Detecting Changes in Elderly's Mobility Using Inactivity Profiles

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Abstract. Abnormal inactivity indicates situations, where elderly need assistance. Systems detecting the need for help models the amount of inactivity using inactivity profiles. Depending on the analysis of the profiles, events (e.g. falls) or long-term changes (decrease of mobility) are detected. Until now, inactivity profiles are only used to detect abnormal behavior on the short-term (e.g. fall, illness), but not on the long-term. Hence, this work introduces an approach to detect significant changes on mobility using long-term inactivity profiles, since these changes indicate enhanced or decreased mobility of elderly. Preliminary results are obtained by the analysis of the motion data of an elderly couple over the duration of 100 days and illustrates the feasibility of this approach.

Keywords: inactivity profiles; AAL; mobility; elderly;

1 Introduction

Staying in their own home as long as possible is a great challenge for elderly, since risks of living on their own home rise. The risk of falling is reported to be a major risk for elderly since it might take hours until they are found and help is provided [1]. However, not only falls are a great risk for elderly, but also the decrease of mobility results in a lower quality of life [2]. Studies either focus on detecting events directly (e.g. falls [3–5]) or detecting events indirectly by detecting abnormal inactivity (e.g. [6–8]). The latter offer the advantage to detect different critical circumstances at the same time (e.g. falls, illness) but only analyze short-term behavior (i.e. less than 24 hours). Hence, the aim of this paper is the detection of mobility changes of elderly by introducing long-term analysis of inactivity profiles (i.e. over the duration of several months). Detecting a decrease of mobility already at an early stage ensures that countermeasures can be taken to prevent the further decrease of mobility. Moreover, an increase of mobility indicates a more active and thus healthy lifestyle.

Detection of falls using inactivity zones is introduced by Nait-Charif & McKenna [8]. The scene is modeled using entry, exit and inactivity zones. Inactivity zones are areas, where almost no activity is detected (e.g. bed). If a person is located outside a pre-defined inactivity zone and no activity is detected over a longer

period of time, an alarm is raised. This information is then used to detect falls, since falls are defined as unusual inactivity occuring outside of inactivity zones.

Cuddihy et al. [6] and Floeck & Litz [7] introduced methods to detect abnormal long inactivity based on motion and door sensors. Both calculate inactivity profiles, i.e. the duration of inactivity at a specific time of the day is measured and a standard behavior is trained. In the work of Floeck & Litz [7], a day is divided into i timeslots, the integral of the inactivity of each timeslot is calculated and stored as a vector. The vector is then compared to a pre-trained reference vector and deviations raise alarms. This comparison is calculated once a day, since the data of the whole day is taken into consideration. In contrast, Cuddihy et al. [6] calculates an alert line from the training data and compare each timeslot to this alert line individually. If the inactivity of a specific timeslot is above the alert line, an alarm is raised immediately.

The rest of this work is structured as follows: Section 2 introduces the proposed approach to detect long-term behavioral changes in mobility using inactivity profiles, whereas Section 3 presents preliminary results of our work. Finally, a conclusion is drawn in Section 4.

2 Methodology

In contrast to the state-of-the-art, this work proposes the anlysis of changes in the long-term behavior in order to detect a change of mobility. The algorithm of Cuddihy et al. [6] detects an unusual inactivity if the inactivity level is above the trained alert line. Hence, short-term changes (i.e. in the range of hours) are detected (e.g. illness, fall). The alert line is calculated using a rolling window, i.e. the last 45 days are considered during the calculation of the alert line. This ensures that the algorithm is able to adopt to changes and thus reduces the number of false alarms. However, due to the adoption, a slow change of activity (e.g. over the course of a year) can not be detected since the algorithm is adopted on the basis of the rolling window. Due to this, the approach introduced in this paper compares alert lines (e.g. on a monthly basis) in order to be able to extract a general trend and detects significant changes of mobility over the course of a year.

