Leveraging RF signals for human sensing: fall detection and localization in human-machine shared workspaces

Sanaz Kianoush*, Stefano Savazzi*, Federico Vicentini†, Vittorio Rampa*
and Matteo Giussani†
*Institute of Electronics,Computer and Telecommunication Engineering (IEIIT) of the National Research Council of Italy (CNR),
Via G. Ponzio, 34/5, 20133 Milano,Italy,
Email: {sanaz.kianoush, stefano.savazzi, vittorio.rampa}@ieiit.cnr.it.
†Institute of Industrial Technology and Automation (ITIA) of the National Research Council of Italy (CNR),
Via E. Bassini, 15, 20133 Milano, Italy,
Email:{federico.vicentini, matteo.giussani}@itia.cnr.it.

***Abstract*—Safe human-machine interactions promote high flexibility in collaborative workspaces. Fall detection and localization of the operator are major issues in ensuring a safe working environment. However, many proposed solutions are not applicable for deployment in industrial environments due to their performance limitations in practical contexts. In this paper, we propose an integrated framework for both localization and fall detection of operators inside a shared workspace that employs radio-frequency (RF) signal analysis in real-time. Multipath and non-line-of-sight (NLOS) scattering that affect RF signal propagation can be leveraged for human sensing in complex workspaces: the proposed system continuously monitors the fluctuations of the RF field across the space by a dense network of WiFi compliant radio devices operating at 2.4GHz. To increase the accuracy of the localization system, a sensor fusion algorithm using Extended Kalman Filter techniques is employed. The proposed method may be used for integrating measurements from both RF nodes and an additional image-based system. For fall detection, a Hidden Markov Model is applied to discern different postures of the operator and to detect a fall event by tracking the fluctuations of the wireless signal quality. Fall detector performances are validated through experimental measurements. The preliminary results confirm the effectiveness of the proposed approach for different body configurations and pre-impact postures to correctly detect a fall event. Finally, some results about sensor fusion for improved operator localization are presented.**

I. Introduction

Collaborative human-machine workspaces are increasingly interesting for production flexibility, especially e.g., in the domain of industrial robotics. In such shared workspaces no enclosures are present for extending the possibilities of interaction (see ISO 10218-2 [1] for industrial manipulators) or as the default operational mode (as in automated guidance vehicles, AGV, or in mobile manipulation solutions). Machines remain, nonetheless, hazardous and workers protection is the topmost key issue in manufacturing environments [2]. The range of safeguarding measures relies on the sensing information for extracting context awareness from the cooperative environment. Risk reduction measures, in fact, strongly depend on the possibilities of timely detection of hazardous situations. Hazards notably include the probability of collisions and the misplacement of operators with respect to a given task. Countermeasures for misplacement include, in fact, the operator localization (to detect operators in wrong places) and posture detection (wrong configuration in the right place). Operator fall detection is therefore a major aspect that combines full information about workers safety. It is also a substantial sensory input when working at heights above two meters or in places with dangerous gas and chemical vapors [3]. A fall detection system can be defined as an assistant device whose main objective is to raise an alert when a fall event has occurred. Fall detectors can be broadly categorized into two types: systems based on wearable devices [4] and sensor-based context-aware systems [5]. All solutions regarding both systems, with their strengths and weaknesses, can gain only partial confidence by users about their reliability for the deployment in real industrial environments. Specifically when workers safety is at stake, solid evidence in detection performance is the major driver for the monitoring system design choice. Provided that no single technology can solve the problem related to continuous operator monitoring (i.e., localization, status of proximity to machines, onset of hazardous events), the most promising solution is based on integrated data fusion methods. In this view, we propose a technique that is devised to contribute to such worker sensing ecosystem, making use of a distributed communication infrastructure that may be also be used for standard M2M tasks.

In this paper, we propose a novel approach to context-aware fall detection and operator localization that leverages the Radio-Frequency (RF) signal fluctuations for human sensing. Human motion and time-varying posture affects both RF signal attenuation and multipath propagation in such a way that it can be leveraged for ubiquitous sensing of humans in complex spaces. Recent research shows that the perturbations of the RF fields that are usually adopted for wireless data transmission (i.e., in the 2-5GHz bands) can be used as powerful sensing tool for a number of applications ranging from human body motion detection to localization. Radio devices deployed in the industrial space can therefore not only serve as ubiquitous communication interfaces, but they are also expected to incorporate novel sensing capabilities with

