Technological Approach for Behavior Change Detection toward Better Adaptation of Services for Elderly People

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Abstract: Aging process is associated with behavior change and continuous decline in physical and cognitive abilities. Therefore, early detection of behavior change is major enabler for providing adapted services to elderly people. Today, different psychogeriatric methods target behavior change detection. However, these methods require presence of caregivers and manual analysis. In this paper, we present our technological approach for early behavior change detection. It consists in monitoring and analyzing individual activities using pervasive sensors, as well as detecting possible changes in early stages of their evolution. We also present a first validation of the approach with real data from nursing home deployment.

1 INTRODUCTION

Early detection of behavior change is keystone for service providers to better adapt their services for elderly people. Existing psychogeriatric methods for behavior change detection are inconvenient, as they are time-consuming and require manual analysis work from caregivers.

According to existing definitions (Cao, 2010), behavior change is defined as any continuous modification or transformation in way and manner of behavior execution. Behavior change characterizes possible instabilities, variations, impairments, declines, increases or improvements in behavior performance.

Behavior change has significant impact on quality of life. For example, emergence of orientation problems (Cockrell and Folstein, 2002), eating difficulties (Vellas et al., 1999) and mood impairments (Parmelee and Katz, 1990) leads to serious decline in quality of life. On the other hand, any improvement in managing personal finances (Barberger-Gateau et al., 1992), managing household (Lafont et al., 1999) and mobility (Mathias et al., 1986) has positive influence on quality of life.

Early detection of behavior change is major enabler for more efficient intervention, by taking necessary actions in early stages of behavior change. Autonomy of elderly people is consequently improved, by reducing symptoms and evolution of sensor, motor and cognitive diseases.

In this paper, we propose a technological approach for behavior change detection. Changes are detected at temporal scale; i.e., compared to past habits of one particular person.

Our employed technologies (*e.g.,* movement and contact sensors) do not interfere with monitored behavior. These technologies are ubiquitous. They disappear in the environment, without generating unwanted behavior change, and without affecting individual privacy.

Our approach conducts long-term analysis of behavior for detection of continuous changes. We do not study snapshots of behavior, but we analyze overall behavior over long periods. This enables to differentiate between transient and continuous deviations.

Following, section 2 discusses state of the art of behavior definitions and change detection methods. Sections 3 and 4 present our methodology for behavior change detection and our implementation approach. Section 5 introduces a first validation of the proposed approach through real results from nursing home deployment. Section 6 concludes this paper.

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2 RELATED WORK

Researchers study behavior change from two different perspectives: initiation and maintenance of behavior change, and detection of behavior change.

2.1 Behavior Definitions

Cao defines behavior as actions or reactions made by individuals (Cao, 2010). Behavior is a response to internal or external stimuli or inputs.

From sociological point of view, Wilson considers behavior as interactions between individuals (Wilson, 2000). It can be influenced by family structure, work or school environment relationships, health conditions and psychiatric issues.

Economists recognize behavior as processes consumers go through or reactions they have toward purchasing or consuming products or services (Perner, 2008; Szwacka-Mokrzycka, 2015). It is influenced by internal factors, such as attitudes, needs, motives and preferences. External factors have also significant influence, such as marketing activities, social, economical and cultural aspects.

In the medical field, behavior refers to persons' beliefs and actions regarding their health (Miller et al., 2007; Lavikainen et al., 2009). While positive behaviors promote healthy life (*e.g,* maintain moderate alcohol intake, not smoke and avoid snacks), negative behaviors present health risks.

These definitions consider behavior as a response to internal or external factors, such as intentions, desires, social interactions and marketing activities. However, individuals respond differently to these factors; e.g., being hungry stimulates individuals to prepare meals with different duration, frequency and difficulty. Therefore, we define behavior as the way and manner individuals perform actions, inactions and beliefs.

2.2 Behavior Change Initiation and Maintenance Models

Numerous models have been proposed to predict the amount of effort individuals require for behavior change initiation and maintenance (Ormrod, 2013). In fact, initiating and maintaining behavior changes are related to individuals' perception of their own ability to perform demanding or challenging tasks. This perception is influenced by individuals' prior success in those tasks or related tasks, their psychological state and outside sources of persuasion.

