Home Lab - Context-Aware Fall-Risk Assessment at Home

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Abstract. For the elderly, falls are among the most frequent causes of severe injuries or even death. Therefore it is highly desirable to develop methods for early recognition. Numerous indicators have been proposed and thoroughly validated, that allow medical staff to identify persons at a high risk of falling. However, these indicators suffer from pragmatic drawbacks impeding their widespread application. To overcome this, we present the concept of a context-aware system, using low-cost accelerometers to collect motion data at peoples homes, from which a fall-risk prognosis is computed automatically. The underlying design principle can be generalized to other medical settings, opening up a promising field for the application of context-based technologies.

Key words: Statistical Activity Recognition, Fall Risk Assessment, Context-based E-Health

1 Introduction

Severe injuries from falls rank along with well-known diseases such as cancer or hypertension as leading causes for the hospitalization of elderly people ([1]). As a result, therapies aiming at reducing these risks have been developed, like special training programs. An important prerequisite for the targeted application of these therapies is the availability of precise indicators allowing for the early recognition of persons at an increased risk of falling (in a rather long follow-up period, like 12 month). Apart from the obvious requirement to detect as many persons in danger as possible, it is also important to reduce false alarms in order to limit resulting costs. Accordingly, the problem of finding and validating such indicator variables has received much attention in the geriatric community. These include questionnaires, bio-mechanical assessments and tests of basic physical skills. Albeit thoroughly validated, all of these indicators are costly due to important resource requirements. This prevents their widespread use and consequently a large part of the elderly population is not covered by early fall-risk recognition. This yields the motivation for our proposition: A system that uses low-cost wearable accelerometers to permanently collect motion data at peoples homes and automatically (without interaction of medical staff)

analyses this data to establish a fall-risk prognosis. As only data sampled in particular situations is suitable for this prediction, such a system must necessarily be context-aware, as will be outlined.
The organization of the remaining paper is as follows: We briefly review existing work on fall-risk indicators and their drawbacks. Then we introduce our proposal, motivating our choice of sensor devices for the system and presenting the context-based key idea for the realization of the fall-risk prognosis module. Then we give some statistical background and conclude with an outline of future work.

2 Related work on Fall-Risk Assessment

Methodologically, the de facto standard in this area are prospective studies, comprising the following stages: First, potential indicator variables are identified heuristically (feature selection). After that, these variables are measured for each member of an appropriate test population. This population is then tracked during a predefined follow-up period (one year by convention of the fall-risk community, see [2]), during which all fall events are recorded. Finally, the data records (features and binary target variable encoding (non-)occurrence of fall event(s)) gained in this way are statistically analyzed (using for example logistic regression or classification theory).

Fall-risk indicators studied in this way can be divided into the following main categories:

- Bio-mechanical parameters
- Temporal parameters describing standardized tasks
- Gait parameters
- Cognitive Skill Tests
- Combinations of these factors

The first category comprises a variety of parameters recorded during standardized physical tasks; examples are muscle strength tests ([3]) and measurement of inertial acceleration of different body parts ([4], [5], [6], [7], [8]). A prominent instance of the second category is the time a person takes to get up from a chair ([9]). Gait parameters ([2], [10], [11], [12]) are treated later on in greater detail, as they provide the basis for our approach. Cognitive skill tests comprise memory tests as well as logical ones ([13]). Finally multi-factorial approaches ([14], [15], [16], [8], [17]) consider combinations of different features, which is plausible as falling is certainly not a mono-causal phenomenon. Nevertheless, in order to ensure practicability, it is desirable to find a small number of features with high predictive power. As mentioned, two indicators playing a major role for the realization of our approach will be revisited in greater detail. For now, it suffices to summarize that these indicators suffer from major pragmatic drawbacks: Albeit thoroughly validated in terms of accuracy and designed for clinical use, data acquisition takes a lot of time and requires medical staff and/or expensive equipment. In addition to that, these methods entail a considerable impairment of targeted patients: They have to make an appointment with a specialized institution and undergo time-consuming physical and/or mental test procedures; unwanted psychic side-effects of this have not yet been investigated. All these factors prevent established methods, which have the potential to save lives, from being made available to wide parts of the population in question. This gave rise to the approach described subsequently.

3 Permanent Low-cost Fall-Risk Assessment At Home

As mentioned in the introduction, the overall vision is to provide a cheap system, that, by means of wearable sensor devices, permanently records data in persons everyday lives, without any further impairment. Then, by a recurrent off-line analysis of the gathered data (for instance once a month), a fall-risk prognosis is to be generated automatically, as if the person had attended a clinical fall-risk assessment.