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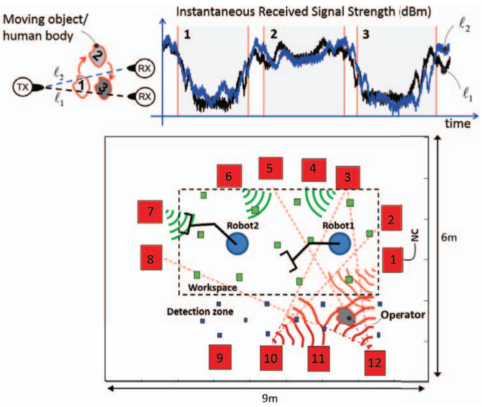

Fig. 1. Wireless network deployment in the Human-Robot shared environment: example of RF signal inspection for human sensing inside the detection area.

the goal of acquiring an accurate human-scale understanding of space and motion. The proposed system is designed to continuously monitor the fluctuations of the RF field across the workspace by a dense network of radio devices (see Fig. 1). These devices form a pre-existing or a newly deployed network placed at arbitrary locations around the monitored area and able to exchange digital information by exploiting any wireless industrial communication protocol (e.g., WiFi, IEEE 802.15.4, WirelessHART, ISA SP100). RF signals of interest are either narrowband or wideband, in licensed or unlicensed frequency bands, preferably above 2GHz to better capture human-induced fading. The presence, position and motion of a human body affect the nearby RF field in a predictable way, making possible to estimate and track its activity without the need to deploy and calibrate any additional wearable sensor (sensor-free detection), neither to ask for specific user actions (non-cooperative detection).

In this study, a log-normal model is defined where the received signal strength (RSS) mean and variance are expressed as functions of the human movement. When fall event is occurred, power fluctuation received by the wireless link in the covered area increases, while it reduces in stable situations, like sitting, standing or lying down. We apply Hidden Markov Model (HMM) [6] during real-time detection. We train the HMM using RF signal perturbations and the outputs i.e., human motion transition state and its observation probability, describe a reliable human fall detection indicator.

An important issue in human motion detection is the timing of sensing (refresh rate and latency). In this study, a robust sensor fusion approach is applied with a twofold purpose. First, a general sensor information blending is reckoned to be efficient when full reliability can only be obtained from the combination of multiple sources. Second, due to the relative low rate of RF and e.g., vision sources, the sensor fusion techniques make use of prediction filters that provide a faster likely detection at the cost of some larger spatial uncertainty.

The main contributions of this paper include: i) the definition and the experimental validation of a HMM method for fall detection and real-time localization of the operator in the workspace using fixed WiFi compliant devices deployed around the workspace area; ii) the design of a sensor fusion framework that integrates the sensor-less RF-based human sensing technology with image sensors (i.e., 3D Time-of-Flight cameras) for the purpose of fast real-time estimation of the most likely location/posture of operators by using slow samples.
The paper is organized as follows: the related work is reviewed in Sect. II. The proposed method for human fall detection is described in Sect. III, while in Sect. IV experimental measurements using software-defined radio devices are conducted. The sensor fusion framework is illustrated in Sect. V for operator localization inside the workspace area. Conclusions are presented in Sect. VI.

II. Related work

Systems and solutions developed to detect and localize the fall event can be divided into two main approaches based on the sensing technologies employed. The first approach is based on the use of wearable devices and sensors, such as accelerometers, wireless and posture sensors [7]. The second, classified as a context-aware system, is based on camera/video data, acoustic sources and/or other event sensing [8]. In most cases, the performance of the detector is expressed in terms of sensitivity (SE) and specificity (SP). The sensitivity is the ability of a detector to correctly classify a fall as a fall, while the specificity is the ability of a detector to correctly classify an activities of daily living (ADL) as ADL [9].

A. Wearable devices and sensors

Fall detectors on wearable devices and sensors can measure acceleration combined with other methods [10]. Their main objective is to discriminate between fall events and activities of daily living (ADL), like sitting down or going from standing position to lying down.

The vast majority of wearable fall detectors are in the form of accelerometer devices . Some of them also incorporate other sensors such as gyroscopes to obtain information about the position. The use of applications based on accelerometers and gyroscopes in gait and balance evaluation, fall risk assessment and mobility monitoring has been actively explored [11]. Cheng et al. [12] implemented daily activity monitoring and fall detection using a decision tree: A decision tree is applied to the angles of all the body postures and recognize posture transitions. They considered the four types of falls: from standing to face-up lying, face-down lying, left-side lying, and right-side with SE equal to 95.33 %. Dynamic gait activities are also identified using Hidden Markov Models through surface electromyography signals along with the acceleration signals.