In the medical field, behavior change refers to abandoning health-compromising behaviors and maintaining health-improving behaviors. Rosenstock suggests that individuals' belief about health problems and perceived benefits of actions plays important role in adopting health-promoting behaviors (Rosenstock, 1974).

Schwarzer considers behavior change as two continuous processes: goal setting and goal pursuit (Schwarzer, 2008). While goal setting is related to factors that motivate behavior change, goal pursuit consists in planning and performing intended change.

Prochaska *et al.* propose a five-step model of behavior change (Prochaska and DiClemente, 2005). In the first step, individuals have not thought about changing their behaviors. Then, individuals begin thinking about changing particular behaviors. Afterwards, they prepare their plans for behavior change. In the fourth step, individuals adopt and perform new behaviors. Finally, they consistently conserve their new behaviors.

While these models target behavior change initiation and maintenance, detection of behavior change enables better fulfillment of both objectives. In deed, methods for behavior change detection allow to make better decisions of when to initiate new behavior changes, and which services to select for behavior change initiation and maintenance.

2.3 Behavior Change Detection Methods

In the literature, we distinguish psychogeriatric and technological methods for behavior change detection. While psychogeriatric methods use formal tests and questionnaires, technological solutions are developed to automate detection of anomalies.

2.3.1 Psychogeriatric Methods

Psychologists and geriatricians propose several internationally validated methods for behavior change detection (Table 1). Using formal scales and questionnaires, trained clinicians and caregivers request that seniors reply to specific questions and perform specific tasks, such as "How many falls did you have in the last six months?" (Tardieu et al., 2016) and "Could you please get up and walk three meters away!" (Mathias et al., 1986).

Following, we present the psychogeriatric tests of Table 1:

- **Short Emergency Geriatric Assessment (SEGA)** allows to evaluate frailty of elderly people (Tardieu et al., 2016). It considers multiple behavior changes, such as falls, nutrition

Table 1: Examples of Psychogeriatric Tests for Behavior Change Detection.

	SEGA	**MMSE**	**4Tests**	**GDS**	**IADL**	**AGGIR**	**GetUp AndGo**	**MNA**	**BEHA VEAD**	**NPI**
ADL	X				X	X			X	X
Mobility	X					X	X			
Cognition	X	X	X		X	X		X	X	X
Social Life	X				X	X		X	X	X
Nutritional Status	X					X		X		
Biological Status	X				X	X		X		
Mood and Emotions	X			X					X	X

problems, mobility impairments and memory troubles.

- **Mini Mental State Examination (MMSE)** targets detection of changes in cognitive abilities, such as orientation problems, attention difficulties and language troubles (Cockrell and Folstein, 2002).
- **Benton, Five Word, Clock and Verbal Fluency Tests (4Tests)** target changes in cognitive functions, such as learning problems, memory troubles and construction difficulties (Neuropsy, 2016).
- **Geriatric Depression Scale (GDS)** investigates changes in mood and emotions (Parmelee and Katz, 1990); e.g., feeling sad and that one's life is empty is associated with possible depression.
- **Instrumental Activities of Daily Living (IADL)** identifies changes in activities of daily living that are associated with autonomy loss, such as using telephone, using means of transport, taking medicines and managing personal finances (Barberger-Gateau et al., 1992).
- **Autonomie Gerontologique et Groupes Iso-Ressources (AGGIR)** investigates changes in autonomy of seniors, such as movement troubles, household difficulties and orientation impairments (Lafont et al., 1999).
- **Get-Up and Go** targets motor behavior changes (Mathias et al., 1986). This test asks elderly people to get up, walk and turn around, in order to analyze task execution and identify possible mobility impairments.
- **Mini Nutritional Assessment (MNA)** investigates changes in nutritional status, such as eating difficulties, weight loss and protein intake insufficiency (Vellas et al., 1999).
- **Behavioral Pathology in Alzheimers Disease (BEHAVE-AD) and Neuropsychiatric Inventory (NPI)** allow to detect possible behavioral impairments for elderly people, such as presence of hallucinations, aggressiveness and anxiety (Reisberg et al., 1997) (Cummings et al., 1994).