Technically, the type of sensor devices and their positioning had to be determined, keeping in mind usability constraints. In the literature we found that 3D-accelerometers have successfully been used for a number of similar tasks (see [18],[19]). Furthermore, a sample rate of 40 Hz is generally considered to be sufficient to capture human motion ([20]). Regarding the integration respectively positioning of such a sensor, we chose wrist-worn clock-like devices. The major advantage of this is the high degree of familiarity persons have with that kind of device. This familiarity is important for at least the following to major reasons: First, user acceptance is increased and secondly, no intervention by medical staff is needed, because persons can handle the device on their own. However, as a fall-back solution, we keep the possibility to fix the device to a belt, more closely to the center of mass of the human body.

So far, we have said nothing about the heart of the system, namely the fall-risk prognosis module intended to process the raw data. Subsequently, we will work out the challenges related to its realization and our proposed context-based solution.

3.1 Key Idea: Context-Aware Data Collection

One might be tempted to mechanically apply the approved method of prospective study: Establishing statistical relationships between the data sampled by the sensor device (sequences of three-dimensional acceleration vectors) and the target variable indicating falls in the follow-up period, in order to implement these findings in the prognosis module. However, such an approach is likely to fail, due to the absence of an obvious hypothesis about a potential interrelation. To point out this crucial fact, we would like to oppose our situation to rather clear settings like the proposal of [9], measuring the time a person takes to get up from a chair; here the reasoning "the longer it takes", "the worse his constitution" and hence "the higher his risk of falling" is more than plausible and allows for standard modeling like logistic regression.

As an answer to this challenge, we have searched for approved fall-risk indicators, which

- have already been prospectively validated
- are potentially reconstructible from the acceleration data

With such indicators at hand, we argue that it is possible to establish fall prognoses in a "transitive" way:

- Use recorded acceleration data to compute approved indicators
- Use these indicators to establish fall prognosis

As these parameters are measured under standardized conditions in appropriate laboratories, it is right here that context comes into play. The above sketched procedure can only be applied to data sampled during intervals where the laboratory conditions were approximately met. This consideration leads to the following three stage process, being the conceptual backbone of our system:

- Filter out intervals conforming to (different) lab condition
- Use recorded acceleration data to reconstruct approved indicators for these intervals
- Use these indicators to establish fall prognosis

In an obvious way, one gains a general scheme by abstracting from the concrete setting of fall-risk prognosis. This scheme can be customized towards different medical scenarios, involving costly laboratory-based methods. Exemplarily, we cite early recognition of movement disorders in patients affected by multiple sclerosis ([21]) and motion assessment of Parkinson patients ([22]). In other words, our proposal can be seen as a first blueprint for a promising class of applications for context-based technologies.
However, we focus back on fall-risk assessment and proceed by briefly introducing the two approved fall-risk indicators we claim to be reconstructible from the acceleration data.

3.2 Gait Variability

In [2], Hausdorff investigates the usage of `Gait Variability` as an indicator of fall-risk. To calculate this parameter, a person is simply asked to walk at his desired speed. Using force-sensitive insoles, for instance, the time stamps of the respective initial ground contacts of each foot are recorded. Defining the gait cycle times to be the differences of two subsequent time stamps for an arbitrary but fixed foot, one can calculate the mean gait cycle time and finally the mean deviation from this quantity. Formally, let N be the number of steps and $t_l(n)$ the time stamp of the n-th initial ground contact of the left foot. Then the mean gait cycle time MGC is defined by:

$$MGC := \frac{\sum_{n=1}^{N-1}(t_l(n+1) - t_l(n))}{N-1}$$

Finally, the Gait Variability GV is defined as:

$$GV := \sqrt{\frac{\sum_{n=1}^{N-1}(MGC - (t_l(n+1) - t_l(n)))^2}{N-1}}$$

The confirmed hypothesis is again that a higher value of this quantity indicates uncertainty in walking and thus a higher risk of falling.

3.3 Postural Sway

The second indicator is the so called `Postural Sway` (see [8]). Here, the standardized lab setting is very simple: Persons are asked to stand still and trunk oscillation in both forward-backward and left-right direction is recorded. Then the discrete Fourier transform of the resulting sequence is calculated and aggregates of the frequency spectrum are determined (mean, standard deviation).

4 Theoretical and Empirical Background

This section contains a brief sketch of the statistical modeling underlying the system, the studies that must be performed in order to both validate these models and evaluate the overall system.