Today's smart-phones come with a rich set of embedded sensors, such as an accelerometer, digital compass, gyroscope, GPS, microphone, and camera [13]. However, looking to the industrial domain, the trend towards smart phone-based detectors poses several problems. Smart-phone devices were not initially intended for fall detection and localization nor for safety critical applications [14]. In addition, in some cases they are not applicable for industrial workplaces where operators are not allowed to use personal devices.

B. Context-aware systems

These systems use sensors (i.e., cameras, floor sensors, infrared sensors, microphones, sound and pressure sensors) deployed in the environment to detect falls. Their main advantage is that the operator in workplace does not need to wear any special device. However, their operation is limited to confined spaces where the sensors have been previously deployed [8].

Liu et al. [15] investigate acoustic fall detection system to recognize backward, forward and sideways falls (balance, lose consciousness, trip, slip, reach chair, couch) with 97% specificity. However, the proposed approach performance is closely related with different ground and floor.

Li, et al. [16] use a audio sensors (i.e., microphone together with a floor vibration sensor). However, only limited results on automated fall detection are reported. Sensors, from other devices, for example the Kinects infrared sensor can also be used to create a fall detection system.

Video-based technologies are also exploited for fall detection [17], but video-based technology has the weak script of limited detection range, and it may disclose the personal privacy.

Although there has been much research on both wearable devices and context-aware systems, there are still significant issues which could hinder the system performance, particularly for industrial workspace [18]. Moreover, in the context of functional safety, not all plant operators are supposed to wear a radio tag supporting fall detection and localization.

III. RF-BASED FALL DETECTION

The system under consideration consists of a pre-existing deployment of networked wireless field devices exchanging digital information and measuring the RSS from multiple links, forwarding these measurements to a Gateway node serving as access point (AP) (see the simplified setting in Fig. 2). RSS fluctuations have been analyzed to identify human motion and localize the operator [19]. The problem under study in this section is to identify and discriminate operator falling (described by the state variable F_1) from a "safe state" (indicated as F_0) corresponding to an operator located in a known position $\mathbf{x}_t$ inside the workspace and in safe conditions (i.e., sitting, standing or walking inside the detection area). Human fall detection is carried out by processing the RF signal strength (received signal strength - RSS) measurements taken over L peer-to-peer links and real-time collected/processed by the AP up to time t. Note that the operator does not need to carry any electronic device and is assumed to freely move within the detection area by covering (in the safe state F_0) the locations $\mathbf{x}_t \in \{\mathbf{H}_m\}_{m=0}^{N_H} = \bar{\mathcal{H}}$, with $\mathbf{x}_t = \mathbf{H}_0$ indicating the operator located outside the detection zone and N_H the number of monitored positions. Fall detection carried out in this section assumes the position $\mathbf{x}_t$ of the operator in the shared workspace as known or estimated ($\widehat{\mathbf{x}}_t = \mathbf{H}_{\widehat{m}}$) by following the procedure illustrated in [18], and also summarized in Sect. V.A. The operator falling state is not directly observable and is hidden in to the RSS measurements: this suggests the adoption of an Hidden Markov Model (HMM) approach.

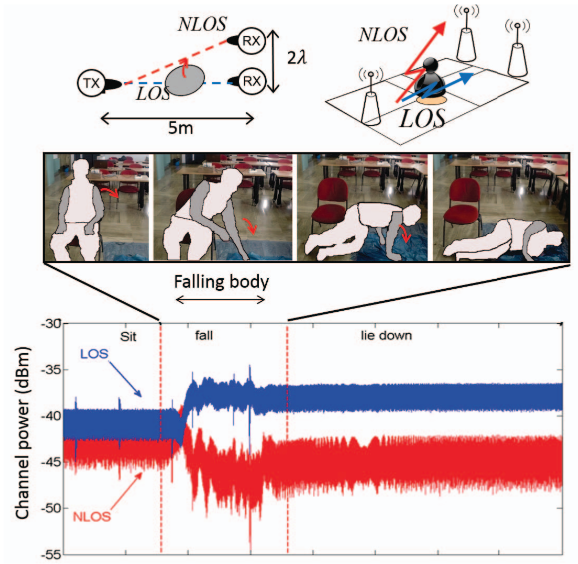

Fig. 2. RF signal perturbations over time for two co-located wireless links (in Line-of-Sight - LOS - and non-LOS, respectively), considering an operator in non-safe state (sitting, falling and lying down).

