling factors, orthogonal axis misalignment and measurement biases [7], and continuous errors that evolve over time due to random noise processes, including numerical quantification, random gyroscope angle walking, continuous random walk, bias stability, and continuous measurement drift [8]. Constant error sources are handled with unique static calibration while continuous errors are compensated with dynamic calibration over time. The iterative least-squares method proposed by [9] was used for acceleration measurement calibration since it does not require any external equipment and based on a large acceleration data set of multiple sensor positions. Since the direction and magnitude of the Earth’s gravity is known and constant, the compensation coefficients of the accelerometer model can be determined to correct acceleration vector norm that should ideally represent a unitary sphere centered at the origin. The rotational speed instantaneous bias is corrected firstly by subtracting the average rotational speed offset while the gyroscope is stationary (\( \omega = 0 \)). Then, correction of rotational speed bias drift is proceed by integrating the gyroscopes rotational errors with respect to the product of natural phenomena, with a probability density function of the mean or variance of feature signals segmented according to different time windows. The temporal mean \( \bar{s}(t) \) of a feature signal \( s(t) \) and a time window sampling \( \tau \) is given by

\[
\bar{s}(t, \tau) = \frac{1}{\tau} \int_t^{t+\tau} s(t) dt
\]

then, the temporal sampling variance is given by

\[
\sigma_s^2(t, \tau) = \frac{1}{\tau} \int_t^{t+\tau} (s(t) - \bar{s}(t, \tau))^2 dt.
\]

The extreme values of the feature signals are characterized according to two models of probability distributions. First, the normal distribution \( \mathcal{N}(\mu, \sigma^2) \), describing random events of natural phenomena, with a probability density function of a random variable \( X \) given by

\[
\text{pdf}_{\text{norm}}(X) = \frac{1}{\sigma \sqrt{2\pi}} \exp\left(-\frac{(X-\mu)^2}{2\sigma^2}\right), \quad x \in \mathbb{R}
\]

where \( \mu \) is namely the mean and \( \sigma \) the standard deviation.

Then, the Gumbel distribution \( \mathcal{G}(u, \beta) \), also known as the generalized extreme value distribution of type I (\( k = 1 \)), commonly used to predict rare events or extreme values of normal-type or exponential initial distribution data [14]. The probability density function is given by

\[
\text{pdf}_{\text{gumbel}}(X) = \frac{1}{\beta} \exp\left(-\frac{(x-u)}{\beta} \exp\left(-\frac{(x-u)}{\beta}\right)\right), \quad x \in \mathbb{R}
\]

where \( u \) is namely the distribution locality and \( \beta \) the scale, estimated by resolving the equation system based on maximum likelihood method [15] with \( \beta > 0 \).
D. Detection theory

The present study focuses on binary statistical test, also binary classification theory, which defines a mathematically formalized decision-making method based on known statistical models in order to make a predictive decision using an independent data set. The null hypothesis $H_0$ defines the decision that the event did not occur and the alternative hypothesis $H_1$ as the decision that the event did occur. The probability rates of event detection $P_D$ when the event actually occurred and the probability rate of a false alarm $P_{FA}$, also known as the type I error, are defined by the following equations:

\[
P_D = \Pr\{H_1|H_1\} \quad (9)
\]
\[
P_{FA} = \Pr\{H_1|H_0\} \quad (10)
\]

The detection performance is calculated according to the number of "positive" (P) and "negative" (N) results of detection as well as by their classification as "true positive" (TP), "false positive" (FP), "true negative" (TN) and "false negative" (FN) as follows their true classification. The accuracy indicates the detection behavior by evaluating the results of true predictions without considering the classification of the tests.

\[
\text{Accuracy} = \frac{(TP + TN)}{(P + N)} \quad (11)
\]

The Matthews correlation coefficient (MCC) is commonly used to evaluate the performance of predictive models, especially in personalized medicine (genetic testing, molecular analyzes, etc.), and represents a discretization of Pearson correlation for binary classification of two distinct groups [16]. The MCC given by

\[
\text{MCC} = \frac{(TP)(TN) - (FP)(FN)}{(TP + FP)(TP + FN)(TN + FP)(TN + FN)} \quad (12)
\]

reflects better evaluation of detection performance over accuracy.

