A Pervasive Solution for Risk Awareness in the context of Fall Prevention

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***Abstract*—In the present work, we introduce Fallarm, a pervasive fall prevention solution suitable for hospitals and care facilities, as well as for home settings. We applied a multifaceted intervention strategy based on closed-loop information exchange between proactive and reactive methods: comprehensive assessment protocols determine the individuals' risk of falling; an innovative device continuously monitors subjects' activities, and it provides patients with constant feedback about their actual risk. Thus, it increases their awareness; simultaneously, it realizes measures to prevent adverse events, and it reports any incident and aims to reduce the level of injury. As a result, our solution offers a comprehensive strategy for the remote management of a person's risk of falling 24 hours a day, enabling many vulnerable people to remain living independently. In this paper, we detail the architecture of our system, and we discuss the results of an experimental study we conducted to demonstrate the applicability of Fallarm in both clinical and home settings.**

Keywords-activity monitoring, multimodal feedback, patient safety, telemedicine.

I. INTRODUCTION

Patient falling is the most reported adverse event within the majority of organizations that provide inpatient services. Although 96% of trips and slips result in minor injuries or no harm [1], falls have both human and financial consequences: individuals suffer from distress and loss of independence, and patients can experience a significant decrease of confidence in the level of care provided [2]. Furthermore, older people who have fallen once and have suffered from fall-related injuries are at a higher risk of falling again [3], and they experience a fear of falling that progressively isolates them. Severe harm occurs in a minority of events [5], but falls can cause serious damage (occasionally, they can also lead to death) and generally they increase the length of stay [1]. Additional consequences involve patients' relatives and hospital staff, who can feel anxiety and guilt. The monetary cost of falls has also a noteworthy impact on the finance of hospitals and geriatric care institutions [4]. This might involve short-term costs (i.e. additional investigations and healthcare) as well as long-term expenses (i.e. prolonged treatments, rehabilitation, and legal actions, such as claims of negligence). Huge amount of research studies reports about residential communities and, more substantially, hospitals. According to [1], the overall cost of falls in hospitals in the UK is estimated as £15 million per year. Over £3 million are spent for compensations after litigations. Moreover, the worldwide cost of falls is expected to reach £22 billion in 2020 [4].

Recently, subjects falling at home gained the interest of health professionals. In the last decade, methodological strategies and technological interventions were defined to prevent adverse events. Unfortunately, these measures were generally found to be too restrictive (from a patient's mobility point of view), and limited in terms of efficacy [6]. All the current systems realize targeted interventions, either on the service provider side (i.e. assessment tools, incident reporting) or on the client side (i.e. technological aids for individuals).

Conversely, we adopted a multidisciplinary approach, and our aim is to offer a scalable solution for hospitals and for geriatric care facilities, as well as for home settings. Our system takes into consideration that risk of falling increases proportionally with the exposure to a multitude of different factors (over 400 were identified). Although many different classifications exist, we focused on the causes of falls that are categorized as intrinsic and extrinsic [19]. The former is related to the biological situation of the patient (i.e. age, decline of physical faculties) and to behavioral factors (i.e. unbalanced diet, sedentary attitude). The latter comprises environmental conditions (i.e. slippery surfaces, narrow stairs) and socioeconomic factors (i.e. unprivileged economic status). To this end, our system supports the risk assessment tools (i.e. Stratify, Tinetti balance scale) that are currently employed to proactively evaluate patients who are at risk [20]. Moreover, there are circumstances (i.e. taking a shower, going to the toilet) in which the probability of falling arises. Thus, Fallarm realizes activity monitoring using a wearable device attached to patients' wrist. Our system interacts with the users, who are provided with multimodal feedback about the current risk of falling, in order to increase their awareness. Furthermore, Fallarm realizes a closed-loop integration of proactive and reactive techniques: upon detection of an adverse event, our system instantaneously reports the incident to the care provider, and it solicits immediate intervention; nevertheless, data about adverse events are organized into fall investigation documents that can be used to plan additional, long-term countermeasures.

The rest of this document is structured as follows. In the next section we describe the main achievements of the state of the art. Then, we bring in the architecture of our system, and we detail the Care Service and the Monitoring Device in section 3, 4 and 5, respectively. In section 6, we discuss the preliminary results of an experimental study involving both hospitalized patients and home-resident subjects. We conclude with section 7, in which we also introduce our future work.

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II. Related Work

During the recent years, hospitals and care facilities mainly focused on the assessment phase. Nonetheless, the most supported intervention strategies aim at increasing the awareness. With respect to the staff, visual cues (i.e. colored wristbands or bedside symbols) distinguish classes of patients at risk of falling (i.e. high, medium, or low). However, there is no evidence that such methods reduce the number of falls [7], because they are not clearly noticeable to the staff. On the other hand, the main concern with visible symbols involves loss of privacy [1]. Furthermore, visual cues are not suitable for Ambient Assistive Living (AAL). Other policies consist in moving the patients who are most likely to fall into an area in which they can be constantly controlled by nurses or volunteer caregivers. This reduces patients' privacy and introduces additional stress. Moreover, apart from being expensive, these policies have no significant impact on the reduction of the fall rates [8].

