Monitoring of bedridden patients: Development of a fall detection tool

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Abstract - Falls of patients are an important issue in hospitals, it causes severe injuries to the patients, increases hospitalization time and treatment costs. The detection of a fall, in time, provides faster rescue to the patient, preventing more serious injuries, as well as saving nursing time. The MovinSense® is an electronic device designed for monitoring patients to prevent pressure sores, and the main goal of this work was to develop a new tool for this device, with the purpose of detecting if the patient has fallen from the hospital bed, without changing any of the device original features. Experiments for gathering data samples of inertial signals of falling from the bed were obtained using the device. For fall detection a sensitivity of 72% and specificity of 100% were reached. Another algorithm was developed to detect if the patient got out of his/her bed.

Index terms: Biomedical Engineering; Bed falls; Fall detection; Accelerometry.

I. INTRODUCTION

Generically, a fall is an unexpected event in which the subject comes to rest on the ground, floor, or lower level [1]. A single fall may result in death, severe lesions or simply a fear of falling that can begin a downward spiral of reduced mobility, leading to loss of function and greater risk of falls [2], [3], [4], [5]. Hospitalization increases fall risk because of the illnesses, treatments and especially the unfamiliar environment [6], [7], [8], and hospitalized patients have a higher risk of falling than people in the community [9]. Falls and relating injuries are devastating to patients, family members, clinicians, and the healthcare system [7].

In the United Kingdom, falls of inpatients are the most common patient safety incidents reported, and treating inpatient falls alone costs the English National Health Services (NHS) more than £15 million per year[1]. Some 3 to 20% of inpatients fall at least once during their hospital stay. These falls result in injuries, increased lengths of stay, malpractice lawsuits, and more than £4000 in excess charges per hospitalization. Falls are related to increased treatment costs and increased length of patient stay [2], [9] but the risk varies, with more patients falling in geriatric wards followed by general medical and surgical wards [6].

Empirical data collected by different institutions reveals a high variance of falls in hospitals, and studies reveal that the majority (42 to 60%, according to Fonda et al. [10]) of inpatient falls were either bed related or patients were found in their bed spaces after falling, being often the result of confusion, attempts to walk or climbing over bedrails [11]; little has been said about the fall from the hospital bed. Also, some inpatients escape from the hospital bed during the internment time, and this also can enhance the risk of falling or injuring themselves while walking around.

It is important to point out that several research groups have investigated and proposed many different mechanisms for detection of falls during a walk or performing daily life activities, but few studies were found on the detection of bed related falls. Moreover, Brandis et al. [12], referred that the best way of preventing falls of inpatients is to detect that they left the hospital bed. So, the main goal of this study was to develop a software tool, for the MovinSense® device, which, using a single tri-axial accelerometer attached to the patients' chest would send feedback to the healthcare staff when the patient has fallen or is getting out of his/her bed and he/she is walking. The hospital nursing staff needs real help in preventing and alerting for falls and escapes from the hospital beds. As Huang et al. [13] stated, although one cannot prevent fall accidents completely, a real-time fall alarm to caregivers when it happens turns out to be important. Urgently attend a person who has fallen is of major importance for the healthcare system.

Nowadays, there are several approaches to detect a fall of an inpatient from the hospital bed [14]: (i) camera-based, (ii) ambiance devices and (iii) wearable devices. All strategies have its advantages and disadvantages but this study is focused on the wearable devices.

There are many studies performed on falls with accelerometers, especially on the elderly, but there is still no consensus on the number of sensors needed or their locations (chest, trunk, shoulder, ankle, wrist, knee, leg, pocket, waist, hip, or thigh [15], [16]) and none of the methods is completely efficient. The assessment of unintentional fall is difficult due to the subtle and complex nature of body movement, which requires accurate and reliable measuring techniques [13]. The

[1] *Clinical guideline and quality standard – Falls draft scope for consultation* - National Institute for Health and Clinical Excellence, 2011 (http://www.nice.org.uk/)

majority of falls can be divided into three phases: start of the fall (acceleration decrease), fall impact (acceleration peak), and posture after the fall [17], [18], [19]. The acceleration pattern during a typical fall corresponds to a decrease in acceleration followed by a fast increase [20], [21] and the reason for this pattern is that the acceleration at rest is 1 g[2] and when a person starts falling, the acceleration decreases to around 0.5 g, as the perfect free fall is never achieved under the typical scenarios of falling [20]. An increase in the acceleration is measured when the impact with the ground occurs, due to the ground reaction force [20].