The ROC curves or $P_D/P_{FA}$ are also commonly used to conduct a visual performance analysis for the entire detection range ($P_D \in (0,1)$). In this study, MCC is used to determine optimal time window sizes and critical states detection thresholds.

III. Theory

A. Man down situation definition

For the purpose of MDS detection, a global definition is proposed according to the observation of three distinct critical states, namely the immobility state (I), the fall state (F) and down position state (D). The combination of these critical states describes most of emergencies faced by workers in industrial workplaces. In this study, the fall state is defined as the falling phase pre-impact, characterized by a free fall and a large variation of the inclination of the body, and the fall-impact phase, which is characterized by a great force resulting from the collision of the body with either the ground or another object. The immobility state is defined as a low level of movement of the worker’s body during a significant time period. Finally, the down position state is simply defined by the near horizontal bodys angle.

![Fig. 1: Venn diagram of man down situations critical state sets](image)

The proposed hypothesis is that fusion of these three critical states enables a more accurate and reliable MDS detection. More specifically by looking for multiple combinations of concurrent critical states, named combinatorial state, describing each a particular set of MDS:

- F-I combinatorial state defines an emergency in which a person who has fallen remains inert thereafter, regardless of his final position;
- F-D combinatorial state defines an emergency in which a person who has fallen remains lying down on the ground thereafter;
- I-D combinatorial state defines an emergency in which a person is inert and lying down on the ground;

The man down situations are represented in the Venn diagram in Figure 1 as a function of critical state occurrences, summed up in the set $(F \cap I) \cup (F \cap D) \cup (I \cap D)$. However, the F-I-D combinatorial state is already implied in the combinatorial states sets and will not be referred to herein.

B. Detection algorithms

The extreme values of the feature signals from the inertial measurements constitute the detection strategy variables in regards to the fall, immobility and down position states characterization. The detection strategy consists of several processing and analysis stages in order to train the algorithm and predict the critical states occurrence. The training phase begins with the building of statistical distribution models of extreme values of feature signals, segmented by their respective optimally-sized time windows. Then, the optimal threshold for the detection of the critical states is based on the analysis of the fusion of the detection probability provided by the feature signals statistical models. At last, the F-I, F-D and I-D combinatorial states are obtained by applying a simple logic AND function on pairs of detected critical states considering the signal segmentation as well by optimal time window sizes. The prediction phase is the application of the detection strategy on independent data, based on the previous critical states characterization. Considering a given extreme value signal $E_s(t, \tau)$ of the feature signal $s(t)$ segmented according to a time window size $\tau_s$, as well as a detection...
threshold $\gamma_s$, the detection probability can be found by

$$P_D = \int_{E_s(t, \tau) \geq \gamma_s} \Pr\{E_s(t, \tau) | H_1\} dE_s(t, \tau)$$

(13)

$$P_{FA} = \int_{E_s(t, \tau) \leq \gamma_s} \Pr\{E_s(t, \tau) | H_0\} dE_s(t, \tau)$$

(14)

where the detection condition differs depending on the observed extreme value, the minimum (min) or maximum (max) extreme values of the feature signal.

1) Fall detection: The fall detection is based on the extreme values analysis of the average of acceleration norms $A(t)$, rotational speed norms $W(t)$ and tilt angle derivatives $\dot{\rho}(t)$ signals. The extreme values of these feature signals are analyzed and studied through the database fall scenarios, applying segmentation by time window to calculate the arithmetic mean over the time segment. The time window sizes differ depending on the transient nature of signals. Considering the proposed fall state definition, the extreme values analysis of fall detection feature signals are given by

$$E_F(t, \tau) = E_{F_{\min}}(t, \tau_{\min})$$

(15)

where $\tau_{\min} = [\tau_{\min}, \tau_{\max}]^T$ are the time window sizes. Since the feature signals transients do not necessarily coincide in time, the fusion function is defined as the product of the maximum detection probabilities from the individual extreme values analysis over a common time segmentation, as

$$L_1(E_F(t, \tau), \gamma_1, L) = \prod_{i=1}^{M_1} \frac{\text{mean}(\text{pdf}_{i}(E_{F_i}(t, t+\tau_{1,L}))}{\text{max}(\text{pdf}_{i})}$$

