Unobtrusive Technological Approach for Continuous Behavior Change Detection Toward Better Adaptation of Clinical Assessments and Interventions for Elderly People

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Abstract. Behavior change indicates continuous decline in physical, cognitive and emotional status of elderly people. Early detection of behavior change is major enabler for service providers to adapt their services and improve the quality of life of elderly people. Nowadays, existing psychogeriatric scales and questionnaires are insufficient to observe all possible changes at a daily basis. Therefore, we propose a technological approach for behavior change detection, that employs unobtrusive ambient technologies to follow up elderly people over long periods. In fact, we study significant behavior change indicators (*e.g.,* sleep impairments, visits and go out) and investigate statistical techniques that distinguish transient and continuous changes in monitored behavior. Furthermore, we present a preliminary validation of our approach through results based on correlations between our technological observations and medical observations of two-year nursing home deployment.

Keywords: Behavior change detection · Elderly people · Unobtrusive technologies · Statistical analysis techniques

1 Introduction

Detecting behavior change in early evolution stages is keystone for better adaptation of provided services to elderly people and improvement of their quality of life. In fact, aging process is associated with significant behavior change and continuous decline in physical and cognitive capacities. Existing psychogeriatric methods diagnose limited number of possible changes at assessment time and in

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assessment place [1]. We propose a technological approach for behavior change detection that uses unobtrusive technologies to monitor elderly people over long periods in their living environment and detect possibilities of long-term changes in their behavior.

Behavior change is a continuous modification or transformation in the way and manner of executing activities of daily living [2]. Behavior change is associated with mobility impairments [3], memory troubles [4], eating difficulties [5], and problematic management of household and personal finances [6,7].

Early detection of behavior changes is major enabler to adapt provided services and change treatments [8]. Significant information on behavior change allows to conduct more advanced medical assessments, change medical equipment, improve nutritional program and adapt living environment. This delays the negative evolution of their autonomy problems and enhances their quality of life at home [9].

We propose in this paper a technological approach for behavior change detection that targets long-term changes at temporal scale (*i.e.,* compared to past habits). We employ unobtrusive ambient technologies (*e.g.,* movement sensors) to monitor elderly people without affecting their privacy and interfering with their natural behavior.

Compared to our previous work [10], we (i) investigate a new bootstrap-based technique that differentiates between transient and continuous changes, (ii) study new behavior change indicators such as sleep impairments, visits and go out, and (iii) discuss new results based on correlations between our technological observations and medical observations of nursing-home team such as mobility, nutrition and cognition problems.

Following, Sect. 2 presents state of the art behavior change detection methods. Sections 3 and 4 introduce our behavior change detection methodology and implementation approach. Section 5 discusses second validation of our approach. Section 6 concludes this paper.

2 Related Work

Psychologists and geriatrics often use scales and questionnaires for behavior change detection, whereas researchers propose technological methods to detect behavior changes, using environmental technologies (*e.g.,* movement sensors, bed sensors, cameras and microphones) and wearable technologies (*e.g.,* smart phone, smart watch and neurosensors).

Following, we discuss existing psychogeriatric and technological methods for behavior change detection (Table 1). In fact, psychogeriatric methods are often used in the medical field, but present certain inconveniences (*e.g.,* hard to recall all past events at assessment time). Furthermore, technological methods has been successfully integrated in the medical field, but (i) mainly focus on short-term change detection, (ii) retrospectively detect changes in advanced stages, (iii) consider changes at population scale, or (iv) use inconvenient technologies (Table 1).

Table 1. Comparison of behavior change detection methods

	Psychogeriatric methods [3–6, 11]	Technological methods [12–25]	Our proposed approach
Automated detection	no	yes	yes
Objective observation	yes/no	yes	yes
Unobtrusive monitoring	no	yes/no	yes
Long-term changes	yes	yes/no	yes
Early changes	yes/no	yes/no	yes
Personal changes	yes	yes/no	yes

2.1 Psychogeriatric Methods

In the medical field, formal scales and questionnaires are often used to diagnose abnormal behavior changes. Clinicians ask patients to reply to given questions or perform required tasks, such as "How many falls did you have in the last six months?" [6] and "Could you please get up and walk three meters away!" [3]. Analyzing elderly people replies and their task execution allows to determine possible behavior changes.