A. Signal model for fall detection

As depicted in the example of Fig. 2, a human body falling from a safe position $\mathbf{x}_t = \mathbf{H}_m \; \forall m > 0$ (e.g., from sitting or standing in safe state F_0) is monitored by two co-located wireless links. Body movements result in a pattern of RSS shifts with predictable stochastic properties. We define the temporal sequence of T RSS observations corresponding to a human body falling as $\mathbf{O}_\ell = \mathbf{O}_\ell(F_1) = [o_{\ell,1}, o_{\ell,2}....o_{\ell,T}]$, with $o_{\ell,t} = o_{\ell,t}(F_1)$ being the RSS observed at time $1 \leq t \leq T$ and over a wireless link $\ell \in \mathcal{L} = \{1, \ldots, L\}$. Observation (or RSS) at time t embed the information about hidden state $q_{\ell,t}$

$$o_{\ell,t}(F_1|\mathbf{H}_m) = q_{\ell,t}(F_1|\mathbf{H}_m) + w_{\ell,t}(F_1|\mathbf{H}_m) \tag{1}$$

with superimposed disturbance $w_{\ell,t} \sim N\left[0, \sigma_\ell^2(F_1|\mathbf{H}_m)\right]$ accounting for random fading, background noise and possible time-warping effects during RSS collection. Hidden states $q_{\ell,t} \in \mathcal{S}_\ell(\mathbf{H}_m) = \{S_1, S_2, ..., S_{N_\ell}\}$ model the "embedded" temporal sequence of average RF signal attenuations (or shifts) observed over link ℓ and corresponding to the human body falling from position $\mathbf{H}_m$. The states follow the Markov property and are therefore characterized by a stationary state transition probability distribution $\mathbf{A}_\ell(\mathbf{H}_m) = \{a_{ij}\}$, where

$$a_{ij} = P[q_{\ell,t+1} = S_j | q_{\ell,t} = S_i], \qquad \forall i, j. \tag{2}$$

In the following section, we investigate fundamental problems, regarding the Hidden Markov Model (HMM) design, namely: the evaluation of the probability (or likelihood) of a sequence of observations given a specific HMM model (evaluation phase) and the adjustment of model parameters to best account for the observed signal (training phase). Calibration o HMM parameters is instead discussed in Sect. III.B.

B. Hidden Markov Model-based fall detection

The hidden Markov model for monitored link ℓ and operator falling from position $\mathbf{H}_m$ is characterized by the following elements: i) the N_ℓ states $\mathcal{S}_\ell(\mathbf{H}_m) = \{S_1, S_2, ..., S_{N_\ell}\}$; ii) the state observations manifold, i.e., in terms of M RSSs in the range $\mathbf{V}_\ell = \{v_1, v_2, ..., v_M\}$ with $v_1 = \min_t[o_{\ell,t}]$ and $v_M = \max_t[o_{\ell,t}]$; iii) the state transition probability distribution $\mathbf{A}_\ell(\mathbf{H}_m)$; iv) the observation probability in each state j, $\mathbf{B}_\ell(\mathbf{H}_m) = \{b_j(k)\}$,where

$$b_j(k) = P[o_{\ell,t} = v_k | q_{\ell,t} = S_j], \qquad \forall j, \quad \forall k; \tag{3}$$

v) the initial state distribution $\boldsymbol{\pi}_\ell = \{\pi_i\}$,

$$\pi_i = P[q_{\ell,1} = S_i], \quad \forall i. \tag{4}$$

Given a RSS observation sequence over T samples $\mathbf{O}_\ell$ and the corresponding HMM model sets $\lambda_\ell(\mathbf{H}_m) = (\mathbf{A}_\ell, \mathbf{B}_\ell, \boldsymbol{\pi}_\ell)$ $\forall \ell, i$ characterizing the operator falling for each monitored link and operator position, the detection system iteratively computes the likelihood functions $P[\mathbf{O}_\ell | \lambda_\ell(\mathbf{H}_m)]$ of the observation sequence and makes a decision based on this value.