Using these tests, clinicians observe task execution and analyze senior behavior, in order to identify cognitive impairments, autonomy problems, rapid mood changes, nutritional and behavioral anomalies.

Certain inconveniences limit the efficiency of psychogeriatric tests. In fact, it is inconvenient for seniors to recall past events with full details at assessment time. It is also often not convenient for elderly people to move to assessment place.

Besides, requesting that individuals reply to given questions and perform determined tasks has potential negative impact on their future behaviors after assessment. For example, anxiety of seniors can increase in case they feel their inability to correctly reply to orientation questions or perform mobility tasks. Furthermore, subjective evaluation of assessment results cause possible assessment inaccuracies.

2.3.2 Technological Methods

Different technological methods target behavior change detection. They employ technologies deployed in the environment (*e.g.,* movement sensors, bed sensors, cameras and microphones) or worn by seniors (*e.g.,* smart phone, smart watch and neurosensors). These methods conduct advanced analysis of acquired data, in order to detect changes in monitored behaviors.

Allin *et al.* propose technological method for social behavior change detection (Allin et al., 2003). This method detects emergence of physically and verbally aggressive interactions. It employs cameras and microphones for continuous collection of video and audio recordings. Using hidden markov models, complex analysis of these recordings allows to build typical movement patterns for anomaly detection. However, employed cameras and microphones affect privacy of individuals.

Avvenuti *et al.* target detection of wandering and falls from bed during sleep (Avvenuti et al., 2010).

They study correlation between brain activity and body movement, in order to define rules and derive threshold values for anomaly detection. This method employs modern neurosensors placed on person's scalp to record brain activities. Yet, neurosensors limit individual movements indoors and outdoors.

Another technological method studies mental state changes that lead to possible depression (Magill and Blum, 2012). It provides objective feedback to patients using body and environmental sensors, in addition to subjective questionnaire-based records for their health. Content and timing of questionnaires are personalized for individuals and altered over time as individual's mental health changes. However, it has been reported that technical trial of developed system reveals acceptability issues from participants regarding questionnaires.

Kaye *et al.* investigate changes in computer use (Kaye et al., 2014). Based on statistical analysis of mouse events, they compare frequency and duration of computer use between two aging populations with or without mild cognitive impairments (MCI). They conclude that MCI patients use computers less than regular persons.

Hayes *et al.* target detection of medication adherence changes (Hayes et al., 2009). Using electronic pillbox, subjects take medicines twice per day at specific times. This method monitors number of days when subjects take both medicines, and verifies whether volunteers adhere to given times. It compares two senior groups with low or high performance in given cognitive tests, and concludes that lower performing group has risk of non-adherence.

Another technological study investigates motor behavior changes (Hayes et al., 2008). Careful in-series placement of wireless infrared sensors at home identifies how quickly and frequently seniors pass through sensor lines per day. Comparing two aging populations with or without MCI, MCI patients show a coefficient of variation in median walking speed as twice as high compared to regular subjects.

Petersen *et al.* propose further solution to detect changes in telephone use (Petersen et al., 2014). Employed land-line phone monitors record phone events, such as dialed numbers and ring rate. These recordings allow to have a picture on size and contact frequency of friend, family and acquaintance network. Results show that seniors with high cognitive abilities receive significantly more phone calls.

These last four studies detect behavior changes between different individuals. However, they do not target detection of behavior changes that affect one particular individual.

3 BEHAVIOR CHANGE DETECTION METHODOLOGY

We target behavior change detection at temporal scale. Over long periods, we analyze behavior of elderly people, in order to identify changes compared to past habits. Our technologies do not interfere with monitored behavior and do not affect individual privacy.

Our behavior analysis identifies indicators of behavior change, such as activities of daily living, mobility and social life (Figure 1). These indicators are associated with changes in physical and cognitive abilities of elderly people.