Nowadays, a wide range of commercial devices [9] (i.e. bed pressure pads) are available, especially for the elderly. Most of them belong to the category of the so called inactivity monitoring systems, because they ensure that patients are not at risk of falling until their mobility is restricted. These devices mainly rely on proximity sensors: they remind subjects to wait for assistants' help whenever they attempt to move from their position. Unfortunately, there is no evidence that inactivity monitoring systems are effective in preventing falls [1]; also, they introduce frustration, and they are not suitable for patients whose mobility should be encouraged, even though they are at high risk of falling (i.e. subjects in rehabilitation).

Different research groups focused on fall detection. Tamura et al. [10] developed a device to be attached to the left lumbar region of the subject. It relies on a photo-interrupter to record the time at which falls occur in an ambulatory. The authors of [11] present a Body Area Network of smart sensors that continuously monitor physiological signals (such as blood pressure and ECG) of patients. In [12] accelerometers are integrated with wireless technology so that sensors mounted in cellular phones can exchange data with a network of services for AAL. Specifically, after a suspected fall is detected, the phone is used to request a vocal response (or a key press) from the user; nonetheless in the case that a user is not responding, the phone will automatically call an operator who will analyze the situation, using video streamed by the camera included in the phone. BigNurse [15] monitors patient at home or at the hospital, but it does not take into consideration the problem of falls. Nowadays, wearable fall detectors to be attached to the hip are commercially available [13]. Indeed, they are distressing, especially during sleep. Instead, [14] details a comfortable fall detector embedded into a wrist watch. However, the algorithm is unable to cope with the six degrees of freedom of the arm, because the device does not have a reference position.

Unfortunately, all the above solutions suffer from poor efficacy, and there is a high number of false alarm and missed detections. Hybrid fall detection systems (implementing user-centric inertial sensors and wall-mounted vision-based devices) may be more reliable, as they achieve better performances, but at the cost of a more complex infrastructure. Simbad [16] and UbiSence [17] use respectively pyroelectric sensor arrays and cameras to track patients during their movements. In [18], when a suspected fall is detected by the accelerometers mounted on a unit attached to the subject, fixed image sensors transmit information about their field of view to the monitoring center: an operator analyzes the posture of the subject and determines if an accident occurred. Nevertheless, vision based systems are effective only if the whole environment is equipped with cameras. Also, image sensors may fail in hospitals and where more there is more than one subject in their field of view.

III. Fallarm

Our idea exploits the integration of proactive and reactive methods (already used by health care services) with activity monitoring (realized real-time by a wearable equipment) to improve the performance of our fall detection system. This consists of an interactive device that is attached to patients' wrist. This acquires information about the mobility parameters of the subjects by means of inertial sensors. Clinical know-how is exploited to assess the individuals' risk of falling and to associate a mobility profile to a given class of risk. The system is designed to learn from the user and to adapt its response to the actual inertial patterns of each patient, so that it is able to more precisely identify patients' activities. Upon detection of parameters that can be correlated to an adverse event, the system raises an alert. Nonetheless, the threshold for the recognition of a suspected fall is calibrated from time to time in accordance with the specific mobility patterns acquired from the subject, and the instability introduced by unpredictable movements of the wrist is compensated by information stored in the knowledge-base. As a result, the activity monitoring sensors should achieve better accuracy and the fall detector gains in reliability.

Also, the purpose of our interactive device is to increase the individuals' awareness of their risk of falling, so that they learn to prevent situations that typically lead to adverse events. To this end, each subject is constantly informed about his risk level (which is computed using information derived from the assessment protocol and the results of real-time analysis of individual's activity). Non-invasive multimodal feedback is conveyed to the users with a traffic-light system involving three levels of alert. The general strategy is coherent with visual cues described in [1]. Consequently, we decided to attach the device to the wrist, because alerts can be easily noticed. Besides individual's awareness, feedback is transmitted remotely to the staff or to subject's assistants (by means of wireless links), so that they are able to immediately realize specific intervention measures, and to identify and plan additional precautions.

Fig. 1 depicts the modular architecture of Fallarm, and it describes the interactions between its components. In our design, we used the client-server metaphor. The *Service* (S), which is realized by hospitals, care facilities or telemedicine providers, is organized into four layers: the *Risk Assessment Protocol* (S1-RAP), the *Patients' Activity Knowledge Base* (S2-PAKB), the *Intervention Measures Repository* (S3-IMR), and the *Adverse Events Database* (S4-AED). The *Device* (D) acts as a client, and it consists of four components: the *Risk Awareness Provider* (D1-RAP), the *Activity Monitoring Sensors* (D2-AMS), the *Fall Detection Manager* (D3-FDM), and the *Communication and Localization Module* (D4-CLM).

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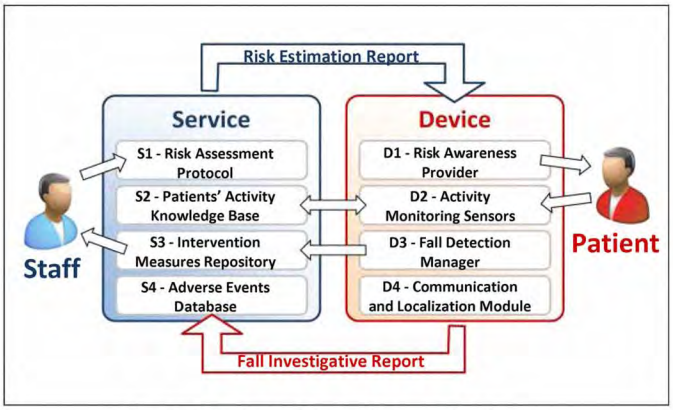

Fig. 1. Overview of the architecture of Fallarm.