Several authors have defined different threshold values for the upper peak of the total sum vector or root-sum-of-squares (RSS) when a fall occurs, and to distinguish it from activities of daily life (ADL) [13] [19] [21] [22]. However, such a simple peak analysis does not ensure a reliable detection because of the large variability of the parameter [23]. To impose that the initial position of the body has to be lying, reduces the number of harmful activities that produce comparable accelerations. In addition, it is shown to be effective to complement the acceleration peak detection with the check of the body tilt [22] or end posture/resting time. The time used for detecting the ending posture of a fall varies between different authors and types of fall. Chen et al. (2005), [22], and Kangas et al. (2008, 2012) [18], [21]), defined the time of rest to be 2 s after the impact. On the contrary, Karantonis et al. (2006), [24], highlighted the 60 s post-fall interval (ignoring the first 5 s due to potential residual movement relating to the fall). Gjoreski et al. (2011), [20], preferred 10 s for the detection of the ending posture. A major issue in these systems is the minimization of the number of false positives while avoiding the occurrence of false negatives. Also, the use of the immobility after the fall event for a long period of time to reduce the number of false positives has the drawback that possible user attempts to stand up may lead to a false negative [25].

Regarding the walking motion detection, it is not usual to detect it with a sensor attached to the chest, instead, accelerometers attached to the thigh or ankle, are used to study leg movement during walking [26], [27]. The range of signal frequencies in the studies for walking motion detection has fundamental importance; Barralon et al. (2005), [28], defined it as 0.6 to 2.5 Hz, for sensors located under the arm pit; Godfrey et al. (2008), [29], associated walking motion to approximately 2.5 Hz; while Najafi et al. (2003), [30], described 0.6 to 5 Hz using a sensor located in the chest. In their human motion analysis study, Najafi et al. (2003), [30], reached a sensitivity of 96±1% in 70 trials, for at least three steps in subjects aged more than 65 years old. On the other hand, Godfrey et al. (2011), [26], reached 100% and 98±1% of sensitivity for young and old subjects, respectively. They performed 60 trials with the sensor also placed in the chest and a walking distance for detection of 10 m. The biggest limitation of their method was the 5 s calibration needed before each trial, which invalidates continuous detection. Also, Najafi et al (2003), [30], used the DWT; wavelet transform techniques have been shown to be effective in removing noise from signals with sharp transients, while leaving these transients intact, but they also have shown to be computationally complex and to require large power computational consumption [26]. It was due to this fact, that the wavelet transform was not explored in this study.

[2] 1 g= 9.8 m/s^2

II. MovinSense®

The MovinSense®, from Tomorrow Options Microelectronics S.A., is a small and light-weight device that monitors the movement of bedridden patients during their stay in an hospital, clinic or healthcare center. It is intended for patients who are not able to move easily, to make sure that patients do not lie too long in the same position by enabling a better management of repositioning routines and therefore prevent bedsores. This product consists of three basic elements: the MovinSense software®, the MovinSense transmitter® device and the MovinSense receiver® device. The small transmitter is attached to the patient's chest (as illustrated in Figure 1), has a single inertial sensor, and transmits this information to the MovinSense receiver®, through ZigBee, for processing and recording by the MovinSense® software. If the patient has not changed position within a set amount of time, a local or remote signal is sent, alerting the healthcare staff with a notification to the computer, pager or phone. In this way it can be ensured that patients are moved at regular intervals, thus reducing the likelihood of bedsores and, therefore, saving valuable nursing time and healthcare costs.

Theoretically, increasing the distance from the sensor to the body center of mass would result in higher oscillations measured by the sensor. However, it is not yet possible to predict how the body will impact with the ground, in a bed fall. Attaching the kinematic sensor to the chest not only minimizes discomfort but also avoids interference with usual activities [30].

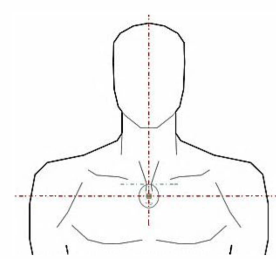

Figure 1 - Positioning of the MovinSense® in the patients' body.