Among existing psychogeriatric scales, Get-up-and-Go scale is used to detect mobility impairments [3]. Mini Mental State Examination (MMSE) is applied to diagnose memory troubles [4]. Clinicians evaluate nutritional status with Mini Nutritional Assessment (MNA) [5]. They also diagnose autonomy problems with Autonomie Gerontologique et Groupes Iso-Ressources (AGGIR) [6]. Behavioral anomalies such as aggressiveness and anxiety are investigated using Behavioral Pathology in Alzheimer's Disease (BEHAVE-AD) [11].

These psychogeriatric assessments identify significant behavior change indicators. However, it is often difficult for elderly people to recall all past events at assessment time and move to assessment place at a daily basis. Their anxiety increases if they are not able to provide the right answers. Possible assessment inaccuracies can also occur due to subjective evaluation.

Our proposed approach employs technologies to remotely and unobtrusively monitor elderly people in their living environment at a daily basis. Unobtrusive ambient technologies do not affect elderly people privacy and do not interfere with their natural behavior. Therefore, our objective technological observations usefully enrich medical observations.

2.2 Technological Methods: Short-Term Change Detection

Technological solutions are proposed to detect short-term changes, such as falls, wandering at night, showering for too long and leaving the wash-room tap on [12–15]. In order to detect these anomalies, researchers apply classification and semantic techniques to analyze data collected from real deployments using wearable and environmental sensors.

Whereas these technological methods study snapshots of behavior in specific time periods, the novelty of our approach is studying overall behavior over long periods to identify long-term changes. Clinicians and caregivers are not only interested in diagnosing short-term anomalies, but also in analyzing their long-term evolution; e.g., diagnosing not only falls, but also investigating changes in fall frequency over months.

2.3 Technological Methods: Retrospective Change Detection

Further technological solutions are developed to retrospectively detect long-term changes after they occur; e.g., invite elderly people to a reflection session after six months of monitoring using electronic pillbox to either confirm their own-confidence in medication adherence or re-assess it [16], and invite clinicians to review bed sensor data and investigate potential correlations with health events (*e.g.,* falls, emergency room visits and hospitalizations) after they occur [17].

Whereas these technological methods retrospectively detect changes in advanced stages of their evolution, our proposed approach targets behavior changes in early stages of their evolution. In fact, early detection of behavior changes enables better adaptation of provided services and provides significant information for more advanced medical assessments and interventions [8].

2.4 Technological Methods: Population-Scale Change Detection

Further studies compare behavior of different populations for change detection. They investigate influence of mild cognitive impairments (MCI) on sleep quality using pressure mats [18], computer use using mouse events [19] and medication adherence using electronic pillbox [20]. It was reported that MCI patients have less disturbed sleep, use less frequently computers and present more risk of medication non-adherence than elderly people with higher cognitive function.

Whereas these technological methods compare different populations to identify segments of populations that show potential risk and require close monitoring, our proposed approach analyzes personal behavior and detects changes compared to past habits. In fact, personal change detection enables personalized health assessments and interventions.

2.5 Technological Methods: Obtrusive Change Detection

Researchers use wearable technologies to inspect personal behavior changes; e.g., wearable bracelets with RFID reader to detect changes in coffee making [21] and neurosensors placed on the scalp to detect wandering and falls from bed during sleep [22]. Furthermore, they study global video and audio statistics to identify changes in interpersonal interactions in nursing home [24], and apply online-based questionnaires to identify mental state changes toward depression [25].

These technological methods use obtrusive technologies (*e.g.,* wearable sensors, cameras, microphones and online-based questionnaires) to collect precise information on elderly people behavior. However, elderly people often reject wearable sensors and can not operate them [26], and refuse to complete daily questionnaires [25]. Furthermore, cameras and microphones capture video and audio sequences that affect the privacy. Therefore, our proposed approach uses unobtrusive technologies (*e.g.,* movement sensors) that are deployed in the environment, do not affect the privacy and do not interfere with the natural behavior.

3 Proposed Behavior Change Detection Methodology

We propose a technological behavior change detection methodology that analyzes elderly people behavior over long periods, in order to identify long-term behavior changes associated with continuous decline in their physical and cognitive abilities.