There are two classes of users in Fallarm: the staff on the Service side, and the patient on the Device side. The former performs S1-RAP and they produce the *Risk Estimation Report*. This defines a score for each patient and associates subjects with their specific risk class. Individuals' activity is monitored by the D2-AMS. Simultaneously, the D1-RAP provides patients with feedback about their actual probability of having an accident in the current situation, according to the information coming from the S1-RAP and from the D2-AMS. Upon detection of an adverse event, the D3-FDM uses data about activity patterns from the S2-PAKB to evaluate the circumstance and, eventually, to classify the episode as a fall. In this case, the S3-IMR activates the intervention measure associated to the specific situation. At the same time, a new record is added in the S4-AED. Bidirectional client-server communication is realized by the D4-CLM for the exchange of information and for localization purposes. The *Fall Investigative Report* closes the loop between proactive and reactive methods, because it collects data about adverse events and it updates the knowledge-base of the system.

IV. Health Care Service

The *Service* is realized by the health care facility (hospital or telemedicine provider). This component involves two aspects: human contribution and technological resources. The former is exploited for the assessment phase, in which clinical know-how is crucial; also, medical staff is necessary for the delivery of immediate assistance; moreover, the Service has the competences for planning extensive intervention measures over the long period, according to the safety requirements indicated by information from incident reporting. Technological resources consist of informative systems that manage patients' data and perform extensive analyses to extract additional knowledge about risk. Moreover, the server supplies the communication infrastructure for exchanging information with the device, particularly upon detection of a fall.

A. Risk Assessment Protocol

In our system, the software component for the Risk Assessment Protocol (S-RAP) associates each patient with his specific class of risk. Many different criteria and several instruments for assessing the individuals' risk of falling (i.e. evaluation tools and checklists) are available in the literature [20]. Usually, they are widely adopted in care facilities that already realize fall prevention. Therefore, rather than introducing a new method, we decided to reuse current instruments, so that no change has to be done to the ongoing process. However, each of the tools in the literature allows the staff to assess only one specific dimension. Conversely, in our approach, the S-RAP component takes into account the many diverse factors and exploits their comprehensive integration. Indeed, a multidisciplinary team identifies the key dimensions for risk (intrinsic and extrinsic factors) and the proper assessment tools (i.e. to evaluate the inherent conditions of the patient, the environment, and the treatments). To this end, the component for the S-RAP is designed to seamlessly interface with any of the tools already implemented by hospitals, using electronic replicas. For any of the dimensions, information about the individual's risk of falling is introduced in the system as a score s_t that ranges in $S_t = [s_{MIN_t}, s_{MAX_t}]$ as defined by the tool t. This may also contain n intervals representing different risk classes defined between $n+1$ thresholds m_{i_t}, where $i_{0_t} = s_{MIN_t}$, and $i_{n_t} = s_{MAX_t}$. Within the risk assessment component, each s_t is converted into a risk score rs normalized in the range $RS = [0, 100]$. To preserve the risk class specific to each tool, we associate a value m_i' to any m_{i_t}, and we derive rs from $m_{j_t} < s_t < m_{k_t}$ as follows:

$$rs = \frac{s_t - m_{j_t}}{m_{k_t} - m_{j_t}}\left(m_k' - m_j'\right) + m_j'. \quad (1)$$

The output of the S-RAP component is the estimated risk class erc_{rs} (i.e. high, medium or low) associated to the weighted average of the risk scores rs_t correlated to the dimensions that have been considered. The evaluation can be performed periodically by the staff; consequently, the risk class can be updated after the first assessment (which usually occurs at patients' admittance).

B. Patients' Activity Knowledge Base

The purpose of this component is to profile the patients according to their inertial parameters, and to correlate the estimated risk class of a subject to his actual risk level. To this end, the S-PAKB contains the most significant traces extracted from data recorded during subject monitoring. This centralized database is organized according to the risk classes defined in the assessment phase. Hence, inertial patterns and other parameters (i.e. occurrence and duration of each sequence of movements represented as a function over three axes) are analyzed, so that Fallarm associates each of the erc_{rs} classes to a virtual set of mobility patterns $VMP_a(erc)$ for each activity a. Moreover, for any patient p, the S-PAKB stores an actual set of mobility patterns $MP_a(p)$ Therefore, in order to recognize the activities of a user whose class of risk is 3, the classifier of the monitoring system starts by analyzing only the patterns in $VMP_A(3)$, where A is the set of all the activities that can be recognized. If no match is found, the system queries the other sets, i.e. $VMP_A(2)$ and $VMP_A(1)$. Upon successful classification of a, the system updates the user profile by adding record to $MP_a(p)$ in the S-PAKB. Also, the virtual set VMP_A is periodically revised to maintain it consistent with all the actual sets MP_A. Furthermore, the S-PAKB is also stored in the SD-card included in the device.