(19)

where $M_1$ is the number of feature signals and $\gamma_1$ is the time window size of the feature signals fusion. The expression of the immobility detection status signal is defined as

$$y_H(t) = \begin{cases} 0 & \text{if } L_1(E_F(t, \tau), \gamma_1) \leq \gamma_1 \\ 1 & \text{if } L_1(E_F(t, \tau), \gamma_1) > \gamma_1 \end{cases}$$

(20)

where $\gamma_1$ is the immobility state detection threshold.

3) Down detection: The body tilt angle variable is commonly used in fall detection algorithms to eliminate most of false positive results, by monitoring the vertical to horizontal transition of the body position (0° to 90°), where the post-impact stage of fall event is defined by a critical tilt angle value [17], [18]. Considering that a MDS does not necessarily involve a fall, down position state is, as proposed, an independent critical state. The down position state detection is based on extreme values analysis of the average tilt angle feature signal over a time segment, given by

$$E_D(t, \tau_D) = \left[\frac{\text{max}(\text{pdf}_{i}(E_{F,i}(t, t+\tau_{D}))}{\text{max}(\text{pdf}_{i})}, \tau_{D} \right]$$

(21)

where $\tau_D = [\tau_{D\min}, \tau_{D\max}]$ is the time window size. The interpretation of $\tau_{D\max}$ data can be altered by several unknown factors such as ground level, infrastructures, etc. Thus, the down position detection threshold is chosen by setting the type II error rate to 1% or $P_D = 0.99$. The function of down position state $y_D(t)$ is defined by

$$y_D(t) = \begin{cases} 0 & \text{if } E_{D}(t, \tau_D) \leq \gamma_D \\ 1 & \text{if } E_{D}(t, \tau_D) > \gamma_D \end{cases}$$

(22)

where $\gamma_D$ is the down position state detection threshold.

4) Man down detection: This study on man down situations solves the detection problem by generalizing these emergencies according to the combination of independent critical states occurrences, namely the combinatorial states. Indeed, based on the proposed global MDS definition in section [III-A] the detection strategy comes down to detect at least two different critical states occurrences in a certain time frame to identify a MDS. The combinatorial states detection is defined by the logical fusion of pairs of independent critical state detection, basically an AND operation over ANY critical states occurrence over specific time segmentation, as

$$y_{F-D}(t) = \bigvee \{y_{F}[t, t + \tau_{F-D}] \} \wedge \{y_{D}[t, t + \tau_{F-D}]\}$$

(23)

$$y_{F-D}(t) = \bigvee \{y_{F}[t, t + \tau_{F-D}] \} \wedge \{y_{F}[t, t + \tau_{F-D}]\}$$

(24)

$$y_{F-D}(t) = \bigvee \{y_{[t, t + \tau_{D}] \}} \wedge \{y_{D}[t, t + \tau_{D}]\}$$

(25)

where $\tau_{F-D}$ and $\tau_{D}$ are time windows of each combinatorial state. Thus, the MDS prediction is defined as the inclusive disjunction of the combinatorial states, expressed as a logical OR operation over the combinatorial states detection signals, as

$$y_{MDS}(t) = y_{F-D}(t) \vee y_{F-A}(t) \vee y_{D}(t).$$

(26)
C. Physical tests protocol

In order to validate the MDS detection strategy and the solution implementation within the CRITIAS digital earpiece, a formalized physical tests protocol is proposed. This validation also tests the detection algorithms using head movements, which differ from inertial measurements with IMU positioned at the waist as done in SisFall database. Also, the scenarios created by state-of-the-art protocols used in fall detection studies are not suitable for workers typical activities. Thus, the proposed physical tests are designed to mimic some ADL and typical worker activities that highlight extreme cases and frequent false alarms situations as well as test scenarios involving the critical states F, I and D, executed in a controlled environment.