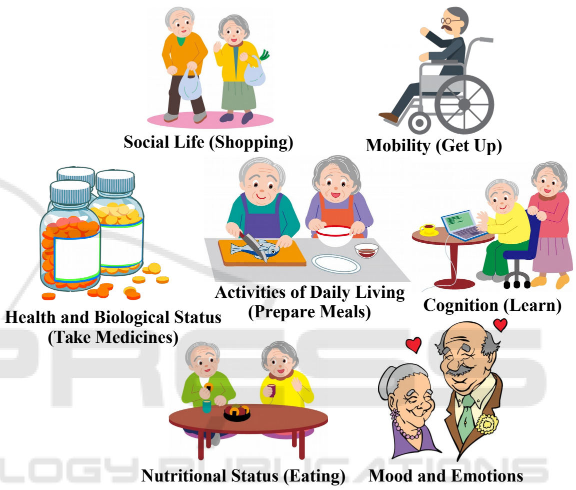

Figure 1: Examples of Behavior Change Indicators.

We also analyze these indicators considering different dimensions, such as quantity, duration, time and location. These dimensions are metrics that quantify collected data and allow to apply algorithms on these data for change detection.

Furthermore, we correlate identified changes with global context, such as weather conditions, family status and house architecture. Considering these factors provides better understanding of detected changes; e.g., senior stays at home for seven days due to heavy snow and not due to eventual social isolation.

3.1 Behavior Change Indicators

We have considered different validated psychogeriatric scales (*e.g.,* SEGA, AGGIR, MNA and NPI) to identify indicators of behavior change. That can be captured via ambient technologies (Table 2). Analyzing these indicators allows to detect significant changes in physical and cognitive abilities. Figure 1 shows following examples of indicators:

- **Activities of Daily Living** are essential complex tasks of daily living that demand important physical and cognitive capacities, such as performing household, preparing meals, dressing, hygiene, and urinary and fecal elimination.
- **Mobility** refers to motor behaviors, such as moving indoors and outdoors, getting up, turning around and walking.
- **Cognition** includes essential cognitive tasks such as learning, language and managing financial situation. These complex tasks are associated with temporal orientation, spatial orientation, attention, calculation and construction.
- **Social Life** refers to social behaviors, such as communicating with others, using means of transport, shopping and participating in collective free time activities.
- **Nutritional Status** is related to serving oneself and eating.
- **Health and Biological Status** targets health behaviors that indicate vision, audition and vital sign impairments, such as irregularities in taking medicines and increased hospitalization number.
- **Mood and Emotions** correlate with physical and cognitive functions and are significant depression and stress indicators.

Table 2: Examples of Ambient Technologies for Behavior Change Indicator Monitoring.

Environment	Technologies
Indoor	Movement, contact, proximity, vibration and pressure sensors
Outdoor	Smart phone and smart watch with beacons

3.2 Metrics

We analyze selected behavior change indicators regarding different dimensions. These dimensions are metrics that quantify way and manner of performing these indicators, and allow to apply algorithms on collected data for change detection. Following, we discuss four significant metrics:

- **Quantity** refers to number and amount of behavior execution; e.g., number of friend visits decreases due to social isolation, number of movements decreases due to walk impairments, number of sport center visits increases thanks to raised interest in physical exercise and number of hospitalizations decreases thanks to health status improvement.
- **Duration** is related to length of behavior execution; e.g., duration of preparing meals increases due to cognitive impairments, duration of stair climbing increases due to walk impairments, time spent out of home increases thanks to raised interest in social interactions and time spent in free time activities considerably increases thanks to raised interest in active aging.
- **Time** refers to start and end times of behavior execution; e.g., sleep hours are irregular due to sleep troubles, eating meal hours are inappropriate due to nutritional problems, going out hours are changing thanks to raised interest in social activities and taking medicine hours are adhered thanks to cognitive status improvement.
- **Place** describes where behavior is executed; e.g., detected falls outdoors become more frequent due to fear of going outside, visiting senior activity center becomes less usual due to social isolation and visiting city park becomes more frequent thanks to raised interest in physical exercise.