C. Intervention Measures Repository

Information coming from the S-RAP classifies the patient according to his risk class; knowledge extracted from the S-

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PAKB associates activities to individual's mobility patterns; inertial parameters acquired real-time by the D-AMS allow the system to evaluate the current risk. All the above are the working memory of the S-IMR. This component consists of three levels of alert *AL* (low, medium, and high) for each class of risk *erc*. Alert levels are activated by a rule-based system: upon verification of one or more conditions, the alert level changes. Simultaneously, Fallarm activates the intervention measures associated to the crentu *AL*. As a default intervention measure, the D-RAP provides the subject with multimodal feedback about the changes in the level of alert (i.e. visually, with green, yellow or red lights, using the traffic light metaphor). On the Service side, a multidisciplinary team defines the set of conditions (alert thresholds) that have to be verified for each alert level. These can be associated to quantitative parameters (i.e. inertial patterns) and to qualitative attributes (i.e. class of risk) of intrinsic factors and extrinsic dimensions. The software component for the S-IMR allows the users to build trees of nested rules, using logic operators. Each of the nine sets can be drilled down, to specify conditions that trigger only one event, instead of increasing the alert. Furthermore, once rules are defined for a class of risk *erc*, they can be customized for each patient, in order to meet his specific requirements in terms of assistance and to fit his actual situation.

D. Adverse Events Database

Whenever a suspected adverse event is confirmed as a fall by the detector, the system immediately generates a Fall Investigative Report. This document, which is stored in the S-AED, contains a set of parameters that can be analyzed to understand the circumstances of the incident (i.e. date, time, inertial patterns, and performed activities). Moreover, from time to time, the historical data about falls stored in the S-AED is automatically processed by a classifier. This scans the entire dataset to identify any correlation between the parameters, in order to produce additional information that can be analyzed by the service staff to introduce new knowledge in the system.

V. MONITORING DEVICE

This component consists of a non-intrusive wearable device mounted on a wristband. The system is powered by a battery. It embeds an accelerometer that acquires inertial parameters from the movements of the subject. The on-board processor analyzes the motion patterns and classifies them either as activities or as suspected adverse events. Significant traces are stored into the included memory. The main purpose of the device is to continuously monitor patient's activity, and to provide him with feedback about his current risk of falling (i.e. high, medium or low). Moreover, upon detection of a fall, it raises an alarm, and it alerts the staff or patients' relatives by means wireless connectivity.

A. Risk Awareness Provider

This component communicates the actual level of alert, conveying multimodal feedback to the user according to the (almost static) risk class evaluated in the assessment protocol, and to the dynamic risk factor related to current activities performed by the subject. In addition to visual icons (colors), tactile alarms can inform the user about any change that affects his risk status. Also, short pre-recorded audio messages can ask the user to execute specific actions. Consequently, different options can be customized to ensure that feedback is perceived properly by subjects, and that it is conveyed according to their individual needs and preferences.

a) Component for visual feedback. Risk of falling is delivered with a multicolor Light Emitting Diode (LED) producing bright light in different patterns of the Red-Green-Blue (RGB) scale. Despite its size (5 × 8 × 3.5 mm) and its low-power requirements (from 2.4 to 3.8 V), this component has great intensity (from 6000 to 8000 mcd) and a wide viewing angle (25 degrees). Thus, it is suitable for either indoor or outdoor lighting. We adopted this solution due to its energy efficiency (current absorption of 20 mA), high reliability (duration over 100000 hrs), and low cost. In our implementation, risk is represented by three different colors: red, amber and green to indicate high, medium and low risk of falling, respectively.

b) Component for tactile feedback. Different tactile alarms will alert users about any change in their risk status. They are realized using one pager motor akin to those embedded into mobile phones to generate vibrations. This transducer, which is manufactured by Precision Microdrives Ltd, operates at low voltage (from 2.5 to 3.8 V), and it has limited current absorption (85 mA). We used miniaturized (10 × 10 × 3 mm) and light-weight (1 g each) button-style (without shaft) motors, having response time of 2 ms and maximum speed of 12000 rpm. Vibrations introduced by pager motors do not affect the performance of activity monitoring sensors, because either they are negligible, or they have clearly distinguishable inertial patterns. Vibrations can be modulated in frequency, length and amplitude to discriminate between different events. In our current implementation, the motor is fired with an ascending pattern (higher frequency and rising amplitude, but shorter vibrations) when the risk level increases; conversely, a descending pattern signals the transition to a lower level of risk. In addition to these, which have short duration (from 3 to 5 seconds depending on subject's sensibility), continuous vibration (high frequency, strong amplitude and short pulses) will occur as long as rhe subject persists in a dangerous situation (i.e. he is moving when he was required to wait for an assistant).

c) Component for auditory feedback. We embedded miniaturized (10 × 10 × 4.2 mm) dynamic speakers with metal frame and Mylar diaphragm, as they provide extended frequency range (from 600 Hz to 20 KHz), good sensitivity (110 ±3 dB), high power (input level from 10 to 50 mW), and great efficiency. Moreover, they have negligible weight (1 gram), and they can operate in extremely humid (up to 90-95% at 40°C) environments (i.e. bathroom). In our prototype, we did not activate auditory feedback.