The setup of the digital earpiece prototype is shown in Figure 2. A Bluetooth wireless module enables the IMU data transmission to a computer for post-processing purpose. The inertial data from the IMU was sampled at 100 Hz, which is half frequency used by the reference SisFall database.

The proposed physical tests protocol, described in Table I, includes tests that have already been used in protocols from other fall detection studies [19]–[21] and were also inspired from firefighter’s fitness assessment test [22]. The equipment used to perform the physical tests are: a chair, a flight of stairs, a mattress (≥0.75 m thick), a stick (1.5 m); a ball (0.30 m diameter, 10 kg); and a sled (20 kg).

![Fig. 2: Digital earpiece prototype](image)

### IV. Results

#### A. Detection algorithms

The fall scenarios from the SisFall database were used to characterize the distributions of extreme values of each critical state feature signals since they simulated all three critical states. Figure 3 presents the distributions and the estimated statistical model obtained through the optimal detection analysis, while the model parameters and the optimal time windows size, according to the maximum MCC values, are given in Table II. The time windows size results are given in samples which had 5 ms period in the database case. The detection algorithms performance and the parametric analysis from the training phase are presented in Figures 4, 5 and 6. Table III shows the performance results of critical states, combinatorial

| #   | Description                        | Time (sec) | Chair | Mattress | Stick | Ball | Sled |
|-----|------------------------------------|------------|-------|----------|-------|------|------|
| 1   | Take a Ground Object               | 5          | ✔     |          | ✔     |      |      |
| 2   | Long Bend (1 time)                 | 10         |       | ✔        | ✔     |      |      |
| 3   | Lean repeatedly (5 times)          | 10         | ✔     |          | ✔     |      |      |
| 4   | Lie down on the back               | 10         | ✔     | ✔        | ✔     |      |      |
| 5   | Lie on the floor on your stomach   | 10         | ✔     | ✔        | ✔     |      |      |
| 6   | Lie on the ground on the right side| 10         | ✔     | ✔        | ✔     |      |      |
| 7   | Lie on the ground on the left side | 10         | ✔     | ✔        | ✔     |      |      |
| 8   | Sit on a chair                     | 10         | ✔     | ✔        | ✔     |      |      |
| 9   | Stay                               | 10         | ✔     | ✔        | ✔     |      |      |
| 10  | Fall forward                       | 10         | ✔     | ✔        | ✔     |      |      |
| 11  | Fall backward                      | 10         | ✔     | ✔        | ✔     |      |      |
| 12  | Walk (20 meters)                   | 10         | ✔     | ✔        | ✔     |      |      |
| 13  | Run (20 meters)                    | 10         | ✔     | ✔        | ✔     |      |      |
| 14  | Alternate walk-run (40 meters)     | 20         | ✔     | ✔        | ✔     |      |      |
| 15  | Cough                              | 5          | ✔     | ✔        | ✔     |      |      |
| 16  | Up, down stairs (10 steps)         | 10         | ✔     | ✔        | ✔     |      |      |
| 17  | Jump on the spot                   | 5          | ✔     | ✔        | ✔     |      |      |
| 18  | Jump from the top of a chair       | 5          | ✔     | ✔        | ✔     |      |      |
| 19  | Jump a length without momentum     | 5          | ✔     | ✔        | ✔     |      |      |
| 20  | Jump a length with momentum        | 5          | ✔     | ✔        | ✔     |      |      |
| 21  | Roll                               | 10         | ✔     | ✔        | ✔     |      |      |
| 22  | Ground Crawl                       | 10         | ✔     | ✔        | ✔     |      |      |
| 23  | Roll a ball while moving           | 10         | ✔     | ✔        | ✔     |      |      |
| 24  | Roll a ball back                   | 10         | ✔     | ✔        | ✔     |      |      |
| 25  | Push a sled to weight              | 10         | ✔     | ✔        | ✔     |      |      |
| 26  | Hammer with two hands              | 5          | ✔     | ✔        | ✔     |      |      |