3.3 Global Context

Analyzing behavior in correlation with global context enables better understanding of behavior change. Following, we discuss influence of general personal information, general context information and specific temporary information on behavior change.

General personal information are general descriptors of persons; e.g., age over 85, health care history including more than three physical and mental diseases, and inconvenient family status increase the probability of behavior changes (Tardieu et al., 2016).

General context information describe the environment of behavior execution; e.g., changing one's house affects activities of daily living, moving television in room not easily accessible by elderly people reduces watching television frequency, opening smart city subways adapted for elderly people has positive influence on outdoor activities and building senior activity centers raises interest in social interactions.

Specific temporary information refer to short-term events, such as several consecutive days of heavy snow that obligate senior to stay at home, recent hospitalization of husband that raises wife's anxiety, and recent friend visits that improve emotional state.

4 IMPLEMENTATION APPROACH

We perform a first implementation of our behavior change detection methodology in our ambient assisted living platform UbiSMART (Aloulou, 2013; Aloulou et al., 2013). This platform uses environmental sensor data for activity recognition, detection of abnormal activity change and provision of personalized services for elderly people (Figure 2).

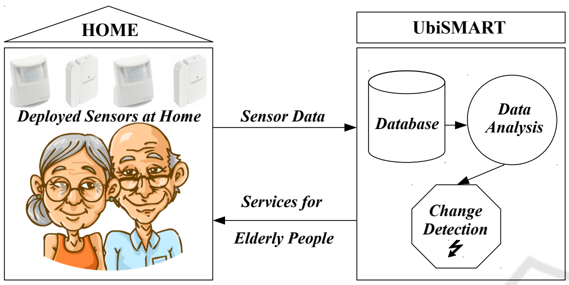

Figure 2: Overview on our Ambient Assisted Living Platform.

Our implementation approach considers following stages:

- **Deployment** consists in installing our hardware infrastructure. This includes environmental sensors (*e.g.,* movement and contact sensors), gateways, receivers and internet access points.
- **Data Acquisition** is essential to build our database. Via internet, data are transmitted to our dedicated server for permanent storage.
- **Data Pre-processing** allows to discard inaccurate and erroneous data for better analysis quality.
- **Data Analysis** quantifies data by considering different metrics, such as daily number and duration of shopping activity. Afterwards, we apply algorithms on these data to detect possible changes at temporal scale; e.g., these algorithms identify decrease in shopping activity periods.

4.1 Algorithms

We select statistical algorithms for our data analysis, as they differentiate between transient and continuous deviations; e.g., these statistical algorithms ignore occasional decreases in going out frequency, and consider only continuous decreases as significant changes in going out frequency.

We can distinguish offline and online algorithms for change detection in the literature (Basseville et al., 1993; Liu et al., 2013). Offline algorithms require fully available data as input, such as full history of free time activity number and duration. However, online algorithms iteratively operate on data one by one, such as number and duration of free time activity day by day.

Existing online algorithms use probabilistic models (Takeuchi and Yamanishi, 2006), singular spectrum analysis (Moskvina and Zhigljavsky, 2003) and cumulative sum control charts (Mesnil and Petitgas, 2009). Existing offline algorithms apply relative density-ratio estimation (Liu et al., 2013) and cumulative sum control charts with binary segmentation (Andersson, 2014; Cho, 2015) or bootstrapping (Taylor, 2000).

In order to detect changes as early as possible, we select online algorithms. Following, we discuss two algorithms investigated in our research; i.e., cusum-based (Page, 1954) and window-based (Bland and Altman, 1995) algorithms. These algorithms apply different filters on detected deviations and identify changes with different granularity.

4.1.1 CUSUM-based Algorithm

Page proposes Cumulative Sum Control Chart (CUSUM) algorithm for change detection in time series (Page, 1954). This algorithm considers two phases: reference phase and analysis phase.