B. Activity Monitoring Sensor

Activity monitoring is performed using micro-electromechanical systems (MEMS)-based acceleration sensors. The monitoring device embeds the MMA7456L low-g (1.5 g) tri-axial accelerometer manufactured by Freescale Semiconductors. This digital component already implements amplification, signal conditioning, low-pass filter and temperature compensation. Its sensitivity is ±800 mV/g, and therefore it allows accurate detection of fall, as well as motion.

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It has small size (3 × 5 × 1 mm) and low-power requirements (1.8 - 2.8 V). To reduce current consumption, we defined a long sleep/wake-up duty cycle. In each period, the accelerometer is kept in standby mode for 90 msec, so that the average current absorption is approximately 75 mA.

In order to classify subject's movements, as the initial axial position of the equipment is not known, the activity monitoring component needs to auto-calibrate the orientation of the device with respect to the ground. To this end, the subject is required to keep his arms steady down for five seconds when he first wears the system, so that the D-AMS acquires the inertial reference value $R\{a_L, a_F, a_S\}$ for the acceleration along the longitudinal, the frontal and the sagittal axes. During operation, in order to have a rough approximation of the orientation of the device, the D-AMS samples the inertial acceleration A as triples $\{Aa_L/Ra_L, Aa_F/Ra_F, Aa_S/Ra_S\}$, so that the static acceleration due to gravity ($9.81ms^{-2}$) can be compensated. Values are recorded at a frequency of 10 Hz, and they are stored in a buffer that can accommodate up to 15 seconds of observations.

The D-AMS realizes three different tasks: orientation recognition, activity classification, and fall detection. The former is approximated from the analysis of inertial velocity during periods in which the device is almost static. To this end, we compute the norm of the acceleration vector over the three axes as

$$v = \sqrt{\left(\int \frac{Aa_L}{Ra_L} dt\right)^2 + \left(\int \frac{Aa_F}{Ra_F} dt\right)^2 + \left(\int \frac{Aa_S}{Ra_S} dt\right)^2} - \int 9.81\, dt \quad (2)$$

and we update the last known orientation lko of the device when v is smaller than the norm of the static velocity due to gravity $\int 9.81dt + ec$ (error compensation). This is calculated every 500 milliseconds. Also, a counter is increased at each unsuccessful update, as a measure of the reliability of the last calculated orientation. The counter is reset when it reaches the value of 10, and the device is assumed to be positioned at the default orientation for the current activity (MP_a). For movement classification, the D-AMS analyzes the inertial patterns in the buffer, and it compares the values with the MP_A stored in the local PAKB of the device. This is done at intervals of 5 seconds by a pattern recognition algorithm based on supervised learning. In addition to inertial coordinates, the PAKB maintains other parameters of each entry in MP_A, such as average acceleration and maximum velocity. Upon successful classification (confidence > 90%), it will append a new record in the activity log and the buffer will be cleared. Otherwise, the classifier will run on VMP_A: if there is a match, the pattern will be added to MP_a. Otherwise, the time window will be increased by five seconds. If the activity is not recognized within three trials, an unsuccessful match will be added to the log, and the observations (150 samples) will be moved from the buffer to the storage unit.

As many activities, also falls have identifiable patterns: first, speed usually increases proportionally with the inertial parameters of the subject, and it diverges from the maximum inertial velocity of a conventional movement; secondly, acceleration has a predominant negative component along the axis perpendicular to the ground; moreover, there is an impact, followed by a change of orientation, resulting in a period of subject's inactivity, whose length is related to the magnitude of the damage. The D-AMS exploits this sequence and it evaluates the presence of the components described above to classify patterns as suspected falls.

C. Fall Detection Manager

Given the unpredictable response of the six degrees of freedom of the arm, mere pattern recognition would be inaccurate for fall identification. Moreover, as this is a critical task, it has several constraints (e.g. time, reliability), and requires fast execution. Nonetheless, even though it is not possible to precisely evaluate the position of the device during a fall, the initial and the final orientation can be derived from the lko values acquired by the D-AMS. The D-FDM uses a magnitude detection algorithm based on the norm of the acceleration vector calculated as

$$fv = \sqrt{\left(\int \frac{Aa_L}{lko_L} dt\right)^2 + \left(\int \frac{Aa_F}{lko_F} dt\right)^2 + \left(\int \frac{Aa_S}{lko_S} dt\right)^2} - \int \frac{9.81}{lko} dt \quad (3)$$

The algorithm associates subject's acceleration to a fall when fv is greater than $\max(v_a) + \Delta$, where Δ can be proportional to the class of risk erc of the subject (or defined as the standard deviation of either v_a in MP_a). We take advantage of the last known orientation to obtain a rough approximation of the real values of the acceleration towards the ground. In the above formula Aa refers to the negative components only. The last known position is introduced to improve the compensation of acceleration due to gravity. The magnitude detection algorithm is processed real-time with sampling. Upon recognition of $fv > max(v_a) + \Delta$, the D-FDM activates the silent alert state (the alarm is internal to the system, but invisible to its users): it sends a request to the Service (using the D-CLM). Inertial parameters and contextual information are analyzed using both information in the S-PAKB, and Fall Investigative Reports in the S-AED. At the same time, the D-AMS examines the subject's mobility patterns in order to identify the three components of a fall (acceleration, impact, rest). The silent alert state lasts up to 10 seconds: within this interval, either the D-AMS (whose cycle unit is 5 seconds) is able to classify the activity patterns, or the Service replies with the result of its evaluation. Upon confirmation of an adverse event (either by the D-AMS or by the Service), a real alarm is generated and the intervention measure defined in the S-IMR is initiated. Otherwise, the subject has a certain amount of time (30 seconds) to manually turn the alert off.