III. Materials and Methods

In all experimental tests the MovinSense® device was used for data collection, attached to the patients' chest. Participants in this study were healthy volunteers (n = 50), 28 females and 22 males with an average and standard deviation age of 23±16 years old (max = 77, min = 4), 169±18 cm of height (max = 193 cm, min = 105 cm) and 66±21 Kg of body mass (max = 110 Kg, min = 18 Kg). All subjects were either barefoot or using their usual walking shoes (no high-heels or hard-soled shoes). The signal processing was performed in MATLAB® and the statistical analysis was based on simple percentages of sensitivity and specificity [5].

With the aim of guarantee that none of the other typical movements triggers the detection alarms, such as balancing the trunk, seating, lying down and quickly getting out of the bed, coughing, tapping on the device and the device falling itself, these actions were performed for exclusion of the false-positive alarms. An analysis of entire nights was also performed, in which the MovinSense® device was attached to the chest of a subject and the data was saved for at least 4 hours during the night.

III.1 FALL DETECTION

For fall detection, after positioning the MovinSense® each subject was asked to lay in a bed or couch and then roll and fall to the floor. Each subject was asked to fall to the floor at least twice. The rolling movement performance was not controlled. The majority of the subjects used blankets and pillows to sustain the free fall, since falling in the hard floor would neither be safe or ethically acceptable; this might have contributed to an attenuation of the actual maximum acceleration of the fall associated impact. The average and standard deviation of the height of the falls studied was 48.03±11.19 cm (max = 75 cm, min = 40 cm).

The first data analysis was performed offline, when an acceptable detection rate was reached, this algorithm duly optimized was implemented in the MovinSense Software® and real-time tests were performed in order to validate the process. In this case, the participants were healthy volunteers (n = 37), 24 females and 13 males with an average and standard deviation age of 25±8 years old (max = 51, min = 18), 168±16 cm of height (max = 188 cm, min = 150 cm) and 70±24 Kg of body mass (max = 98 Kg, min = 45 Kg); and each participant fell at least four times to an inflatable mattress. To check for false positive alarms, with real-time detection, all the subjects were asked to get up, sit and lay down between each fall, which makes a total of 444 events (n=37; 4 repetitions; 3 conditions).

III.2 GETTING-OUT-OF-BED DETECTION

Informal talks with four nurses from four different hospitals as well as videos and documents kindly provided by them; served as reference for the typical behavior of inpatients under this scenario. In the getting-out-of-bed detection, after positioning the MovinSense® on the subjects' chest, each subject was asked to get out of the bed and walk. The walking movement was performed at three different velocities: self-paced (starting from the standing position and lying down), slow as they were in pain, and fast. All the instructions were verbal. The experiments were divided in the three velocities and the two conditions *less than five steps* and *five steps or more* for each one of them. At least 100 trials were analyzed for each condition.

IV. ALGORITHM DESCRIPTION

IV.1 FALL DETECTION

Regarding the time, a fall event lasts roughly 1 to 2 s. After several tests, 32 samples, at a sampling rate of 10 samples per second – 3,2s – was the value empirically found to be the most adequate for the analysis window, such that the falls oscillatory characteristics were more evident. Given the variety and complexity of falls, the pre-impact detection, becomes challenging. Usually when a fall occurs, one can observe a short term oscillation after impact with a resonance frequency of approximately 2 Hz correspondent to the deceleration of the body mass and the impact resonance frequency is not observable when the device hits the ground itself because of its low mass. This was one of the factors to take into account when building the fall detection algorithm.

After receiving the signal its processing starts with the computation of the Short Term Fourier Transform (STFT). Then, signal sections with a frequency higher or equal to 2 Hz are selected and its power per mass unit (sum of the square amplitudes of all the windowed samples) is stored in a vector. This calculus is applied to each acceleration axis and to the RSS. A threshold was defined empirically, at ±1.5 g for the acceleration peak, since the patient can fall of the bed in any position and, depending on orientation the fall occurs, the acceleration in the correspondent axis changes more sharply. No conclusion was drawn, however, regarding the power spectral content in fall signals (mean value 49,33±16,2 W/Kg) though it was noticed that in less abrupt movements that value is lower (mean value 14,52±10,34 W/Kg).

In the fall detection algorithm built for the MovinSense®, once the microprocessor *wakes up*, the program calculates the STFT for the whole 32 samples window and also the power associated to the frequency component above 2 Hz. To effectively detect a fall, the last condition for the alarm to be given, is that the power of the determined frequencies per unit of mass, has to be below 50 W/Kg, for at least 5 seconds after the acceleration peak; which translates to none or a to a low level of movement after the impact. After the fall alarm, or if the fall is not detected, the microprocessor returns to the *sleeping mode*. In an attempt to reduce the number of false positive alarms, the acceleration threshold was later increased to 1,7 g.

