Phone Based Fall Risk Prediction

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Abstract. Falls are a major health risk that diminishes the quality of life among older people and increases the health services cost. Reliable and earlier prediction of an increased fall risk is essential to improve its prevention, aiming to avoid the occurrence of falls. In this paper, we propose the use of mobile phones as a platform for developing a fall prediction system by running an inertial sensor based fall prediction algorithm. Experimental results of the system, which we still consider as work in progress, are encouraging making us optimistic regarding the feasibility of a reliable phone-based fall predictor, which can be of great value for older persons and society.

Keywords: Fall Prevention, Fall Risk Prediction, Inertial Sensors, Older people, Gait analysis, Smartphone.

1 Introduction

The progressive ageing of population is creating new social and economic challenges, concerning people's health and well-being. Particularly, falling is a serious and common problem facing older people that frequently leads to injury, suffering, fear, depression, loss of independence, reduced quality of life and death [1]. This is further problematic for older people living in the community, where help or medical assistance can be provided late [2].

To give a faster assistance when a fall occurs, several strategies to alert its occurrence have been developed. These are essentially reactive and don't prevent fall occurrences and some of their related consequences [2].

"Fall prevention" is therefore becoming increasingly important. Besides external risk factors (e.g. slippery floor), medicaments intake, chronic diseases, gait or balance disorders and hazardous activities also contribute to the occurrence of a fall [1]. Consequently, older people presenting some of these risk factors can be considered a high risk target group. Multi-factorial interventions are then applied to modify/eliminate those risks [3].

Nowadays, the risk is based on questionnaires and the assessment of gait and balance disorders, which are among the most consistent predictors of future fall [3]. These tests are typically administered by experts in a clinical environment

K.S. Nikita et al. (Eds.): MobiHealth 2011, LNICST 83, pp. 135–142, 2012.

and are only accessible when a visit to the clinic is necessary, which frequently happens after an injurious fall, so that the application of preventive strategies can be already too late. Also, the equipments used are usually costly, not portable and time-consuming, limiting their use as routine. These clinical-centric models are therefore becoming increasingly unsatisfactory.

1.1 Why Using a Mobile Phone as Fall Predictor

A proactive community-based strategy is necessary in order to earlier recognize increased risks and improve prevention strategies [4]. Some systems based on the use of wearable inertial sensors like accelerometers and gyroscopes have been proposed in recent studies for unsupervised long-term fall risk screening, through the evaluation of functional ability and mobility. These systems have the advantage of being portable, low-cost and easy-to-use. In contrast to clinical tests, these are self-administrable and can be used outside clinical environments, being able to anticipate the detection of problems and therefore to administer/modify prevention strategies at an earlier stage [4].

The popularity of mobile phones is likely to continuously increase in the near future due to decreasing prices, thus projecting an overall acceptance regarding it as a fall prediction platform. Based on these principles, a smartphone is adapted to be used as a fall risk screening tool, using its inertial sensors.

To make maximum explore of phone strengths and to improve fall prevention strategies, other risk factors besides gait and mobility problems were considered. The same questionnaires currently used by doctors were therefore adapted to the phone, so that several risk factors for falling could be identified and monitored over time. Since the information is stored in the smartphone, the historical can be used by the user and/or automatically transmitted to the doctor by gateway capabilities in order to evaluate the risk over time and earlier apply/modify preventive schemes [4].

2 Related Work

In order to detect subtle problems with gait or balance and provide objective measurements of individuals fall risk, instrumented assessments, such as force platforms and cameras, have been developed [12].

Nowadays, the studies focus on the measurement of parameters from wearable inertial sensors signals, which demonstrate advantages in relation with previous methods. Sensors are used to quantify validated medical tests for fall risk screening [2], directed routines with a series of movements/assessment tasks [4] and walking patterns/gait [5,11].

Then, these parameters are proposed to be used to measure the risk of falling, discriminating those at no risk and at risk. Results from [2] suggested that an accelerometer could be used not only to measure the performance of Timed Up and Go Test, but also to extract further data from gait, providing a more depth analysis of the individual's risk. Machine learning techniques can also be used to combine parameters, so that risk stratification can be done [4].

Literature suggests a global quantification of patient's fall risk, not only through measurements of physical performance, but also with other risk factors (e.g. fall history, medication use and balance confidence), emphasizing the multi-factorial nature of falls [6]. As a result, the likelihood of falling is assessed by screening multi-factorial risk factors, and the intervention should be made when a risk factor enters a warning zone [3].

3 Risk Prediction Method

Given the multi-factorial nature of falls and the current problems of solution scalability, we propose a smartphone-based solution which comprises three main modules: the gait analysis test, the clinic questionnaires and the feedback module, as illustrated in Fig. 1.

(a) Gait test (b) Clinical Questionnaires (c) Results

Fig. 1. Purposed Smartphone-based Fall Risk Analysis Solution

Several authors have identified that gait speed alone could be used as a simple and quick option to measure fall risk, possibly as an alternative to more complex mobility tests performed in clinical environments [5]. According to [11], a gait speed lower than $70cm/s$ is associated with an increased risk. In our first approach, the mobile phone was placed at the lower back of trunk, attached at the belt (Fig. 1a). This position is stable and near the centre of mass of the body, moving parallel to it, and has been frequently used in the literature [7].