D. Communication and Localization Module

Bidirectional wireless communication between the device and the components of the service is realized through the 2.4 GHz band of industrial, scientific and medical (ISM) frequencies, using IEEE 802.15.4 compliant MAC for hospitals and care facilities. Also IEEE 802.15.1 can be used for home settings to achieve a trade-off between scalability and cost of infrastructure. Regarding the antenna, we preferred a loop design mainly because of the size required and its low cost of implementation. Communication with the base-station occurs either when inertial parameters diverge from the current profile, or upon detection of an adverse event. As Quality of Service (QoS) is one of the main issues, the network topology requires only one hop for messages to reach the destination.

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When the server receives an alarm from the client, it eventually alerts the staff or user's relatives. This may involve additional transmission of data over heterogeneous networks (i.e. Ethernet, GPRS).

Moreover, by adding localization features to the system, the risk related to the environment can be introduced into Fallarm as an extrinsic dimension. During the assessment, the multidisciplinary team can associate certain parts of the structure with a specific risk level (i.e. stairs or bathrooms). By doing so, the Risk Awareness Provider of the device will inform the subjects whenever they approach areas in which the risk of falling increases, so that they can wait for help. Simultaneously, the system will alert the staff and ask for their intervention. Localization features can be realized with short-range communication technology, such as Radio Frequency Identification (RFId). We did not include this feature in the current implementation.

VI. Experimental Study

As a first step in demonstrating the applicability of our system, we developed eight prototypes of the device and we carried out a preliminary evaluation of Fallarm in two deployment contexts: hospital and home settings. Indeed, for the purpose of this work, we focused on the Risk Awareness Provider, only. Regarding the clinical scenario, we analyzed data about incidents that have occurred in our Institute from March 2003 to June 2008, and we applied our system in the Medical Oncology ward, because it is the division in which falls were found to be most frequently reported.

A. Materials and methods

The study was designed applying the Goal Question Metric (GQM) methodology [21]. Our primary aim was to analyze quantitatively the applicability (goal 1) of Fallarm to the two scenarios described above. Therefore, we acquired individuals' inertial data and we compared the performance of the wrist-mounted device with respect to the fall detector worn on the waist. Moreover, the purpose of our study was to evaluate the usability (goal 2) of our solution from the subjects' point of view. In order to do so, we submitted a questionnaire to participants to receive feedback about their experience with the devices. All the acquired data allowed us to make a comparison between the wrist and waist, and to establish which of the two positions is the most suitable for this application. The server-side distributed system was developed with Microsoft Visual C#.NET.

B. Participants

A total of 20 subjects were recruited to perform the test, 10 for each scenario (clinical facility – *C*, and home setting – *H*). 6 are males and 14 are females, aged from 25 to 88 (average 50.2 ±16.44). The body mass of the participants ranged from 51.8 to 104.3 kg (66.4 ±12.6 kg), and their height was between 154 and 181 cm (167 ±7 cm). All of them had normal sight, hearing and tactile sensitivity, and they were all physically able to walk; however, all the hospitalized patients but three (C3, C5 and C9) used clinical equipment (personal drip instrumentation for drugs that do not have any psychotropic effect) that limited their movements. Four non-clinical patients (H3, H4, H7 and H8) suffer from fear of falling, two of them (H3 and H4) because of previous accidents. Moreover, all the subjects were not assessed as at risk of falling. They are all right-handed, so we tested the left wrist and the right waist only. In order to avoid being intrusive in such delicate condition, all subjects who spontaneously applied for the participation were accepted, and they were not rewarded.

C. Experimental setup and task

Subjects were equipped with two devices: one to be attached to the right hip, and the other on the left wrist. They were required to autonomously put the equipment on, and they were supposed to wear it for 10 hours, while carrying out the typical set of activities they would realize in an ordinary day. As there was very little probability for a fall to occur during such short period, the prototypes were programmed to raise an alarm at random intervals, simulating an increase of the level of risk. At the beginning of the experiment, subjects received a checklist: they were asked to report the times they received an alarm and to annotate the activities they had performed from the previous alert. The users were also supplied with a quick reference to the use of the device and to the experiment. Both the devices monitored the inertial parameters of the subjects for the duration of the whole test and they recorded the data on micro-SD cards. At the end of the experiment, subjects were asked to fill an evaluation questionnaire to indicate their opinion about the device, and to express their preference between the wrist and the waist. Furthermore, they were interviewed individually to discuss about their experience.

D. Results

All the participants recognized the importance of a measure for fall prevention: our solution was accepted by the majority of subjects (95%). They stated that they would recommend our system as a non-invasive customary intervention for subjects at high risk of falling. Regarding the location, they would straightforwardly use it on the wrist; otherwise, they would not utilize it (or they would accept it, but discontentedly, only if they are ought to). C5 showed a preference for the waist, even though it is not significant ($p = 0.14$) to the Student's t-test. C10 would not avail himself of a fall detection system at all.