For a given link ℓ and operator position $\mathbf{H}_m$, the likelihood function is obtained iteratively as [6]-[26]

$$P[\mathbf{O}_\ell | \lambda_\ell(\mathbf{H}_m)] = \sum_{i=1}^{N_\ell} \alpha_T(i). \tag{5}$$

where

$$\alpha_{t+1}(i) = \Big[\sum_{i=1}^{N_\ell} \alpha_t(i) a_{i,j}\Big] b_j(o_{\ell,t+1}), \quad 1 \leq t \leq T-1, \forall i, \tag{6}$$

while at initialization

$$\alpha_1(i) = \pi_i b_i(o_{\ell,1}), \quad 1 \leq i \leq N_l. \tag{7}$$

For fall detection we adopt an hard decision metric on each link: a threshold value τ_ℓ is applied to the likelihood function (5) to detect a possible falling pattern in the surrounding of the considered link. Non informative links are purged according to the known link deployment. Given L links the probability of falling detection given the operator position $\mathbf{x}_t = \mathbf{H}_m$ is thus evaluated as

$$\mathrm{P}_{\text{fall}} = \frac{1}{L} \times \sum_{\ell \in \mathcal{L}} \mathbf{1}_{P[\mathbf{O}_\ell | \lambda_\ell(\mathbf{H}_m)] > \tau_\ell} \tag{8}$$

with $\mathbf{1}_{x>\tau_\ell}(x)$ being the indicator function for link ℓ: $\mathbf{1}_{x>\tau_\ell}(x) = 1$ if $x > \tau_\ell$ and $\mathbf{1}_{x>\tau_\ell}(x) = 0$ otherwise.

For model training, we use an iterative Baum-Welch [6] procedure to adjust the parameters characterizing the HMM $(\mathbf{A}_\ell, \mathbf{B}_\ell, \pi_\ell)$ for each link and operator position. Given a set of training RSS data the HMM parameters are chosen to maximize the probability of the observation sequence given the model.

IV. Experimental activity

In this section, experiments are designed to evaluate the fall detection algorithm performance as well as the ability of the algorithm to discern the fall from other operator activities. Experimental results include the fall detection algorithm sensitivity to different human body types and real time detection, and its specificity to recognize falling from sitting and standing activities.

A. Experimental setup

An hardware platform has been set up for the experiments based on software defined radio devices deployed in predefined positions and exchanging digital information over 2.4GHz bands and using a WiFi (IEEE 802.11b) compliant physical layer radio interface. A depicted in Fig. 2, a single antenna transmitter is communicating with a receiver employing two antennas (with spacing of $2\lambda \simeq 24cm$, and λ being the propagation wavelength), the receiver is connected to the AP and processing the RSSs observations from $L = 2$ wireless links (in Line-of-Sight - LOS - and obstructed by the operator or in non-LOS - NLOS, respectively). The RSS measurements corresponding to human falling have registered for 10 seconds while RSS sampling time is 2 microseconds. We implemented two scenarios regarding two subjects with dissimilar body builds for each scenario. In the first scenario, the subject sits on a chair and falls after 4 seconds, while in the second scenario, the subject stands and falls after 5 seconds. Measurements are obtained for 5 consequent observations for real time monitoring in presence of WiFi traffic interference.

B. Experimental result

1) Hidden Markov Model training: As discussed in Sec. III-B, during training phase the model parameters are estimated. Fig. 4 represents state probability over time for NLOS link. Y axis shows the 7 estimated states using the Markov Model (i.e., defined in terms of relative RSS attenuation with respect to operator in safe state F_0). Colored spectrum shows the evolution of state probabilities over time and highlight the distribution of RF perturbation.

2) Fall detection: In order to detect the fall event, we set threshold value, τ_ℓ for the likelihood corresponding to each link in 5. Fig. 5 shows the likelihood and threshold level corresponding to the LOS and NLOS links for the windowing signal. If the alarm system obtains the likelihood more than the threshold value, the alarm raises.

3) Fall detection for humans with different heights: We have selected two test subjects with 160 and 180 cm heights. Subjects with dissimilar body builds are deliberately chosen to study the potential effect of the height on the results. Fig. 6 shows fall detection and the corresponding likelihood function (5) for LOS and NLOS links for both subjects with threshold levels. Different heights cause different fall velocity and thus different signal perturbations. Fig. 6 confirms that fall detection algorithm tracks fall event accurately, regardless of the human height. Also, the use of fall detection algorithm based on the HMM modeling is effective to balance time-warping effects among partially aligned sequences (due to random/imperfect body movements).

4) Fall detection and pre-impact posture: Fig. 7 shows that the fall detection algorithm recognizes fall event from sitting and standing, pre-impact activities, due to HMM clear discrimination even for small perturbations.