4.1 Modeling

For the first stage, given a finite sequences of vectors recorded during a given time interval, we must segment this interval into a finite number of subintervals labeled with elements of a finite set of activities (concretely: "walking", "standing","something else").
For the reconstruction of time stamps of steps, we must further segment the intervals labeled with "walk" into subintervals labeled with "Swing Phase Left" and "Swing Phase Right"; the desired time stamps are determined by the boundaries of the subintervals.
Both cases lead to the same mathematical model: Vector sequences are to be mapped to activity traces, e.g. functions from the time interval into the set of activities; subintervals are delimited by the discontinuity points of these functions. As there is no intuitive way of finding a deterministic functional relationship, the problem must be tackled statistically, for example by estimating a regression functional. Similar problems arise also in many other settings and have received some attention in the literature (under the name of "activity classification/recognition"). For a systematic review, we refer to [23]. On the one hand, we simply adopt the state-of-the art being described in [23], which makes use of standard machine learning theories, implemented in the well-known Weka tool kit for instance. On the other hand, we have for the first time provided a thorough theoretical justification of this approach, in terms of sufficient conditions under which the stochastic guarantees (yielded by standard theories) to find a classifier near to the supremal accuracy carry over to the non-standard case we are faced with. This work will be published in the near future and is out of the scope of this contribution.
Finally, reconstruction of Postural Sway can be done by twofold numerical integration over the intervals labeled with "standing".

4.2 Validation Studies

The suitability of the theory sketched in the previous section must be validated by means of patient studies, as having an estimator for finding functionals near to the optimal accuracy with high probability does not mean that this optimum is "good" enough for the application at hand. To this aim, our project partner Sophia AG Bamberg, who, among other services, provides technical security equipment for elderly people, recruits elderly probands among his clients. Excluded are persons suffering from special diseases like Parkinson. This is not a real restriction, because it is a priori known that these people are at a high risk of falling

For the validation of the first stage, we are currently letting these probands, wearing our accelerometer, execute everyday tasks, observed by a supervisor who logs the actual activity traces. These samples are aggregated and "fed into" the learning procedures of Weka. According to our analysis conducted so far, we can state that it is possible to reach 90-95 per cent (cross-fold evaluation) accuracy after an individual training phase of 15 minutes for each person. Opposed to the great benefits of the system, this effort seems well justified.

For the validation of the step time reconstruction, persons will be asked to walk, while being equipped with both the accelerometer and insoles like the ones used by Hausdorff. This again yields samples for a supervised training and cross-fold evaluation.

For validation of Postural Sway reconstruction, we will ask probands (again equipped with the accelerometer) to stand on a special platform designed to measure trunk oscillations. Afterwards, we can numerically process (twofold integration) the sequence of acceleration samples and appropriately compare the reconstructed oscillation to the actual one measured directly.

4.3 Evaluation Study

After the (hopefully) successful validation and fine-tuning of the single processing stages, an evaluation of the composite system's fall-risk prognosis must be carried out in the field. To this aim, a group of probands will be asked to wear the sensor devices at home, making available large amounts of data that will be used to compute fall-risk predictions. These will be compared to the prognoses of an approved fall-risk assessment tool, serving as a gold standard.

5 Conclusion and Future Work

We have proposed the concept of a context-based system for fall-risk assessment of elderly persons at home, along with a detailed outline of our development methodology. Beyond the perspective of making fall-risk assessment affordable for a much larger part of the elderly population than it has been achieved up to now, our approach can be tailored towards other medical settings. In the future, we plan to explore parametric statistic models for the key problem of activity classification. Furthermore, in case of positive results of the planned evaluation, it would be desirable to proceed to a prospective evaluation. For this stage, we (resp. our project partners) are planning to come up with a fully functional prototype, including wireless data transmission to a base station connected to some suitable WAN. This prototype is supposed to serve as a basis for a commercial product.