All subjects were able to easily put on themselves both the devices: with respect to this, we found no significant difference ($p = 0.37$) between the wrist and the waist. All the participants but one (H10) carried both the devices almost continuatively for the whole duration of the experiment (10 hours). However, subjects felt 8 times the urgency to put off the device mounted on the waist, and they in fact detached it 5 times because it was distressing. In contrast, just one subject (C5) felt only once the necessity to put off the device attached to the wrist; nonetheless, C3 and C8 reported that they had to detach it twice because of clinical examinations (functional Magnetic Resonance Imaging - fMRI) that are incompatible with electronic equipments. All the subjects were able to perform all the activities they ordinarily carry out. Fig. 2 shows that the device mounted at the waist was found restraining for all the actions but eating. However, in this case the difference is not significant ($p = 0.44$). Conversely, for all the activities in which the wrist was found to be more comfortable, there is a greater disproportion ($p = 0.04$ for walking). Also, the positioning at the waist was found to be embarrassing and harmful in terms of privacy, while the device on the wrist was perceived as less intrusive and even pleasant. In terms of psychological impact,

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http://dx.doi.org/10.4108/ICST.PERVASIVEHEALTH2009.5980

the difference between the two locations is noteworthy (p = 0.02).

The performance evaluation of the Activity Monitoring Sensors regarded only seven activities (see Fig. 2), and it was realized off-line. To this end, we downloaded the inertial parameters from the internal memory of the devices worn by the subjects, and we used the data as the test set of our classifier. The Activity Classification Ratio indicators (see Table 1, ACR^0 and ACR^R) are calculated as the number of samples belonging to classified activities over the total duration of each recording (~350000 samples). Initially, the PAKB was trained with inertial data from only two healthy subjects at low risk of falling. As a result, the classifier recognized only a limited number of activities of a few subjects, leading to very low ACR performance for both the wrist (34.14%) and the waist (46.37%). In the first run, the latter obtains better results, and the difference is significant (p = 0.01). There is an important discrepancy within the two populations: both the devices worn by clinical subjects were found to be more performing (42.75% versus 25.53% for the wrist, and 57.04% versus 35.69% for the waist). We then updated the PAKB with information from the most correctly classified subjects (C6 and H3), and we trained the classifier again. By repeating this, we achieved better results. The ACR^R column in Table 1 shows that the wrist and at the waist obtained an average recognition ratio of 62.06% and 50.77%, respectively. The difference is noteworthy (p = 0.03), but the improvement (see Fig. 3) mainly regarded the wrist (+27.93% versus +4.41%). This is because the device on the waist is able to recognize fewer activities even though it has better accuracy. The dissimilarity between clinical and home subjects persists (71.09% versus 53.04% for the wrist, and 61.5% versus 40.04% for the waist). This is because the hospitalized group realized fewer activities, whose movements are predictable. As a result, once their patterns were identified, the classifier was able to associate a record in the PAKB to most of the groups of samples. Conversely, subjects at home performed actions that were not introduced in the PAKB as a priori knowledge (i.e. cooking), so the activity monitoring system was unable to achieve good results in their recognition. No falls were detected and the classifier did not raise alarms. As all the subjects confirmed that no adverse events actually occurred, there were no false positives.

The Risk Awareness Provider was found to stimulate the users to identify the situations associated with an increase of risk, even though the alarm was fired without any casual relationship with user-related events. The average Perceived Risk Awareness (PRA) reported in Table 1 is 67.5% and 13.33% with the device on the wrist and on the waist, respectively. This means that the users considered almost easy to receive feedback from the former, while they found very difficult to interact with the latter. The average Actual Risk Awareness (calculated as the number of alarms reported in the activities checklist) is 85.83% and 29.08% for the device on the wrist and on the waist, respectively. A motivation of this result might be that subjects were more accurate in noticing the vibrations raised by the device on the wrist, while it was almost impossible to see the risk level signaled by the device on the waist. Also, the above results signify that the real performances of participants were better than they expected, suggesting that subjects underestimated themselves, either due to lack of training or because they felt unfamiliar with such new device.

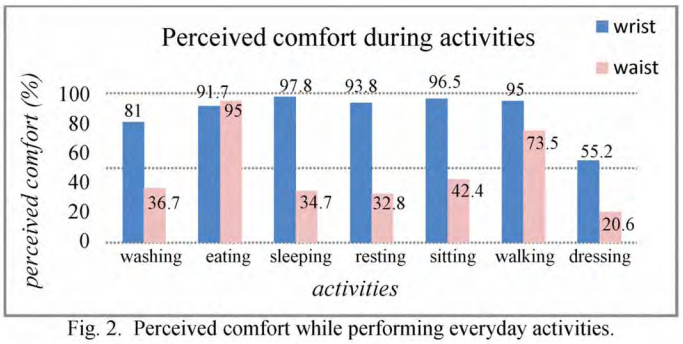

Fig. 2. Perceived comfort while performing everyday activities.