There were no false positives detected in the trials, but the fall detection alarm continued being triggered when the subject hit the device strongly, two solutions were found to avoid such situation: when a subject hits the device strongly, it is expected that the acceleration peaks have a much narrower distribution then in a fall. Also, the body position would be the same if the subject simply hits the device, as opposed to a fall where the position before (normal position) and after (rest period) the acceleration peaks would be different.

IV.2 Getting-out-of-bed Detection

Because of its high variability, and, since the target population of this study were hospitalized patients who are not supposed to get up, we assume their ability to stand up was compromised and such movement would be done slowly and carefully, without significant acceleration peaks. Thus, it was decided to make the detection with basis on the walking movement.

There are several gait styles, and it is difficult to distinguish gait patterns with only one inertial sensor attached to the chest. The first step was to study the predominant frequency components during this activity. The medial-lateral acceleration (a_{ML}, y-axis) showed to be the most variable one and have the most notable attenuation profiles. Not surprisingly, the majority of the scientific papers which describe the walking detection use only vertical acceleration (a_V, x-axis) and anterior-posterior acceleration (a_{AP}, z-axis) [13], [31], [28].

For all the participants on the experiment, the walking frequency ranged from 0.5 to 2.5 Hz since running or ADL were not considered. When a person starts walking, oscillations in the vertical a_V component are detected, at a frequency dependent on the velocity. It is known that the decreasing periods at push-offs and weight acceptance are reflected in the a_V [32]. The a_{AP} pattern is similar to the a_V one but they seem to be in opposite phases. This can be explained by the normal gait cycle, when the foot is in contact with the ground and in order to stop the body from moving forward, there is a positive peak in a_V and a correspondent negative peak in a_{AP}. The a_{AP} has, in the majority of the times, the shape of an ascendant *saw-tooth* that coexists temporally with the a_V peak. The body is moving up while suffering a negative acceleration that prevents it from falling forward.

The developed algorithm detects walking motion from an array of N=32 measurements of 10 Hz raw data with a_V and a_{AP} values. This array size was chosen at the beginning of the experiment in order to maintain the value used on the previously described algorithm. Walking motion detection is then based on several features (the values of the thresholds were defined empirically):

- Significant amount of energy between 0.5 and 2.5 Hz on the vertical and anterior-posterior accelerations, correspondent to the existence of a periodic movement;
- Significant positive average vertical acceleration (standing up) corresponding to a maximum average inclination relative to the vertical of 30°;
- Existence of significant signal in the range of frequencies analyzed (0.5 to 2.5 Hz), with an at most 100° phase lag between vertical and anterior-posterior accelerations;
- Existence of a dominant frequency, at the vertical acceleration higher than 30%, on the frequency range considered.

V. Results

V.1 Fall Detection

For the offline data analysis, the described algorithm was tested and 84 in 100 falls were successfully detected (*Sensitivity* - ability of the algorithm to correctly identify falls - 84%). It is important to point out that the specific height of the falls that were not detected (40 cm) was lower than the height typically used for hospital beds (≈60 cm).

The activities performed to test the fall detection algorithm for false positive recognitions were 800 walking samples, at different speeds (200 slow; 200 self-paced beginning from lying position; 200 self-paced beginning from standing position; 200 fast) and 100 trials of activities as sleeping, moving strongly or balancing the trunk. *Specificity* - ability of the algorithm to correctly identify other activities as non-falls - 83.6%.

For the real time data analysis, 72% of sensitivity was obtained. Specificity was measured to be 100% in the situations considered to be normal for the functions of the device, since the alarm was not triggered in any of the situations previously described. By running the same data used to test the first algorithm for false positive samples, the results showed a specificity of 96.3% (note that the initial threshold was 1.5 g and the final one was 1.7 g).

V.2 Getting-out-of-bed Detection

The results obtained show a high rate of recognition when the subject walks *five steps or more*. For *less than five steps* the correctness percentage is not high, but some cases can trigger the alarm, especially at self-paced velocity. Table 1 shows the results of *sensibility* for the detection of getting-out-of-bed. *Specificity* was 99%.

