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Technological Solution for Pervasive Fall Risk Assessment

Joana SILVA[a,1], Diana GOMES[a] and Inês SOUSA[a]
[a] *Fraunhofer Portugal AICOS, Porto, Portugal*

Abstract. Falls are a well-known danger for older adults. With the worldwide population aging, there has been an increasing interest in assessing the risk of falling. This work presents a novel algorithm for continuous fall risk assessment, relying on a linear regression model whose inputs consist of both measured and self-reported risk factors. Two models were conceived and compared, following two distinct approaches, a theoretical and an empirical one. The system is pervasive and was tested in free-living unsupervised conditions. The results of our fall risk scoring system unveiled a strong correlation with the output of the clinical functional tests POMA and TUG (90% and 89%, respectively), which was deemed a promising outcome concerning the feasibility of pervasive monitoring for fall risk assessment in daily living.

Keywords. Fall risk assessment, gait analysis, smartphone, accelerometer, pervasive technology

Introduction

The worldwide population aged over 65 is growing rapidly. The process of aging impairs mobility, muscle strength and balance, which, allied to other intrinsic (e.g. side effects of medication) and extrinsic (e.g. improper use of assistive devices) [1] factors, increases the incidence of falls among elderly citizens. The consequences of this phenomenon are simultaneously social, health-related and economic, motivating the search for strategies that properly evaluate the risk factors of falls in older people.

Currently, there is not a standard for assessing the risk of falling. Several scales, questionnaires, functional tests, and protocols have been proposed in the past years to overcome the lack of standardized clinical and medical procedures for assessing the risk of fall [2], as the Timed-Up and Go (TUG) [3] and Tinetti's Performance Oriented Mobility Assessment (POMA) [4]. However, these procedures are often only applied after a first fall occurs, which influences the collected parameters. The majority of the proposed assessment scales and questionnaires are also subjective, self-reported, and do not consider several major fall risk factors. Proper methods for the objective assessment of individual gait, strength, and balance are confined to laboratory settings, requiring specialized personnel and equipment, thus leading to higher costs. Moreover, these solutions rely on on-time/site assessments that do not reflect the evolution of risk factors over time. This context discloses a gap that technology can fill through the development of methodologies for continuous and pervasive monitoring of fall risk parameters.

[1] Corresponding Author: Joana Silva, Fraunhofer Portugal AICOS, Porto, Portugal E-mail: joana.silva@fraunhofer.pt

Some research works [5-8] have also been exploring the extraction of automatic gait and activity-related parameters using wearable devices as predictors of the risk of falling. While these have provided insightful information about the potential of daily-living monitoring for fall risk assessment, these solutions are based on the utilization of specific wearable devices, which can decrease user adherence to the system due to its impracticality or even simply forgetting the device. Our method, on its hand, proposes a smartphone utilization-based system, intending full pervasiveness of the solution, and no previous works were found to perform an analysis comparable to the one in this work (smartphone-based, multimodal, free-living, and pervasive).

This work introduces a method for continuous fall risk assessment based on a set of personal information (both objective and subjective) and the extraction of automatic gait, physical activity and postural transition parameters. The method relies on a smartphone application and a scoring algorithm, whose output was compared against standard functional tests applied to a total of 15 users. Besides being told to use the smartphone with our application installed, in the pocket or belt, the users were not given any specific indication on system's usage and the trials were not supervised. Thus, the main contribution of this work consists in an assessment of the feasibility of solely relying on pervasively monitored and self-reported risk factors for continuous fall risk assessment using a smartphone, by implementing strategies to overcome the limitations of free-living usage.

1. Methods

1.1. Fall Risk Assessment App

We have developed a fall risk assessment application (FRA App) based on a continuous evaluation of fall risk factors using the smartphone's accelerometer and self-reported questionnaires, in mobile interfaces. It relies on five main fall risk categories, as follows:

- **Personal Information (PI):** includes the risk factors with higher impact in falls [1], i.e. age, body mass index (BMI; measured as how far the person is from the ideal BMI value), gender, health conditions, number of prescribed medication, number of recent falls (last year).
- **Falls Efficacy Scale (FES):** measures the fear of falling when performing daily living activities. This work used an adapted version of the original FES questionnaire for Portuguese [9]. Higher scores represent higher fear of falling, and the final score ranges between 0 e 10.
- **Physical Activity (PA):** automatic recognition of the user's physical activity using the activity monitoring algorithms previously reported by Aguiar et al. [10]. Low activity time is associated with increased risk of falling.
    - **Walking time**: World Health Organization recommends that adults aged over 65 should do, at least, 150 minutes of moderate-intensity activity or 75 minutes of vigorous-intensity activity during the week.
    - **Resting time**: represents how long a person spent seated or laying during the awake period of the day, which we considered to be 16 hours.
    - **Number of steps**: it is proportional to the activity of the user and should also follow the public health recommendations in terms of steps/day;

