Clinical Decision Support for Active and Healthy Ageing: an intelligent monitoring approach of daily living activities

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Abstract. Decision support concepts such as context awareness and trend analysis are employed in a sensor-enabled environment for monitoring Activities of Daily Living and mobility patterns. Probabilistic Event Calculus is employed for the former; statistical process control techniques are applied for the latter case. The system is tested with real senior users within a lab as well as their home settings. Accumulated results show that the implementation of the two separate components, i.e. Sensor Data Fusion and Decision Support System, works adequately well. Future work suggests ways to combine both components so that more accurate inference results are achieved.

Keywords: decision support, unobtrusiveness, sensors, context awareness, trend analysis, statistical process control, Event Calculus

1 Introduction

Europe's ageing population is drastically increasing in numbers [1], thereby bearing serious health warnings such as dementias or mental health disorders such as depression [2]. Hence, the immediate need for early and accurate diagnoses becomes apparent. Ambient-Assisted Living (AAL) technologies can provide support to this end [3]. However, most of these research efforts fail to either become easily acceptable by end-users or be useful at a practice level; the obtrusive nature of the utilized technologies invading the daily life of elder adults is probably the one to be blamed [4]. To this end, the approach followed in this paper, which is also aligned with the major objective of the USEFIL project [5], is to apply remote monitoring techniques within an unobtrusive sensor-enabled intelligent monitoring system. The first part of the intelligent monitoring system is an event-based sensor data fusion (SDF) module, while the second part consists of two major components, i) the trend analysis component and ii) a higher level formal representation model based on Fuzzy Cognitive

Maps (FCMs) [5]. The aim of this paper is to present a feasibility study of SDF and Trend Analysis components in real life settings and evaluate their capability of intelligent health monitoring.

2 Materials and Methods

2.1 The USEFIL platform

The USEFIL intelligent monitoring system (cf. **Fig. 1**) comprises of three different layers of processing. Low cost sensors provide unobtrusive low level information, e.g. activity, mood and physiological signs. Event fusion module is the intermediary layer, which combines multimodal low level events and translates them into contextual information. A server-side Decision Support System consumes time stamped contextual information and projects them in the long run, producing alerts, upon recognition of data abnormalities or health deteriorating trends. This information is channeled to seniors or their carers via user-friendly interfaces.

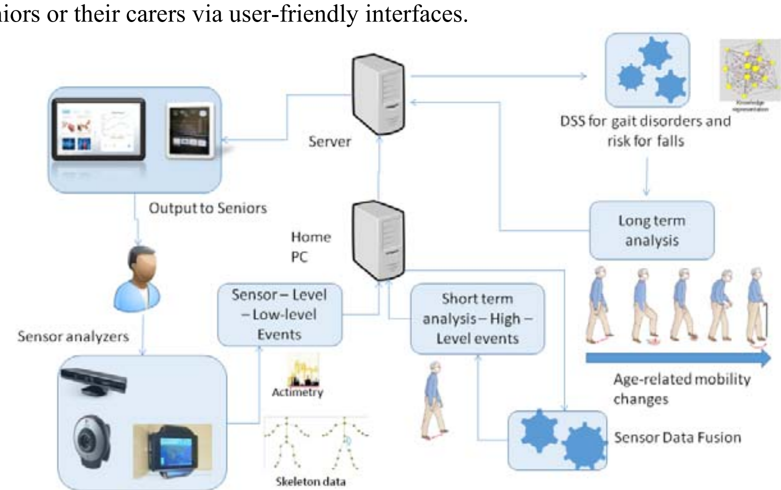

Fig. 1. Intelligent Monitoring components

2.2 Sensor Data Fusion

The role of the data fusion component in USEFIL is to interpret sensor data into a semantic representation of the user's status. Its tasks range from contextualization of sensor measurements to characterization of functional ability. We employ a Complex Event Recognition methodology [7], which allows to combine heterogeneous data sources by means of event hierarchies. In our setting, input consists of a stream of *low-level events (LLEs)* – such as time-stamped sensor data, and output consists of recognized complex, or *high-level events (HLEs)*, that is, spatio-temporal combinations of simpler events and domain knowledge. Our approach is based on the Event Calculus [8], a first-order formalism for reasoning about events and their effects. To address uncertainty, we ported the Event Calculus in the