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References

1. Kannus, P., Sievaenen, H., Palvanen, M., Jaervinen, T., Parkkari, J.: Prevention of falls and consequent injuries in elderly people. The Lancet **366**(9500) (Nov 2005) 1885–1893
2. Hausdorff, J.M., Rios, D.A., Edelberg, H.K.: Gait variability and fall risk in community-living older adults: A 1-year prospective study. Archives of Physical Medicine and Rehabilitation **82** (2001) 1050 – 1056
3. Moreland, J.D., Richardson, J.A., Goldsmith, C.H., Clase, C.M.: Muscle weakness and falls in older adults: a systematic review and meta-analysis.musclefall. Journal of the American Geriatrics Society **52**(7) (Jul 2004) 1121–1129
4. Giansanti, D., Maccioni, G., Cesinaro, S., Benvenuti, F., Macellari, V.: Assessment of fall-risk by means of a neural network based on parameters assessed by a wearable device during posturography. Medical Engineering & Physics **30** (2008) 367 – 372
5. Muir, S.W., Berg, K., Chesworth, B., Speechley, M.: Use of the berg balance scale for predicting multiple falls in community-dwelling elderly people: a prospective study. Physical Therapy **88**(4) (Apr 2008) 449–459
6. Berg, K.O., Wood-Dauphinee, S.L., Williams, J.I., Maki, B.: Measuring balance in the elderly: validation of an instrument. Canadian Journal of Public Health **83 Suppl 2** (1992) S7–11
7. Muir, S.W., Berg, K., Chesworth, B., Klar, N., Speechley, M.: Balance impairment as a risk factor for falls in community-dwelling older adults who are high functioning: a prospective study. Physical Therapy **90**(3) (Mar 2010) 338–347
8. Lajoie, Y., Gallagher, S.: Predicting falls within the elderly community: comparison of postural sway, reaction time, the berg balance scale and the activities-specific balance confidence (abc) scale for comparing fallers and non-fallers. Archives of Gerontology and Geriatrics **38** (2004) 11–26
9. Shumway-Cook, A., Brauer, S., Woollacott, M.: Predicting the probability for falls in community-dwelling older adults using the timed up & go test. Physical Therapy **80** (2000) 896–903
10. Hausdorff, J.M.: Gait variability: methods, modeling and meaning. Journal of NeuroEngineering and Rehabilitation **2** (2005) 19
11. Maki, B.E.: Gait changes in older adults: predictors of falls or indicators of fear. Journal of the American Geriatrics Society **45**(3) (Mar 1997) 313–320

12. Verghese, J., Holtzer, R., Lipton, R.B., Wang, C.: Quantitative gait markers and incident fall risk in older adults. Journal of Gerontology **64**(8) (Aug 2009) 896–901
13. Delbaere, K., Close, J.C.T., Heim, J., Sachdev, P.S., Brodaty, H., Slavin, M.J., Kochan, N.A., Lord, S.R.: A multifactorial approach to understanding fall risk in older people. Journal of the American Geriatrics Society **58**(9) (Sep 2010) 1679–1685
14. Shumway-Cook, A., Baldwin, M., Polissar, N.L., Gruber, W.: Predicting the probability for falls in community-dwelling older adults. Physical Therapy **77**(8) (Aug 1997) 812–819
15. Tinetti, M.E., Williams, T.F., Mayewski, R.: Fall risk index for elderly patients based on number of chronic disabilities. The American Journal of Medicine **80**(3) (Mar 1986) 429–434
16. Koepke, S., Meyer, G.: The tinetti test: Babylon in geriatric assessment. Zeitschrift fuer Gerontologie und Geriatrie **39**(4) (Aug 2006) 288–291
17. Lajoie, Y., Girard, A., Guay, M.: Comparison of the reaction time, the berg scale and the abc in non-fallers and fallers. Archives of Gerontology and Geriatrics **35**(3) (2002) 215–225
18. Mathie, M.J., Coster, A.C.F., Lovell, N.H., Celler, B.G.: Accelerometry: providing an integrated, practical method for long-term, ambulatory monitoring of human movement. Physiological Measurement **25**(2) (2004) R1
19. Aminian, K., Robert, P., Buchser, E., Rutschmann, B., Hayoz, D., Depairon, M.: Physical activity monitoring based on accelerometry: validation and comparison with video observation. Medical and Biological Engineering and Computing **37** (1999) 304–308 10.1007/BF02513304.
20. Sun, M., Hill, J.: A method for measuring mechanical work and work efficiency during human activities. Journal of Biomechanics **26** (1993) 229 – 241
21. Corradini, M.L., Fioretti, S., Leo, T., Piperno, R.: Early recognition of postural disorders in multiple sclerosis through movement analysis: a modeling study. IEEE Transactions on Biomedical Engineering **44**(11) (1997) 1029–1038
22. Hass, C.J., Waddell, D.E., Fleming, R.P., Juncos, J.L., Gregor, R.J.: Gait initiation and dynamic balance control in parkinson's disease. Archives of Physical Medicine and Rehabilitation **86** (2005) 2172 – 2176
23. Preece, S., Goulermas, J., Kenney, L., Howard, D., Meijer, K., Crompton, R.: Activity identification using body-mounted sensors-a review of classification techniques. Physiological Measurement **30** (2009)