VII. Conclusion

Fallarm is a fall prevention system that exploits user's awareness to reduce the risk of an adverse event. It was designed for acute care hospitals in which subjects are at a greater risk of falling because they have serious injury or they undergo surgery. The results of our study show that the system is able to quickly learn from the patients, considering the evaluation coming from the risk assessment and the inertial

TABLE I
Performance Evaluation Results

ID	ARA (%)		PRA (%)		ACR^0 (%)		ACR^R (%)	
	wrist	waist	wrist	waist	wrist	waist	wrist	waist
C1	100	50	100	50	35.6	50.5	61.4	57.4
C2	0	0	0	0	24.1	29.8	51.3	35.4
C3	100	0	66.7	0	42.3	62.6	74.2	67.3
C4	0	0	0	0	48.4	67.6	89.4	72.9
C5	100	0	83.3	0	28.8	31.7	52.1	36.3
C6	50	50	100	66.7	56.8	61.1	79.1	62.4
C7	100	50	83.3	0	54.6	67.2	90.1	73.5
C8	100	40	50	0	39.2	47.9	64.3	52.9
C9	100	0	16.7	0	55.9	83.8	79.1	87.7
C10	100	100	0	0	41.8	68.2	69.9	69.2
H1	100	50	66.7	16.7	35.1	37.5	70.1	37.6
H2	100	0	83.3	33.3	21.2	26.2	38.3	29.2
H3	100	50	100	16.7	35.8	47.1	55.1	57.1
H4	100	0	50	0	21.6	29.1	54.6	29.6
H5	100	0	83.3	0	27.9	33	66.4	37.3
H6	100	66.7	100	0	15.5	26.7	30.7	32.1
H7	100	0	66.7	0	15.2	43.2	37.1	46.2
H8	100	0	100	16.7	33.4	33.4	57.8	39.5
H9	66.67	100	100	50	22	32.1	61.1	42.5
H10	100	25	100	16.7	27.6	48.6	59.2	49.3

ARA = Actual Risk Awareness (percentage), PRA = Perceived Risk Awareness, ACR^0 = first Activity Classification Ratio, ACR^R = Activity Classification Ratio after re-training.

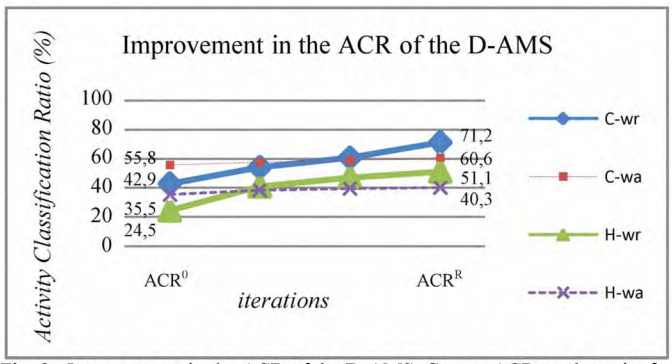

Fig. 3. Improvement in the ACR of the D-AMS. C-wr = ACR on the wrist for clinical subjects, C-wa = ACR on the waist for clinical subjects, H-wr = ACR on the wrist for home residents, H-wa = ACR on the waist for home residents.

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http://dx.doi.org/10.4108/ICST.PERVASIVEHEALTH2009.5980

parameters acquired real-time during activity monitoring. Also, it takes into account that elderly residents in the community have different mobility patterns. Therefore, our solution is also suitable for geriatric facilities, even though this is long-term situation, in which risk is degenerative. Furthermore, our study demonstrated that Fallarm can be also employed in home settings, in which subjects are usually less prone to receive invasive treatments.

Results confirmed the applicability of the device mounted on the wrist. Although the literature suggests that the wrist would not be stable enough to accurately monitor patients' activity, as the integration of knowledge from the Health Care Service improves the reliability of our system, with proper selection of training sets, this location was found to achieve the best trade-off between accuracy and scalability in recognizing subjects' activities. Also, this is the most comfortable position for the subjects. Moreover, during the interviews, subjects stated that the introduction of an interactive device encouraged their mobility because the Risk Awareness Provider helped them to feel safer. In this work we bring in a solution based on the integration between proactive and reactive methods. This closed-loop of information was found to improve the classification of subjects' activities acquired during the experiments. During the experiment, none of the subjects reported a fall, so we could not evaluate the performance of our detector in recognizing an adverse event *in vivo*. However, the system did not raise any false alarms.

Currently, our work is focused on the performance of the detector: we are acquiring inertial parameters of falls. Preliminary tests performed in our laboratory under supervised conditions showed that the classifier is able to associate inertial data of simulated falls to incidents. Moreover, Fallarm is able to immediately report them. As a result, our solution supports the documentation of adverse events (which is still a methodological pitfall in hospitals), also when they happen in association with a loss of consciousness. It is our intention to investigate the correlation between activities and falls, in order to identify the inertial parameters that achieve better accuracy. In the future, we will test the fall detector and we will evaluate the whole infrastructure in the deployment scenario. Hence, the application of Fallarm will be a systematic treatment for the inpatients who are most likely to fall. To this end, we are carefully refining the Risk Awareness Provider, so that feedback and alarms will not to distract the patient from his task, because a strong warning could worry him and increase the risk of falling, rather than preventing it. Furthermore, the device was designed considering the average interval between two assessments in a hospital (about 15 days). To this end, we are working to limit its current absorption and to extend its life to up to two weeks without charge. Also, we are developing a waterproof enclosure, so it can be continuously worn (also under the shower).

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