Acceleration data is read from an Android based mobile phone, and the axis are adjusted according to ISB recommendations [13]. After reading the signals, foot contacts detection is done. Foot contacts are obtained through readings of forward acceleration peaks, preceding a change of signal polarity (from positive to negative values) [9].

After foot contacts detection, discrimination between right and left foot contacts was done by analysis of the medio-lateral acceleration profiles of the trunk. As recognized by [9], the major part of the medio-lateral acceleration is to the left during the right support phase, and vice versa.

Toe offs were detected on the vertical acceleration signal, already excluding the static gravity component.

The minimums after heel strikes were considered the toe offs [10].

Since the time stamps of all events were recorded, all gait phases (i.e. stance, swing, single and double support phases) could be properly delimited, both from a left and right perspective.

The calculation of step length was based on two pendulum models: the first relative to swing phase and the second, with an unknown radius, to the double support phase, as described by [10] and [9] (Equation 1). Step length was therefore calculated as the sum of displacement during swing phase (S_1) and the displacement during double stance (S_2). S_1 was derived from leg length (l) and vertical displacement between the time of toe off and heel strike events (h_1). S_2 was set as a constant equal to foot length [10].

$$Steplength = S_1 + S_2 = 2\sqrt{2h_1 l - h_1^2} + S_2 \tag{1}$$

Vertical displacement was calculated by double integration of vertical acceleration signal, using the trapezoidal rule. To eliminate the problems related with the lack of initial conditions and the presence of acceleration drift, intermediate steps of high pass filtering were required before and after integration [14]. Fast Fourier Transform filtering was used to eliminate the frequencies below the frequency of foot contacts.

Step duration was calculated as the time between two consecutive foot contacts [9]. Mean step length and duration was calculated from all available strides. Mean step length divided by mean step duration was used to estimate walking speed.

Table 1. Risk profile

Risk Factor	Risk profile
Fall History (*Have you fallen during the past 12 months?*)	Y / N
ADL difficulties (*Katz ADL score* $\leq$ *2?* [15])	Y / N
IADL difficulties (*IADL score* $<$ *8?* [16])	Y / N
Gait/Mobility difficulties (*Velocity* $<$ *70cm/s?* [11])	Y / N
Balance confidence (*ABCS score* $<$ *67%?* [17])	Y / N
Medication Use	
Polypharmacy (*Do you take 4 or more medications?*)	Y / N
Cardiovascular system medications (*diuretics, anithypertensives*)	Y / N
Psychoactive medications (*sedatives, antidepressants*)	Y / N
Musculoskeletal system medications (*narcotics, corticosteroids*)	Y / N
Other (*hypoglycaemics, allergy, cold medications*)	Y / N
Medical Conditions	
Musculoskeletal (*arthritis, ...*)	Y / N
Neurological (*stroke, Parkinson's, ...*)	Y / N
Heart diseases (*postural hypotension, arrhythmias, unstable, ...*)	Y / N
Diabetes	Y / N
Dizziness	Y / N
Psychological function (*FSQ score* $\leq$ *70?* [18])	Y / N
Social activities (*FSQ score* $\leq$ *78?* [18])	Y / N
Quality of interactions (*FSQ score* $\leq$ *69?* [18])	Y / N

Our risk prediction approach also tried to include other risk factors for falling, in order to take the first steps on a multidimensional risk screening method, which would include not only an evaluation of gait, but also other risk factors for falling. Several risk factors which could be self perceived by the person through the use of validated questionnaires were selected. Table 1 summarizes risks and tools that could be included on risk profile.

This profile would give rise to an overall health status score (Fig. 1c) and later the time-dependent risk factors could be used to estimate a likelihood of falling changing over time.

4 Evaluation Method

A group of 14 participants (mean age 26 ± 3.6, height $1.74 \pm 0.1cm$ and weight $73.5 \pm 11.3Kg$) without any visible gait problem and able to walk unassisted without using walking aids participated on the test. The aim of this test phase was to evaluate the algorithm's performance on detecting step length, duration and velocity from acceleration signals during normal gait.

The experimental setup comprised a walkway $5m$ long, with distance markers placed on the ground. The phone was placed inside a case and adjusted around the pelvis using a belt. It was positioned with a known orientation relative to the ground and to the walking direction at the lower back of trunk of each participant. Subjects were asked to walk along the walkway at three different self-selected speeds: comfortable normal pace, slower pace and a faster pace. Each test was repeated one time. During each test, a simultaneous recording of a digital video camera parallel to the ground and of phone sensors was done.

Foot length and leg length were measured experimentally. Leg length was measured as described by [8], from the difference between standing and sitting height. Foot length was measured with the shoes on.

Each video was analysed in order to obtain an estimative of the mean step length, duration and velocity. A frame by frame analysis was necessary to determine the time of each heel contact. Each step length was determined using the information of the distance markers on the ground. Video information was used as a reference to evaluate the results obtained from sensors data.