Fig. 1. Examples of behavior change indicators

Based on internationally-validated psychogeriatric scales, we identify significant behavior change indicators (*e.g.,* physical, cognitive, nutritional and social activities) (Fig. 1), that can be monitored via unobtrusive ambient technologies. We analyze these indicators considering different dimensions (*e.g.,* quantity, duration, time and place metrics) to distinguish between transient and continuous behavior changes. In order to validate detected changes, we correlate them with health records (*e.g.,* hospitalizations, falls, diseases and medication change) and context information (*e.g.* weather conditions).

3.1 Behavior Change Indicators

We have investigated internationally-validated psychogeriatric scales (*e.g.,* AGGIR [6], MNA [5] and NPI [27]) to identify significant behavior change indicators that can be monitored via unobtrusive ambient technologies (*e.g.,* movement, contact, proximity, vibration and pressure sensors for indoor monitoring, and beacons for outdoor monitoring).

Among these behavior change indicators (Fig. 1), we identify significant **activities of daily living** that require important physical and cognitive efforts from elderly people, such as managing household, preparing meals, dressing and hygiene [6,7]. We also consider **motor behaviors**, such as moving indoors and outdoors, getting up, turning around and walking [3]. Furthermore, **cognitive tasks** (*e.g.,* learning, language and managing financial situation) are associated with temporal orientation, spatial orientation, attention, calculation and construction [4]. In addition, we study **social behaviors**, (*e.g.,* communicating with others, using means of transport and shopping) [6,7], **nutritional activities** (*e.g.,* serving oneself and eating) [5], and **mood and emotions** [28] that correlate with physical and cognitive functions.

3.2 Analysis Metrics

We analyze behavior change indicators considering different dimensions (*e.g.,* quantity, duration, time and place metrics) to quantify way and manner of performing these identified indicators. Quantifying these indicators enables to distinguish transient and continuous changes.

Quantity refers to number and amount of behavior execution (*e.g.,* number of friend visits decreases due to social isolation). **Duration** is related to length of behavior execution (*e.g.,* duration of preparing meals increases due to cognitive impairments). **Time** refers to start and end times of behavior execution (*e.g.,* sleep hours are irregular due to sleep troubles). **Place** describes where behavior is executed (*e.g.,* detected falls outdoors become more frequent due to fear of going outside).

3.3 Correlation Variables

In order to validate detected changes in our technological observations, we correlate them with significant health records and context information. Whereas **health records** (*e.g.,* falls, diseases and hospitalizations) increase the probability of behavior changes [6], **context information** (*e.g.,* changing one's house and family status) allow better understanding of detected behavior changes. In fact, correlating our technological observations with medical and context observations is essential to evaluate the relevance of detected changes.

4 Implementation Approach

We integrate our behavior change detection approach in our ambient assisted living platform UbiSMART [10,13].

UbiSMART analyzes data collected by environmental sensors to identify anomalies in monitored behaviors and provides new services for elderly people (*e.g.,* sending notifications to caregivers in case anomalies are detected) (Fig. 2). Following, we discuss the implementation phases of our behavior change detection approach:

- **Deployment** refers to installing our hardware infrastructure in the living environment (*e.g.,* environmental sensors, gateways and internet access points).

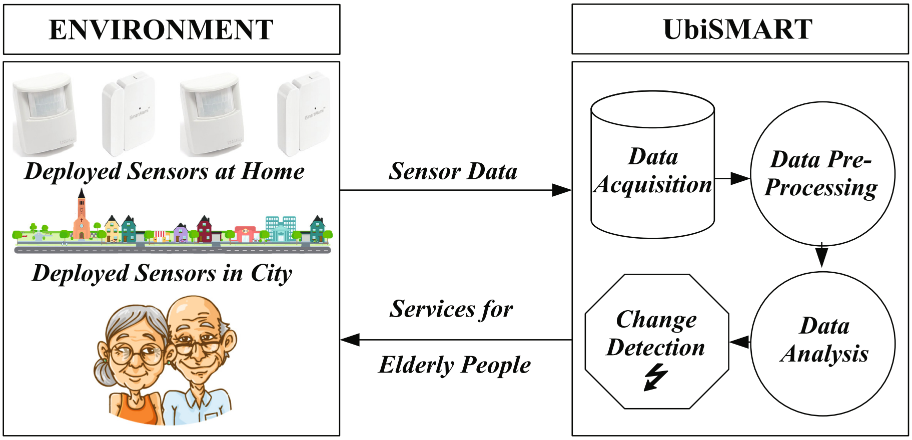

Fig. 2. Implementation phases of our behavior change detection approach

- **Data Acquisition** consists in transmitting environmental sensor data via internet to our remote database for permanent storage.
- **Data Pre-Processing** is essential to extract significant inferred data from raw sensor data (*e.g.,* movement sensor data allow to infer activity periods).
- **Data Analysis** applies statistical algorithms to analyze inferred data and differentiate between transient and continuous changes.