TABLE II: State features detection characterization

| Signal | Dist. | Locality | Scale | Window Size |
|--------|-------|----------|-------|-------------|
| $E_{\text{min}}$ | Normal | $\mu = 0.821 \pm 0.010$ | $\sigma = 0.0711 \pm 0.0033$ | 146±10 |
| $E_{\text{max}}$ | Gumbel | $u = 2.81 \pm 0.18$ | $\beta = 0.699 \pm 0.076$ | 25±3 |
| $E_{\text{F-I}}$ | Normal | $\mu = 3.435 \pm 0.045$ | $\sigma = 0.850 \pm 0.021$ | 81±3 |
| $E_{\text{D}}$ | Normal | $\mu = 2.6039 \pm 0.0059$ | $\sigma = 0.7816 \pm 0.0051$ | 60 |
| $E_{\text{I-D}}$ | Gumbel | $u = -4.8790 \pm 0.0302$ | $\beta = 0.2751 \pm 0.0046$ | 900 |
| $E_{\text{D}}$ | Normal | $\mu = -3.8673 \pm 0.0088$ | $\sigma = 0.8483 \pm 0.0084$ | 900 |
| $E_{\text{F}}$ | Normal | $\mu = -3.8721 \pm 0.0072$ | $\sigma = 0.7719 \pm 0.0060$ | 900 |

| State | $P_D$ | $P_{FA}$ | Window Size |
|-------|-------|----------|-------------|
| F     | 0.966±0.017 | 0.0222±0.0068 | 295±44 |
| I     | 0.828±0.033 | 0.135±0.023 | 530±67 |
| D     | 0.9889±0.0059 | 0.2822±0.0074 | 900 |
| F-D   | 0.955±0.016 | 0.0011±0.0018 | 960±232 |
| F-I   | 0.794±0.031 | 0.0037±0.0042 | 1500 |
| I-D   | 0.815±0.034 | 0.0086±0.0059 | 770±48 |
| MDS   | 0.9944±0.0037 | 0.0107±0.0053 | 1 |

TABLE III: States detection prediction results
states and MDS detection on independent tests using a 10-fold cross validation method.

Fig. 3: Extreme values distributions of critical states features signals

Fig. 4: Fall features performance analysis

Fig. 5: Immobility features performance analysis

Fig. 6: Features fusion performance analysis

B. Application-based validation

The summary of MDS and critical states detection performance of the proposed physical tests protocol are shown in Table IV. Three volunteers (men between 21 and 25 years old) performed 129 physical tests (92 tests of ADL scenarios and 37 tests of MDS scenarios).

| State | Detected | Not Detected |
|-------|----------|-------------|
| F-D   | 17       | 7           |
| F-I   | 18       | 6           |
| I-D   | 25       | 12          |
| MDS   | 30       | 7           |

| State | False Positives |
|-------|-----------------|
| F     | 6               |
| I     | 23              |
| D     | 17              |
| MDS   | 2               |

TABLE IV: Summary of physical tests protocol results
V. DISCUSSION

A. Detection algorithms

Results of fall features signals analysis demonstrates that the transient of extreme values signal \( E^\text{max}_p \) is by far the shortest with an optimal 125 ms (25 \times 5 \text{ ms/sample}) time window size. Other extreme value fall features signals \( E^\text{max}_\rho \), \( E^\text{max}_\rho \), and \( E^\text{min}_\rho \) have much longer optimal time window size, respectively of 300 ms, 405 ms and 730 ms. Fall detection based on \( E^\text{max}_\rho \) feature score the best detection rate, up to 95\%, but also generated the highest false positive rate. Considering the MCC, \( E^\text{max}_p \) had the best performance principally due to lowest false positive rate, making it the most relevant for fall state detection. The global fall scenarios prediction results over the SisFall database show persistent scores with an average accuracy up to 97\%. This rate is congruent with other study [23], which used a same level detection method and tested with same database.

Since the immobility state is based on non-transitory features, the detection certainty and detection performance increase with time window size, thus the optimal time window for each immobility state features is 900 samples (4.5 seconds), the longest window studied considering the finite length of database inertial measurement records. Immobility state features show similar detection performances although \( E^\text{min}_\rho \) is slightly ahead with higher precision rate and MCC.