The proposed method uses the calculation of an alert line described in [6], resulting in an inactivity threshold $ALERT_i$ for every time interval i. The interval is set to one minute, resulting in 1440 intervals per day. Alert lines are stored at regular intervals (e.g. one alert line per month), resulting in t different alert lines. The arithmetic average μ and standard deviation σ of all alert lines t are calculated for each interval i. During the training phase, all alert lines are incorporated to the calculation of the average alert line. After the training phase (e.g. three months), the deviation of the alert line to be added is calculated using the following rule: if the deviation of more than 25% (i.e. six hours) of the alert line intervals is within the range of $\mu \pm 2\sigma$, the average alert line is updated. If more than 25% of the alert line intervals are outside the range of $\mu \pm 2\sigma$, a significant change in long-term mobility is detected. Depending on the direction of

the change (i.e. higher or lower inactivity compared to the reference alert line), a reduction resp. increase of mobility is reported.

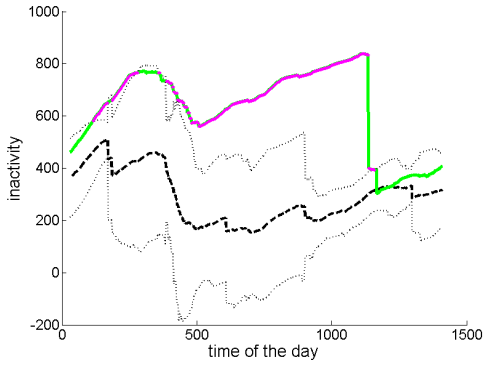

Fig. 1. Deviation of alert line indicating higher inactivity and hence decreased mobility

An example of a deviation is shown in Figure 1: the trained average alert line is shown as thick dashed line, whereas the other dashed lines indicate the range of $\mu \pm 2\sigma$. The alert line to be tested is visualized as green solid line and time intervals outside the range of $\mu \pm 2\sigma$ are visualized as magenta parts of the alert line. In this case it can be also visually verified that more than 25% of the alert line are outside the boundary and hence, a deviation in comparison to the "normal" mobility is detected. Since the alert line indicates a higher inactivity, a reduction of mobility is detected.

3 Results

For the preliminary evaluation the activity data of an elderly couple over the duration of 100 days is analyzed. The couple is 72 resp. 66 years old and in a good health condition, i.e. no problems with mobility or balance were reported. Moreover, activities of daily living can be performed without additional help, hence both are able to live independently. The Kinect was used as motion sensor and placed in the living room of the couple, monitoring the dining table and the surrounding area. This area was choosen since the couple performs regular food intake at the dining table and thus results in regular patterns. Since only a small, but important and regularly visited area of the flat was monitored, no additional devices (e.g. sensors, accelerometers) were used. There was no direct sunlight reported in this area, hence accurate depth data can be obtained. In order to evaluate results, alert lines based on 25 days intervals are generated, resulting in four long-term alert lines. For evaluation the leave-one-out cross-validation method is used, hence three alert lines are used for training whereas the fourth alert line is tested. The algorithm detected one significant decrease of mobility within the test period, depicted in Figure 1, where 64.7% of intervals

are outside the specified range. During this intervall, the couple was on a journey, thus resulting in an increased inactivity. However, all three other alert lines are within the specified range, since only 21.1%, 3.7% and 1% of the time intervals are outside the range and thus considered to be outliers or only minor changes in mobility.

4 Conclusion

Analyzing inactivity profiles on the long-term allows to detect changes in mobility. Since these changes are more likely to be a decrease than an increase of mobility, countermeasures to enhance the mobility can be taken already at an early stage and thus resulting in an enhanced quality of life of elderly. The approach introduced in this paper is able to detect changes in mobility by comparing the inactivity profile with a reference profile and detects deviations automatically. Preliminary results are promising and a decrease of mobility of an elderly couple was detected correctly. However, future work will deal with an more extensive evaluation and validation on a larger dataset.

Acknowledgments. This work is supported by the European Union under grant AAL 2010-3-020. The authors want to thank the whole fearless project team, since techniques and ideas of many researchers involved are used.

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