Table 1 - Sensibility for the getting-out-of-bed detection. (*with lying as initial position)

Sensibility						
Method	Less than five steps			Five steps or more		
	Slow (n=100)	**Self-Paced** (n=200)	**Fast** (n=100)	**Slow** (n=100)	**Self-Paced** (n=200)	**Fast** (n=100)
Walking Motion	23.0%	51.9% (34%)*	35.0%	53.9%	98.5% (91.3%)*	98.3%
Total	36.2%			84.9%		

VI. Discussion

The algorithm developed in this work for the detection of falls occurrence, took into account the impact and the rest time after the fall. Even though the optimal threshold value, if one was giving the same significance either to sensitivity (detected falls) and specificity (non-detected not-fall trials), was 1.5 g, the threshold value defined was 1.7 g. In detecting dynamic activity, a high sensitivity is theoretically more important than high specificity, once it is important to detect all significant movements [33]. Also, it is important to reduce the number of false positive alarms in hospitals nowadays, since there is a high rate of alarms that result in no medical action and that brings desensitization of the nursing staff in relation with the alarm. Furthermore, the height of the beds used for the experiments was lower than the height of the hospitals beds; there was an inflatable mattress sustaining the falls; and the subjects were aware that they would fall withdrawing the uncontrolled and unintentional character of the fall which might have been the cause of the failure in the detection. The results obtained (42 non-detected falls, in a total of 150 trials - 72% of accuracy) were, therefore, very satisfactory and suggest that a higher percentage of sensitivity can be reached in the real environment.

The time of rest after the fall was defined as 5 s. One of the problems arising from the imposed rest period is that if the person moves abruptly but does not fall, the fall has to occur only 5 seconds later in order to be detected, which can be considered a refractory period. The selected time of inactivity after the acceleration peak, empirically defined with the goal of distinguishing falls from other activities, varies within the different studies, in this case, it was chosen by the order of magnitude of the analysis window.

The false positive alarms that arise from strong movements and fast variations of position can occur in result of some specific pathology, but are not expected to happen under normal circumstances. Furthermore, though the average age studied may not correspond to the real target range age for the device (older people), the results are not expected to suffer major variations.

Regarding the detection of the walking motion, the algorithm developed in this work brought promising results of close to 100% of sensitivity for self-paced and fast velocities and approximately 50% for slow motion, with *at least five steps*. These appear to be good results with a simple and fast algorithm, and five steps are usually not enough for the patient to leave the hospital service. The results obtained were satisfactory for the analysis being done, and it is important to test this algorithm in real-time detection for further validation. The poor detection at slower speed samples was not an object of concern, since the subjects were walking very slowly and the variation of the acceleration was almost unnoticeable. In cases like these, an alarm of verticality of the trunk would advise the nursing staff and they would possibly be able to get there in time. This algorithm (sensitivity of 91.4% and 100% for *less than five steps* and *five steps or more*, respectively; and specificity of 98%) can have a significant role on the warning that something is not right with the bedridden patient, or even translate a pre-fall condition.

Running cases were not addressed by this study but, since this is a device for people unable to leave the hospital bed, it is not likely that the patients would run around the ward without people noticing. Nevertheless, the developed algorithm is theoretically capable of detecting people walking fast, which envisages that a run would be detected, though it was not tested.

Although it is not possible to predict if the inpatient is going to leave the hospital bed or to detect it as soon as he/she puts one foot on the ground, if he/she is walking, the algorithm will detect it and send an alarm to the nursing staff. The results obtained, together with the existing MovinSense® software, bring good prognosis on a more efficient and organized hospitals caregivers' service. Caregivers can know where the accident happened in time, so they have no need to inspect the ward frequently and can focus their attention on high risk patients. A valuable amount of time and costs can be saved on the everyday activity of an hospital.

VII. Conclusions

The results obtained from sensors signals analysis suggest that the developed algorithms are capable of detecting either bed falls or walking motion (at least five steps, from self-selected to high speeds) with high rate of good detections; also the study sample was large, and the most real environment was sought. The goal is not to replace the hospital staff, but to amplify and optimize their skills by easing their supervisory rounds and helping in the maintenance of risk patients' safety. The biggest advantages from the kind of alarms developed are its automatic operation: once the MovinSense® is connected to the patient and calibrated, all the alarms are automatic, and the notification to the nursing workstation can be selected by the nursing staff in the software. Also, this device enables the supervision of the patients in a manner compatible to the rights of freedom of movement; it enables long term patient monitoring (the battery lasts for at least 10 days and it is easily rechargeable); and furthermore, the absence of cables can improve the working conditions of nursing staff.

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