In order to analyze data, we investigate statistical algorithms that are robust to outliers and detect continuous changes at a daily basis as early as possible. Following, we discuss three algorithms investigated in our research; cusum-based [29,30], bootstrap-based [31] and window-based [32,33] algorithms. These algorithms apply different filters on detected deviations and identify changes with different granularity:

- **CUSUM-based** algorithm consists of a reference phase and an analysis phase [29,30]. In the reference phase, initial data enable to compute reference parameters that will condition change detection in the analysis phase (*e.g.,* mean and standard deviation). In the analysis phase, cumulative sums for positive and negative deviations are recursively computed to identify continuous changes.
- **Bootstrap-based** algorithm uses an iterative combination of a CUSUM analysis and a bootstrapping analysis (*i.e.,* random re-ordering of data) [31]. In the CUSUM analysis, cumulative sums of differences between data values and data mean are computed to determine the magnitude of the change. In the bootstrapping analysis, 1000 bootstraps are generated by randomly re-ordering original data values to detect a change if at least 95% of these bootstraps have a lower magnitude of change. For each detected change point, data is divided into two new segments and the bootstrapping analysis is repeated to detect additional change points.

– **Window-based** algorithm applies moving window to differentiate between transient and continuous changes. In fact, positive or negative deviations are data values that are higher or lower than $M \pm \alpha * SD$, where M and SD correspond respectively to mean and standard deviation of all previously observed data, and α is set to 1 [32] or 2 [33]. Furthermore, window length depends on analyzed behavior; e.g., 7 consecutive days of staying at home correspond to a change in going out frequency. Positive or negative changes are detected if positive or negative deviations are consecutively detected.

5 Validation

Compared to our previous work [10], we present a second validation of our approach through new results based on correlations between our technological observations and medical observations of two-year nursing-home deployment. In fact, we investigate new behavior change indicators (*e.g.,* sleep impairments, visits and go out) that are monitored via movement sensors (Fig. 3). In order to evaluate the relevance of detected behavior changes, we correlate them with significant health records such as mobility, cognition and nutrition problems.

Fig. 3. Deployment of movement sensors in nursing home rooms

5.1 Data Collection

During two years, we deploy movement sensors in bedrooms and bathrooms of 9 elderly people living in a french nursing home and having an average age 88 years (Table 2).

We employ Marmitek MS13E movement sensors (Fig. 3) that use X10 communication protocol with a frequency of 433 Mhz. In fact, these movement sensors are fired each 10 s after movements are detected within a range of 30 meters. They have 1 year battery life and embedded light sensors that configure movement sensing during light and darkness periods. Furthermore, we simply define an activity period as a period of consecutive movement sensor firings, that are transmitted with time difference less than 1 minute.

Table 2. Resident gender, age and monitoring period

Resident	Gender	Age	Period (months)
A	M	90	5
B	M	89	5
C	M	81	14
D	F	84	11
E	F	95	12
F	F	85	23
G	F	87	23
H	F	92	8
I	F	92	14

5.2 Data Analysis

Collected movement sensor data allow to (i) analyze behavior of elderly people over long periods, (ii) study significant indicators of behavior change (e.g., sleep impairments, room entries, visits and go out) that are associated with physical and cognitive impairments [3,6], and (iii) detect significant possibilities of changes in analyzed behavior by applying different statistical change detection techniques (Sect. 4).

Daily activity periods enable to analyze **sleep impairments** by selecting all sensors and limiting time interval at night (*e.g.,* from 0 h to 6 h). Furthermore, they allow to follow-up **entries to specific rooms** at home by selecting specific sensor (*e.g.,* kitchen, living room, bedroom, bathroom or toilet). In fact, we measure daily duration of all activity periods when person is **alone at home** (*i.e.,* visit and go out periods are not considered, because they have an increasing and a decreasing influence on activity periods respectively).