In reference phase, initial data allow to compute parameters that will condition change detection:

- **M** refers to mean of reference data.
- **SD** is standard deviation of reference data.
- **SHIFT** is related to shift of interest, that determines smallest deviation we target to detect. Ledolter *et al.* set SHIFT to 1x SD (Ledolter and Kardon, 2013).
- **K** refers to allowance parameter, that is related to shift of interest. Mesnil *et al.* set K to 0,5x SHIFT (Mesnil and Petitgas, 2009).
- **H** is decision parameter that determines whether change occurs or not. In the literature, researchers define H with published tables, specific software or set it to 5x SD (Mesnil and Petitgas, 2009; Kibria, 2016).

In the analysis phase, mean and standard deviation parameters allow to standardize data by applying formula 1:

$$data[i] = (data[i] - M)/SD \quad (1)$$

For each datum, cumulative sums recursively accumulate positive and negative deviations, using formula 2 and 3:

$$S_{HIGH}[i] = max(0, S_{HIGH}[i-1] + data[i] - K) \quad (2)$$

$$S_{LOW}[i] = min(0, S_{LOW}[i-1] + data[i] + K) \quad (3)$$

In case S_{HIGH} is higher then +H or S_{LOW} is lower than -H, positive or negative change occurs.

4.1.2 Window-based Algorithm

Based on Bland-Altman analysis, window-based algorithm applies moving window on input data to distinguish between transient deviations and continuous change (Bland and Altman, 1995). Only in case selected number of deviations are consecutively detected without interruption, change occurs.

Positive or negative deviations are data values that are higher or lower than $M \pm SD$, where M and SD correspond respectively to mean and standard deviation of all previously observed data including currently observed datum.

Window length (N) depends on analyzed behavior; e.g., seven consecutive days of staying at home correspond to change in going out frequency or three consecutive months of loosing weight indicate change in nutritional status. Positive or negative changes are detected in case N consecutive positive or negative deviations occur.

5 VALIDATION

Following, we present a first validation of our approach through real data from nursing home deployment. Considering mobility as indicator of behavior change, collected data allow to analyze movements of patients inside their individual rooms.

5.1 Data Collection

Table 3: Patient Gender, Age and Monitoring Period.

Patient	Gender	Age	Period(months)
A	M	90	6
B	M	89	5
C	M	81	2
D	F	84	11
E	F	95	2
F	F	85	13
G	F	87	13
H	F	92	9
I	F	92	4

Over one year, we deploy movement sensors in bedrooms and bathrooms of 9 patients in a french nursing home in Occagnes (Table 3). Average age of patients is 88 years.

5.2 Data Analysis

We use movement sensor data to analyze physical activity periods (PAP) of persons. We simply define a PAP as period of consecutive movements, that are detected with time difference less than 3 minutes.

We do not consider days of inactivity, that correspond to hospitalizations or holidays outside individual rooms. In our analysis, we quantify collected movement sensor data using following metrics:

- **Number** refers to quantity of detected movements and PAPs.
- **Duration** is total length of detected PAPs.
- **Intensity** measures mean number of detected movements per PAP. This corresponds to number of detected movements divided by number of detected PAPs.

5.3 Results

Figure 3 shows our analysis results for patient F over 13 months. For each month, we compute average of daily number of movements, PAPs, their duration and intensity. We also study influence of mean ambient temperature on physical activities.

We observe decrease in movement and PAP number in case ambient temperature increases. However, PAP duration grows and PAP intensity is quite stable. This is also observed for other patients. Higher temperature stimulate them to perform less activities with longer total duration inside individual rooms.

For early change detection, we apply cusum-based and window-based algorithms on collected data after each day. In order to validate their results, we also apply an offline algorithm on full months of data.

In the literature, offline algorithms provide more robust results than online algorithms, as they retrospectively analyze longer periods of data (Basseville et al., 1993; Liu et al., 2013).

We select offline algorithm of Change Point Analyzer (CPA) tool (Taylor, 2000). This algorithm implements an iterative combination of cumulative sum control charts and bootstrapping to detect changes. Table 4 shows dates and values of identified changes in movement number data of patient F.

Results of cusum-based and window-based algorithms are compared to those obtained with CPA tool in Figure 4, considering true positive rate (TPR), precision (P), true negative rate (TNR) and accuracy (A).