7,000-10,000 steps/day are estimated to be equivalent to 30 minutes of daily moderate-intensity activity [11].
  - **Energy**: it indicates how active a person is (proportional to the activity of the user).
- **Gait Analysis (GA):** estimation of specific gait analysis metrics using the activity monitoring algorithms previously reported by Aguiar et al. [10]:
  - **Gait speed**: computed combining the retrieved number of steps and stride length to estimate the travelled distance over the elapsed time. Generally, people walk comfortably at around 1.2 or 1.4 m/s [12]. Someone walking slower most probably experiences difficulties in walking, so the risk of falling is naturally higher.
  - **Stride variability**: inferred by analyzing the (ir)regularity of the coefficient of variation of the stride duration, which can indicate walking disorder and high fall risk.
- **Postural Transitions (PT):** the ability to sit/stand is also an important fall risk factor. A signal processing algorithm was developed to detect a variation of orientation of the inertial sensor placed in the trousers' pocket, to determine the number and duration of postural transitions throughout the day. Higher number of transitions evidence less movement impairments, while slowly sitting/standing disclose problems with muscle strength and balance.

1.2. Data Collections and Description

We have recruited 10 people over 65 years old and 5 younger people. Seven seniors had a history of falls in the previous year (3 persons fell once, 2 fell twice, 2 fell 5 or more times). The remaining subjects did not have a prior record of falls. Initially, standard functional tests for fall risk assessment - TUG and POMA - were conducted with all the participants. Then, the volunteers used the smartphone to collect sensor data during daily living activities in the following 15 days. The smartphone was carried in the trousers' front pocket or belt during the day, for as long as possible, while executing regular daily living activities. The value of each computed parameter was recorded in a backend server, enabling remote tracking of the progress of these unsupervised trials. No additional information was provided to the users regarding system's usage or specific requirements. The full group presented a mean age of 59.1 ± 19.2 y.o., with a seniors' age distribution of 73.6 ± 5.97 y.o. and younger subjects with 33.2 ± 5.5 y.o. Three participants reported walking problems, two of them used walking aid, and another participant had an implanted knee prosthesis. All gave informed consent as per the Declaration of Helsinki.

1.3. Fall Risk Assessment Scoring and Algorithm

In order to develop a fall risk score that takes into account all of the of risk factors, two linear regression models were implemented. The first model (theoretical approach) was based on a direct distribution of categories and parameters' weights based on the theoretical importance of each of them in fall risk assessment, according to the odds ratio reported in the literature [1]. The second model (empirical approach) used a similar weight distribution approach, but each category/parameter was proportionally weighted to the correlation between that variable and the score of TUG and POMA tests. A two-level weight assignment approach took place for both regression models: first to each one of the 5 risk categories and then to each parameter within a category (Table 1). While some parameters are directly proportional to the fall risk (e.g. age), some other are indirectly proportional (e.g. gait speed). For that reason, we normalized each parameter value to a scale ranging from 0 to 10, where 0 is defined as the parameter's recommended value (i.e. no fall risk) and 10 as the value that implies the highest fall risk. If a person does not use the smartphone during the day, insert the personal information or answer the FES questionnaire, there are parameters that we will not be able to compute. In such cases, their weight in the regression will be uniformly distributed by the other parameters. We initialize the personal information with default values in order to have a least one category that can be computed. Following this procedure, we are able to estimate a single fall risk score based on each of the modelling approaches, that outputs a daily value between 0 (low-risk) and 10 (high-risk). A final risk score is then computed, resulting from the average of the daily scores over the previous two weeks. In order to foresee some direct consequences of conceiving a system as pervasive and robust as possible, a method for handling data from days when the user did not use the smartphone or walked long enough was also implemented. As such, the contribution of each computed daily risk score for the overall fall risk score was set as a percentage which varies according to the number of significant risk parameters that the application was able to compute during such day.

Table 1. Linear regression weights of risk categories and parameters for theoretical and empirical approaches.

	PI	Parameters						**GA**	Parameters	
		Age	BMI	Sex	Drugs	Health	Falls		Speed	Stride
Theoretical	0.38	0.20	0.10	0.05	0.10	0.20	0.35	0.20	0.80	0.20
Empirical	0.28	0.32	0.36	0.07	0.00	0.18	0.07	0.30	0.67	0.33

PA	Parameters				**PT**	Parameters				**FES**	
	Energy	Walk	Steps	Rest		Sits	Stands	SitT	StandT		Score
0.20	0.20	0.20	0.40	0.20	0.10	0.25	0.25	0.25	0.25	0.12	1.0
0.10	0.00	0.00	1.00	0.00	0.002	1.0	0.00	0.00	0.00	0.30	1.0

1.4. Validation: correlation with functional tests

In order to understand if our method for pervasive assessment of fall risk on a daily basis provided information as reliable as that of the most commonly used clinical functional tests, we studied the correlation and statistical similarity (t-test) between the output of our scoring algorithms and the score of TUG and POMA tests, which were applied to each volunteer as described in Section 1.2. Since FRA App, TUG and POMA make use of different scales, we mapped the scores of each assessment to a 0 to 1 range, where 0 and 1 represent the lowest and highest risk in our dataset, respectively. The normalization of the output of each assessment was achieved by subtracting the minimum value to each instance and dividing by the difference between the maximum and minimum values. This step took place prior to the correlation computation, ensuring comparable values to be used for correlation analysis. For comparison purposes, we also computed the correlation between POMA and TUG tests.