V. Operator localization and sensor fusion

Stand-alone fall detection of operators in industrial environments pairs with the broader service of operator *localization* inside some man-machine shared workspace. Actions that

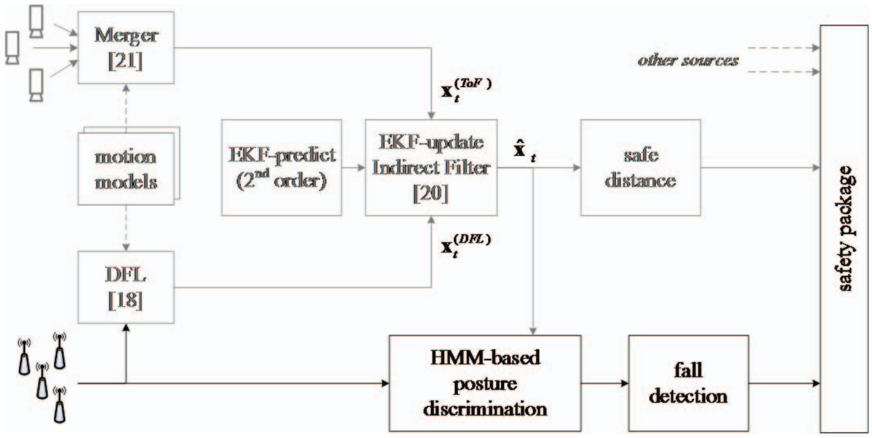

Fig. 3. Integrated sensor fusion scheme for localization (gray) and fall detection (black) modules, all concurring as multiple inputs to a safety package for worker protection.

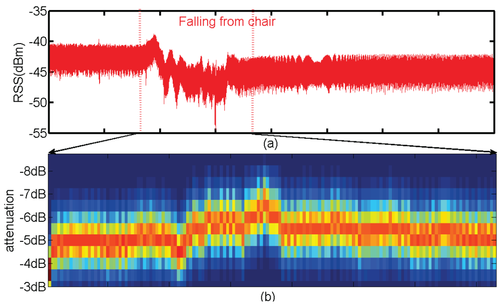

Fig. 4. (a) The recieved signal, (b) Markov model state probability over time for 6 estimated states (i.e., RF signal attenuation level) over NLOS link.

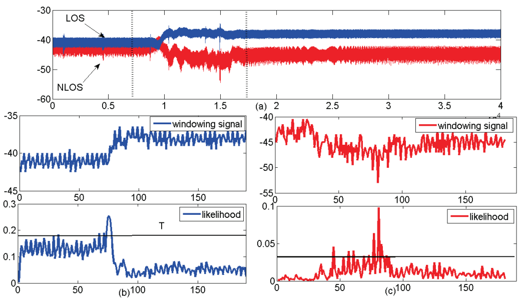

Fig. 5. Likelihood and threshold for fall detection, (a) recieved signal, (b) LOS link,(c) NLOS link

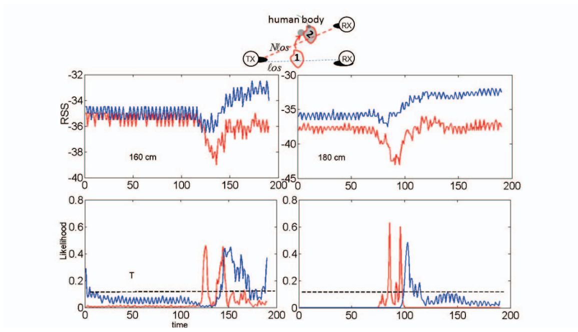

Fig. 6. Fall event and RF signal perturbations and related likelihood for two subjects with different heights, (a) 160 cm, and (b) 180 cm over LOS and NLOS links.

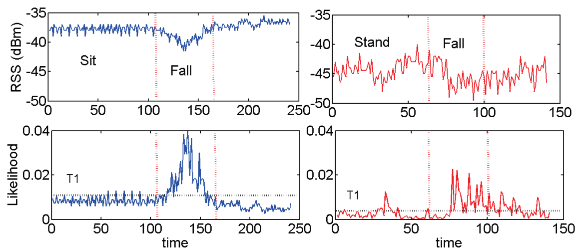

Fig. 7. Real time fall tracking and pre-impact postures, (a) fall from sit, and (b) fall from stand for NLOS link.

might be taken on the onset of falling depend on the analysis of potential hazards, which in turn are task-dependent and, consequently, location-dependent. As introduced in Sect. III, RF systems appear as a complementary enabling technology for workers localization because it differentiates from e.g., vision in strengths/weaknesses. As a matter of fact, sensor fusion is reckoned as the mainstream approach to blend reliable information at a detection rate compatible with worker safety assessment. Workers hazardous situations are intrinsically fast (i.e., falling or walking into collision), in the range of $[0.5, 2]$ m/s of human speed. Sensing information has not only to be fused but also to be provided at frequency high enough to capture such events. The following subsections are discussing (V-A) a sensor-less localization approach making use of the introduced wireless architecture and (V-B) the sensor fusion methodology adopted for human motion over-sampled estimation.