5 Data Analysis and Discussion

Acceleration signals similar to those reported on the literature could be obtained using phone's sensors. On Fig. 2, an example of an acceleration signal with detected foot contacts is provided.

The maximum deviation from expected (i.e. from video results) and estimated (i.e. from sensors signal analysis) mean step length was 17% and the mean deviation was $7 \pm 5\%$. Deviations of the measured mean step length compared with the expected values are either positive either negative and a tendency to over or underestimation is not observed.

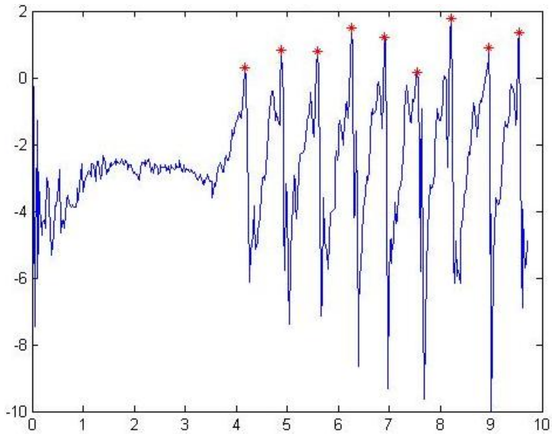

Fig. 2. Foot contacts detection. *blue:* forward acceleration signal (m/s^2) *vs.* time (s); *red:* foot contacts.

The deviations encountered on estimated values seem to be acceptable even if we consider all the sources of error that can be present on step length estimation. First, the model used to estimate this value is more rigid than the real displacement patterns during gait, which presents some variability. For example, leg is not always maintained as a rigid pendulum, like considered, and the displacement during double support not always correspond to foot length, which can be tilt on the direction of progression. Second, errors on acceleration and position signals can be present, so that others are introduced on step length estimation.

The maximum deviation from expected and estimated mean step duration was 3%. No difference was observed in 41% of the considered tests. The mean deviation between measured and real values was very low and equal to $1 \pm 1\%$.

The velocity, calculated as the mean step length divided by mean step duration, is affected by errors at these two estimated values. The maximum velocity deviation from real values is 15%, and the mean deviation is $7 \pm 5\%$. A plot of the comparison between expected and estimated velocities is shown on Fig. 3.

Although errors on velocity estimation are present, they are not very high, so that using phone's sensors to estimate gait velocity seems to be a reliable option when the main purpose is to discriminate high and low risk persons based on velocity. As indication, all the young persons walked at a normal speed higher that $70cm/s$, so that they may not be at risk of falling, as expected.

As a general comment of the adopted method, it can be stated that the walkway had a short size, so that few steps were available, and possibly no enough time was available so that gait was stabilized still within the walkway during each test. In spite of uniform clinical protocols to detect gait abnormalities are lacking, representative measures of gait variability (which are considered as significant fall risk predictors [11]) could be extracted if a larger walkway was available.

For now, nothing can be concluded regarding the kind of signals and quality of detections that are expected to occur when old people (presenting or not

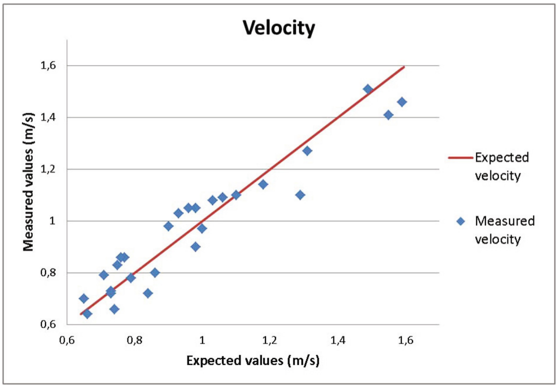

Fig. 3. Expected vs. Estimated velocity. Red line represents the expected velocity.

gait abnormalities) walk. It would be important to validate data from phone's sensors signals on these persons in comparison with the traditional methods of gait analysis, including cameras and force-plates systems.

From the described results, evidences exist that phone's inertial sensors can be used to analyse gait, which would also include the extraction of variability parameters. However, further exploration is necessary.

6 Conclusion

In this paper, a study was done regarding the use of mobile phones as fall risk screening tools, aiming to improve the current fall prevention strategies.

From the results, evidences exist that phone's sensors signals can be used to quantify gait or other movements, by extracting parameters with a relation with the risk of falling. At present, this relation is not well known, but strong evidences exist that several parameters can be combined to screen for fall risk.

Other risk factors can also be assessed using the phone, by using the same questionnaires currently used by doctors at clinics. Evidences exist that in the future all these risk factors can be combined, by attributing time-varying weights to each one, enabling the calculation of a global likelihood of falling. All the assessments can be made in an unsupervised manner and centralized on the phone, so that a complete history of risk factors can be built and transmitted to the doctor.

A greater frequency of assessments would therefore be encouraged, earlier alerting the persons for higher risks and providing new insights about fall prevention strategies.

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