2. Results

We calculated the statistics for the data collected during the trial, reporting the average walking time, number of sits and stands, and number of analyzed days. Each person used the FRA App for an average of 13 days and walked for almost 2 hours each day. The number of detected postural transitions was, on average, 9 sits and 9 stands per day. In 56.8% of the analysed days, all information used in the FRA risk score algorithm was available. Only in 3.5% and 3.6% of the days the users walked less that 10min or the stride variability was not computed, respectively. An average of 18.3% of the analysed data referred to usage of the smartphone in the belt, and so the postural transitions metrics were not computed. In 17.8% of the days, the users did not use the App, meaning that the categories based on inertial measurements were not computed.

The correlation between the risk score of the FRA App for both model implementations and each of the applied functional tests, POMA and TUG, were also computed. POMA and TUG exhibit a correlation of 0.97. Both theoretical (T) and empirical (E) approaches presented strong correlations with the functional tests (T-POMA, 0.80; T-TUG, 0.79; E-POMA, 0.90; E-TUG, 0.89), and were deemed statistically similar to the scaled output of these assessments, presenting p-values < 0.1. These results support the appropriate performance of the method.

3. Discussion

The FRA App provided an estimation of fall risk, based on a set of parameters assessed pervasively using the inertial sensors of the smartphone and personal information. The data collection process was not supervised; we have solely asked the participants to use the smartphone with the FRA App for 15 days, without disrupting their normal daily living activities. Despite that, we were able to collect data from an average of 13 days per person, which is an important outcome of the study, since the users were not given any specific information regarding the system's usage. We were able to detect a daily average of 2 hours of walking time and 18 sit/stand postural transitions. These results support the reliability of our fall risk model, since the parameters that are considered for the fall risk estimation are based on a significant amount of data, even when collected in uncontrolled settings.

The empirical approach presented the strongest correlation with both standard assessments. This approach did not consider some of the parameters weighted under the theoretical approach. In fact, regarding physical activity and postural transitions categories, only one parameter for each was considered. This fact does not indicate that our method and results contradict previous works under which our theoretical assumptions were made, but it could indicate that there are parameters that have higher importance for pervasive fall risk assessment solutions than others. This conclusion is very promising, since it leads to a reduction of the number of parameters to compute.

Another relevant aspect relates with the success of our weighting method for handling days in which there was not enough information for reliably estimating all necessary parameters. In our trial, more than 57% of the analysed days included information from the five risk categories and only a small amount of days (18%) included solely self-reported data. This strategy to overcome the limitations of free-living usage of a fall risk scoring system was never reported by previous literature and can be considered as one of the main contributions of this work. This was a difficulty of developing a fully pervasive algorithm, that does not impose conditions on the user's daily habits or activities. As such, we believe that this outcome is very enlightening concerning the analysis of the feasibility of pervasive fall risk assessment in free-living conditions. However, stronger conclusions should be obtained in a different and larger subset of users, which should be set as future work. The modest number of participants is, however, a limitation of this study. Nevertheless, we believe that their diversity decreased the bias of the test-bed, since approximately half of the subjects experienced falls in the previous year, and there was representation of several types of walking disabilities and subjects without movement impairments. Therefore, despite requiring further validation to fully assess the success of the method, this study discloses an important outcome towards understanding the feasibility of pervasive fall risk assessment solutions. Also, despite the adequate user adherence to system usage during the trials, further research should be carried to address specific challenges, like maximizing smartphone usage, which seniors may forget, or having to place the smartphone in a specific position (to assess postural transitions).

4. Conclusions

This work presented a new algorithm for continuous fall risk assessment in full free-living conditions. The system relied solely on a smartphone application, and its utilization on a daily basis did not impose any restriction on the users' habits. A comparison between approaches of theoretical vs. empirical basis was also performed, indicating that some parameters of theoretical importance may not be paramount for pervasive fall risk assessment using our method. The fall risk scores obtained by our method presented strong correlations of 90% and 89% with clinical functional tests POMA and TUG, respectively, supporting that pervasive monitoring of fall risk-related parameters with a smartphone enables reliable fall risk assessment. As future work, we intend to extend our validation process with more users, in order to study the validity of our conclusions and the generalization of the method considering a broader population.

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