A. Sensor-less RF-based positioning algorithm

The problem is to detect the presence and the position of a single target (i.e., the operator) in safe state (i.e., not falling, nor lying on the floor: F_0) moving inside a workspace shared with moving obstacles, e.g., a robot arm. Standing the same considerations for fall detection (weaknesses in wearable technologies), it might not be straightforward to have workers wearing a radio tag supporting localization. The Device-Free Localization (DFL) approach is based instead on the analysis of the fluctuations of radio-frequency (RF) electromagnetic waves (originated by a pre-existing wireless network) to detect the presence of obstructing people [22]-[23] and, in turn, to track their positions.

Operator localization is based on the RSS measurements taken over the same L peer-to-peer links used for fall detection (see Sect. III). Similarly as for fall detection, the target position $\mathbf{x}_t$ is not directly observable but it is hidden into the noisy RSS measurements $o_{\ell,t}$ Single target localization can be based on the maximum likelihood estimation (MLE) algorithm [18] where RSS measurements $o_{\ell,t}(\mathbf{H}_m|F_0)$ are characterized, $\forall \ell \in \mathcal{L}$, in terms of absence (i.e., $\mathbf{x}_t = \mathbf{H}_0$) or presence (i.e., $\mathbf{x}_t = \mathbf{H}_m$) of the target in the covered area as

$$o_{\ell,t}(\mathbf{H}_m|F_0) = \begin{cases} h_\ell(\mathbf{H}_0|F_0) + w_\ell(\mathbf{H}_0|F_0), & \text{if } \mathbf{x}_t = \mathbf{H}_0 \\ h_\ell(\mathbf{H}_m|F_0) + w_\ell(\mathbf{H}_m|F_0), & \text{if } \mathbf{x}_t = \mathbf{H}_m. \end{cases} \tag{9}$$

For target absent, $h_\ell(\mathbf{H}_0|F_0)$ and $w_\ell(\mathbf{H}_0|F_0)$ represent, in terms of average received power, the effects of fixed obstructions on propagation and the effects of variations in the surrounding environment in terms of random shadowing, respectively. In case of target presence, the measured RSS is subject to a perturbation that depends on the specific location $\mathbf{H}_m$. Therefore, both deterministic path-loss $h_\ell(\mathbf{H}_m|F_0)$ and random fading $w_\ell(\mathbf{H}_m|F_0) \sim N(0, \sigma_\ell^2(\mathbf{H}_m|F_0))$ provide information on the target location and are thus modeled as function of $\mathbf{H}_m$. The target location is estimated with the MLE algorithm: the joint log-likelihood $\Lambda(\mathbf{O}_t|\mathbf{H}_m, F_0))$ with $\mathbf{O}_t = [o_{1,t}, ..., o_{L,t}]$ collecting the RSS observations for all monitored links at time t, is evaluated, $\forall m = 0, ..., N_H$ as

$$\Lambda(\mathbf{O}_t|\mathbf{H}_m, F_0) = \sum_{\ell=1}^{L} \ln \left[P(o_{\ell,t}|\mathbf{H}_m, F_0) \right]. \tag{10}$$

with likelihood function for RSS sample $o_{\ell,t}$

$$P(o_{\ell,t}|.) =$$

$$= \frac{1}{(2\pi)^{1/2}\sigma_\ell(\mathbf{H}_m|F_0)} \exp\left\{ -\frac{1}{2} \frac{\left[s_{\ell,t} - h_\ell(\mathbf{H}_m|F_0)\right]^2}{\sigma_\ell^2(\mathbf{H}_m|F_0)} \right\}.$$

Finally, the target location is estimated as $\widehat{\mathbf{x}}_t = \mathbf{H}_{\widehat{m}}$ where

$$\widehat{m} = \underset{\mathbf{H}_m}{\mathrm{argmax}} \Lambda(\mathbf{s}_t|\mathbf{H}_m, F_0). \tag{11}$$