For down position state detection, \( E^\text{max}_\rho \) feature has also non-transient characteristics, more distinctive with a longer time window, but has a significant error detection rate explained by the large tilt angle positions of some ADL scenarios. The average value of \( E^\text{max}_\rho \) distribution is 1.451±0.003 radian (≈83°), which is a little less than expected value for a horizontal position. The tilt angle threshold is set at 0.87 radian, or approximately 50 degrees, which sets the detection rate at 99\% for down position state based on fall scenarios of the database. The down position state is a good indicator of emergency occurrence despite a 28.2\% false alarm rate, issue that is mitigated by critical states detection fusion. Indeed, the F-D combinatorial state has by far the best potential of MDS detection with an accuracy rate exceeding 98\% and despite detection rates of combinatorial states are slightly lower than individual critical state detection rates, false positive rates are significantly reduced to well below 1\%. Critical state fusion is then essential to the reduction of false alarms rates and related undesirable impacts (loss of time, loss of confidence and costs), which are the main causes of insufficient deployment of MDS detection systems in geriatric practice and industrial sectors [3]. The effectiveness and reliability of the MDS detection strategy, based on the proposed global definition, is demonstrated by impressive overall prediction performance, with precision and detection rates over 99\% and an 1.1\% false alarm rate, thus confirming our hypothesis.

B. Application-based validation

The preliminary results of the proposed physical tests protocol show that time window size is a critical factor for detection of immobility state, mainly in order to reduce false positive. Also, even if inertial data was captured from a different location than data from SisFall database used for the training phase, i.e. the head instead of the waist, the fall detection performed well, correctly detecting 20 fall scenarios out of 24. This confirms the adaptability of the proposed detection strategy, given that only six false positive results of the fallen state were detected, all of which occurred during ADL scenarios involving jumps and high velocity motions. Otherwise, most of critical states detected over ADL scenarios tests were immobility and down position. The potential MDS false alarms were mostly rejected by the fusion algorithm and detection method since only a few critical state detection occurred during the same time window segmentation. Indeed, only two ADL scenario executions were wrongly classified as MDS, a meager 2.2\% false alarm rate, both during a test where the subjects lie down on the ground for a few seconds, which led to misinterpreting these situations as I-D states. These results confirm that the detection fusion function reduces the MDS false alarms conditions compared to the individual critical states detection. Thus, combinatorial states and MDS detection results also indicate a good overall detection performance with a detection rate of 81.1\%.

VI. CONCLUSION

Most research conducted on these types of detection methods have characterized the man down situations by a specific and isolated event such as a fall or the workers immobility, thus achieving a high detection rate of the specific event, but with somewhat more limited performances as to detecting actual man down situations.

This study has broadened the characterization of MDS into various combinations of distinct events, expressed as critical states: a fall (F), lying on the ground (D) and prolonged immobility (I); whereby any one of these critical states, if taken independently, does not fully characterize a MDS. Each critical state is the logical output of a simple detection strategy of its related event, based on an optimally calibrated threshold, which provides the best possible detection rate of the event. A relatively simple decision-making strategy, where these critical states are combined through logical fusion, can achieve a very high detection rate and a very low false alarm rate. The overall result is an integrated solution, using digital earpiece designed by the CRITIAS Chair, for the hearing protection of workers and an efficient man down situation detection device.

An enhanced physical tests protocol including additional MDS scenarios is needed to continue the detection algorithms training and validation process. Ideally, future work should focus on making an initial database using the earpiece on real workers from real work environment to analyze the actual worker’s movements and critical situations. The solution could also be integrated to digital earpieces for hearing aids and thus detect elderly falls, which are a larger-scale problem given that the elderly population tends to live alone and is more vulnerable to falls.

For optimization purposes, more complex machine learning methods such as neural networks can be applied to the proposed detection strategy. The digital earpiece integrating
the inertial platform could be enhanced by a left-right ear strategy in order to add redundancy and correlation between off-centered devices. Monitoring the worker’s vital signs has also been proposed in the literature for the early assessment of health problems, thus, the CRITIAS Chair is developing acoustic methods to measure vital signs with the digital earpiece. The instrumentalized digital earpieces could be used as a “black box” recording relevant information to understand causes of accidents or other events, similarly to the devices used on board aircraft.

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