ProbLog language [10], as in [9]. ProbLog is an extention of Prolog, where inference has a robust probabilistic semantics.
Constructing patterns (rules) for the detection of an HLE, amounts to specifying its dependencies with LLEs and other HLEs. As an example, we use the case study of *Barthel-scoring* of Activities of Daily Living (ADL), adapted from [12]. ADL refers to fundamental self-care activities, while the Barthel Index [11] is considered as the "golden standard" for assessing functional ability in ADL. The *Transfer* ADL refers to the ability of a person to sit down or get up from a bed or chair. The corresponding scores in the Barthel Index are evaluations of the performance in this task, based on the ability to perform and the amount of help needed.

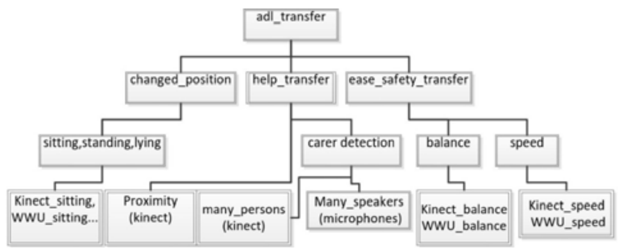

Fig. 2. An event hierarchy for the *Transfer* ADL

Fig. 2 presents an event hierarchy for the *transfer* ADL, developed in USEFIL. The leaves in the tree structure represent LLEs, obtained from sensor measurements, while each node represents an HLE. According to this representation, to Barthel-score the *transfer* ADL (root node), one should determine whether the user changed position, while receiving help for this task, taking into account the ease and safety with which the user performs. Each of these indicators (position change, help offered, ease-safety) is represented by an HLE, defined in terms of LLEs and other HLEs in lower levels of the hierarchy. The reader is referred to [12] for a detailed account of the implementation of such a hierarchy in the probabilistic Event Calculus.

2.3 Decision Support Module

Health trends identification is based on statistical process control principles. Each parameter may be modeled as a random process with a time-varying mean value and standard deviation. In this work we have followed two steps, namely the baseline extraction and the identification of acute events.
A personalized baseline profile is computed through time-series analysis and statistical process control concepts. More specifically, each variable under investigation (e.g. walking speed) is modeled as a time-series, random process with a time-varying mean value and standard deviation. The computations involved are the following:
Time-series observations are divided into n overlapping windows. The mean ($\overline{x}$) and the standard deviation ($\overline{r}$) of each time window are computed. Then, the mean value and the standard deviation of the entire process are averaged based on the individual runs: $\hat{x} = mean\{\bar{x}\}$ $\hat{r} = mean\{\bar{r}\}$ (1)

The baseline profile is also consisted of a confidence interval for both the process mean value and the standard deviation. These intervals are defined by the following limits: $\lim_{low} = \hat{x} - \frac{3\hat{r}}{\sqrt{n}}$ $\lim_{upper} = \hat{x} + \frac{3\hat{r}}{\sqrt{n}}$ (2)

Ongoing monitoring of the process under consideration is facilitated through the characterization of a further follow-up period based on comparison against the control limits of the baseline process. Single runs that are out of the control limits are considered as acute events.

3 Data Collection

In the process of system integration and pilot setup, an e-home like environment was established serving as an Active & Healthy Aging (AHA) Living Lab (see **Fig. 3**). A total of five (5) senior women aged 65+ (mean 74.6±3.85 years) were recruited. All users provided voluntary participation forms to denote that they chose to participate to this trial voluntarily after being informed of the requirements of their participation. The ability of independent living was assessed by the Barthel index. The real testing and use of the environment took place for several days. Seniors executed several activities of everyday life in a free-form manner, meaning that they were left to perform activities without strict execution orders.