B. EKF approach to sensor fusion

The target location from DFL ($\mathbf{x}_t^{DFL}$ in Fig. 3) is fused with other sensors (e.g., cameras) in order to provide an oversampled observation of the target *likely* location.The data from the sensors is fused to a combined estimate resulting in a more accurate localization.The resulting estimation $\widehat{\mathbf{x}}_t$ may be used directly for collision detection of the target (e.g., obstacle avoidance in the case of human-robot workspace) *and* for injecting information on the fall detection function (Fig. 3). The fused target localization is the result of a standard Extended Kalman Filtering (EKF) as in [20]. The predictor is a fast motion estimation based on second-order kinematics model [24] (or a random walk, alternatively). The prediction rate is as fast as 1kHz so to provide timely yet

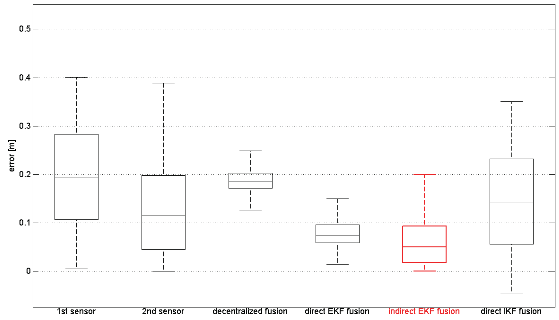

Fig. 8. Performance comparison of sensor fusion schemes: distribution of RMSE along a sample simulated human-motion trajectory. Algorithm with the best performance in red.

inaccurate location information. Recall that for safety purposes it is judged preferable to have spatially uncertain information rather than no information during a blind timeframe between samples. The update step is in the form of the Indirect Filter approach, which plainly merges the fusing sources without pre-filtering and/or feedforwarding/feedbacking. We verified that Indirect Filtering is best performing (see Fig. 8) in the given experimental setup w.r.t alternative schemes [25]. For the purpose of designing the fusion scheme, the fusing sources are generated with different levels of sampling noise and different prediction/update ratios (i.e., number of guesses without sensor information).

The inaccuracy of fused information is derived from the filter covariance. In any estimated position, target inaccuracy can be represented with a circumference centered in the estimated position and radius equal to 2σ. The envelope of these circles create a variable 2D spatial boundary around the estimated trajectory (right part of Fig. 9). The variability of spatial boundary largely depends on the prediction update ratio. Performing the same trajectory with a larger prediction/update ratio, makes the average size of the uncertainty to grow, as reported in Fig. 10.

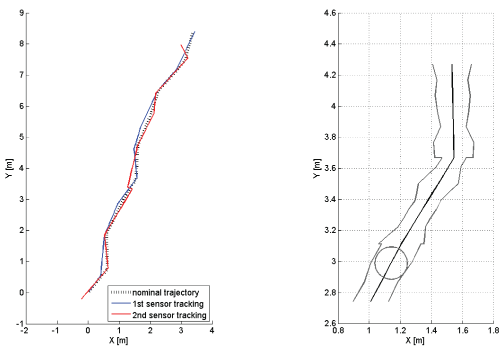

Fig. 9. Sample trajectory 2D projections: (left) nominal trajectory and sensors samples; (right) zoom-in of the estimated target path (black) with a 2σ-wide confidence (gray circle), enveloped (gray) all along the path.

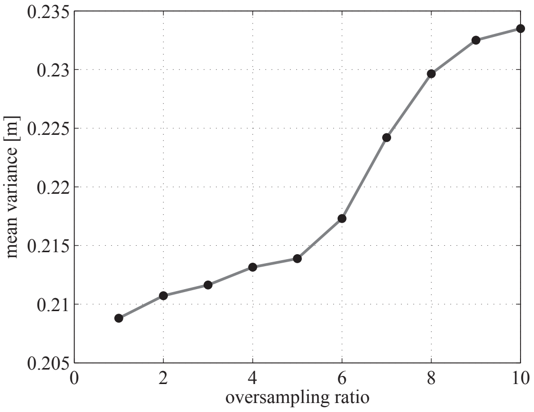

Fig. 10. Mean squared error of the estimated path localization, fused from 2 sources, under different prediction:update ratios. Slow sensors make the ratio to increase, increasing the filter covariance.

VI. Conclusions

This paper described a device-free fall detection and localization approach in human-machine shared workspaces. The proposed algorithm exploits RF signal perturbations, obtained through wireless devices deployed around the workspaces, to extract human motion and posture features. The location-based Hidden Markov Model exploits features to detect the fall event. Also, a sensor fusion scheme using both image-based sensors and RF devices is proposed to provide oversampled measurements to localize the operator. Experimental activity was conducted to validate the algorithms while preliminary results confirm the effectiveness of the approach in terms of sensitivity and specificity to detect fall events. Future developments will be focused on body action/gesture recognition for fall prediction.

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