We analyze social activities at a monthly basis by computing **visit** and **go out** days. Whereas visits are detected based on parallel activity periods in different rooms at home, go out is detected based on long inactivity periods (*e.g.,* we set minimum go out duration to 6 hours, in order to discard sleep periods where few periodic movements are detected even when elderly people are lying in bed).

5.3 Results and Discussion

In order to evaluate the relevance of detected behavior changes (*e.g.,* changes in sleep impairments, room entries, visits and go out), we study their correlation with medical-team observations:

- **Sleep impairment** changes are associated with anxiety periods, health problems (*e.g.,* pain in leg and respiratory problems) and medication change; e.g., two decreasing changes are detected in sleep impairments of resident C on

2016-02-29 and 2016-06-03 and are associated to less anxiety felt by resident C months after undesired entry to nursing home on 2015-09-10 (Fig. 4).
- **Room entry** changes are associated with health problems (*e.g.,* cold and cough, pain in leg and respiratory problems), depression periods and nutritional problems (*e.g.,* weight loss); e.g., a decreasing change is detected in room activity periods of resident B on 2015-07-16 due to pain in leg, and an increasing change is detected in room activity periods of resident F due to wandering periods associated with Alzheimer on 2016-04-07.
- **Visit and go out** changes are associated with caregiver visits when health problems occur (*e.g.,* heart problems and anxiety periods), and go out with family members for dinner and local events; e.g., a decreasing change in visits and an increasing change in go out are detected in same month 2016-05 for resident E after several invitations to family events.

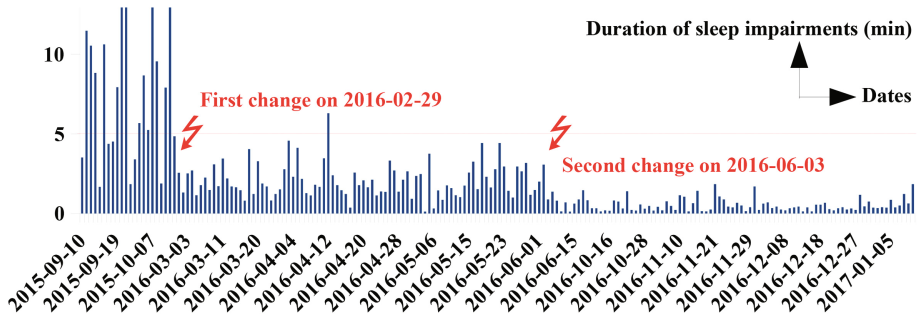

Fig. 4. Detected changes in daily evolution of sleep impairments for resident C

Based on medical-team evaluation, we determine the relevance of detected behavior changes (*i.e.,* the percentage of detected changes that are relevant to medical assessments and interventions). Whereas the precision of bootstrap-based algorithm is 68.55%, the precision of cusum-based and window-based (1SD with W = 3 and 2SD with W = 1) is 19.45%, 23.65% and 11.4% respectively. Considering that the bootstrapping analysis enables more precise recognition of continuous changes, bootstrap-based algorithm is more robust to outliers and detects relevant changes that are missed by cusum-based and window-based algorithms.

6 Conclusion

We propose in this paper a technological approach for behavior change detection that targets long-term behavior changes detected via unobtrusive ambient technologies. In fact, we monitor elderly people over long periods to identify continuous behavior changes associated with continuous decline in physical and cognitive abilities.

In order to validate our technological observations, we correlate them with real medical observations of two-year nursing home deployment. Using unobtrusive movement sensors deployed in bedrooms and bathrooms of nursing home residents, we collect real data on significant behavior change indicators (*e.g.,* sleep impairments, room entries, visits and going outside). Using statistical change detection techniques, we differentiate between transient and continuous behavior changes. Based on medical team feedback, 68.55% of detected changes are significantly correlated with their medical observations (*e.g.,* mobility, cognition and nutrition problems).

In the context of the European project City4Age [34], we are improving our behavior change detection. The City4Age project investigates data generated by technologies deployed in urban areas, in order to provide new adaptable services for elderly people. The objective is to capture frailty of elderly people, and provide subsequent individualized interventions.

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