Fig. 3. Performance of directed activities, interaction with the system

Apart from the lab environment, the system was also installed in home of lone-living seniors for several days lasting from one to three months. Four (4) elderly women aged 75.3±4.1 years provided their informed consent for their participation in the home study. Recordings over several days in these senior apartments measured, among others, gait patterns, emotional fluctuations and clinical parameters.

4 Results

4.1 Short-term monitoring – Scoring of ADLs

In order to evaluate the SDF module, the Transfer ADL was extracted for each senior. Carers examined seniors and assessed all of them as totally independent, with a Barthel score equal to "3", which is the ground truth for all cases. Therefore, an overall confusion matrix for all five seniors is built in **Table 1**. As shown, SDF several times scores seniors as needing help with the Transfer Activity (scores "1" and "2"), although they are totally independent. This paradox can be attributed to the presence of a facilitator during the monitoring sessions.

4.2 Long-term monitoring – Gait trends

Data from an initial period of two to four weeks were used so as to calculate the baseline for each elderly participant. The rest of the period was used as a "follow up period", where the actual monitoring was examined. Walking speed as measured by the Kinect sensor was used as the gait parameter to monitor in the long run. **Fig. 4** illustrates the baseline process formation of a senior suffering from mobility problems due to osteoporosis. During the monitoring period there are significant deviations from the baseline process (42.4% of days were out of control). This means that older woman's walking speed decreases with respect to her baseline period. Walking speed levels decrease might correlate to early health risk signs, such as falls.

Table 1 Confusion matrix of ADL Transfer scoring for all 5 participants

		Predicted class		
		ADL TransferScore1	ADL TransferScore2	ADL TransferScore3
Actual class	ADL TransferScore3	11	7095	6358

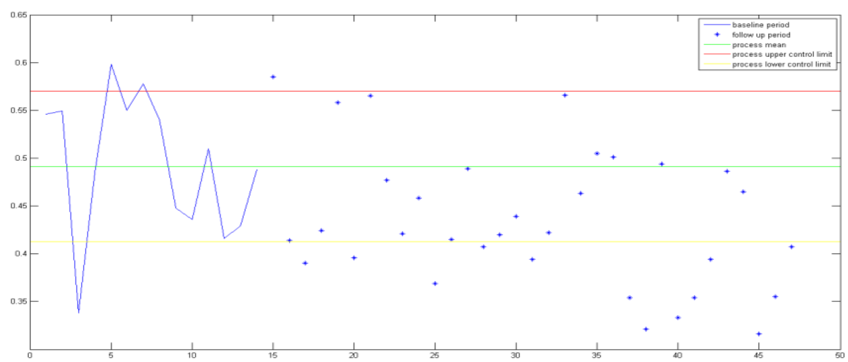

Fig. 4. Walking speed control chart. Yellow line: lower control limit, Red line: upper control limit, Blue continuous line: baseline period, Dots: follow up days.

5 Discussion

In this paper, mechanisms towards a truly intelligent and unobtrusive monitoring system for active and healthy aging were demonstrated together with a sample of the first series of results. Short-term context awareness was tested with the ADL scenario, while long-term trend analysis with the gait patterns scenario. In the first case, there were many false positives, due to the challenging, unconstrained nature of the experiment. Personalized thresholds would help SDF algorithm to avoid scoring Barthel equal to "1". Trend analysis' baseline extraction and process control limits would possibly refine latter inference results. On the other hand, long term analysis, may

benefit by the SDF output, since outliers found to be out of control, could possibly be annotated as logical "noise" through context awareness. This way pathological values may be interpreted as normal based on a-priori knowledge of the context.
This whole notion is remarkably appealing, as it could lead to potential applications where the synergy between the short-term component of the SDF and the long-term Trend analysis component may prove pivotal. Further data collection from home environments, will prove pivotal upon integrating successfully the two components.

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