Cusum-based and window-based (N=5 and N=4) algorithms show true positive rate of 28%, 40% and 45% respectively, as they do not detect all changes. Their precision is 64%, 56% and 33% respectively,

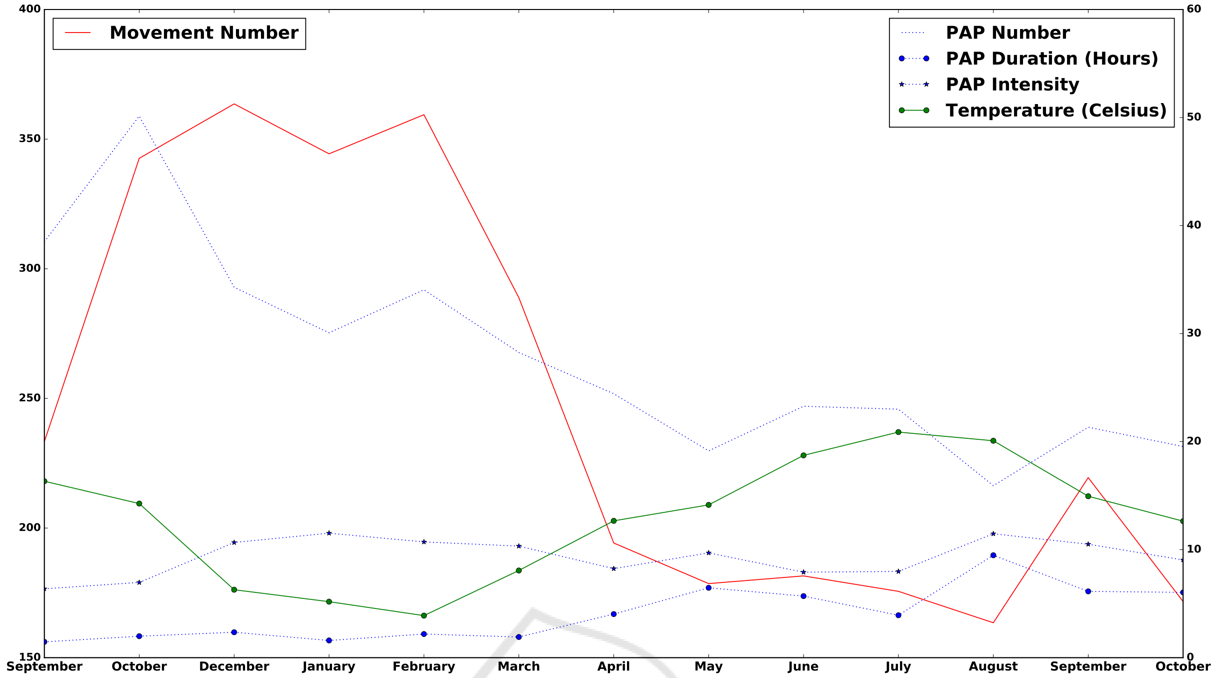

Figure 3: Monthly Average of Movement Number, PAP Number, Duration and Intensity for Patient F.

Table 4: Change Dates and Values of Movement Number for Patient F.

Change Date	From	To
2014, October 3	239	354
2015, March 15	354	253
2015, April 3	253	180
2015, September 13	180	282
2015, September 18	282	176

which indicates that not all identified changes are relevant.

However, true negative rate is 99%, 99% and 98% respectively, as they correctly identify almost all normal data. Their accuracy is 97%, 98% and 97% respectively, which corresponds to good overall results.

6 CONCLUSION

We propose a technological approach for behavior change detection at temporal scale. We analyze overall behavior to identify changes compared to past habits over long periods. Our technologies disappear in the environment, in order to avoid generation of unwanted changes and protect individual privacy.

We also present a first validation of our methodology through real data from nursing home deployment. Over months, employed movement sensors allow to monitor physical activities of patients. Collected data are quantified considering different metrics, such as number and duration. Our selected statistical change detection algorithms provide good overall results.

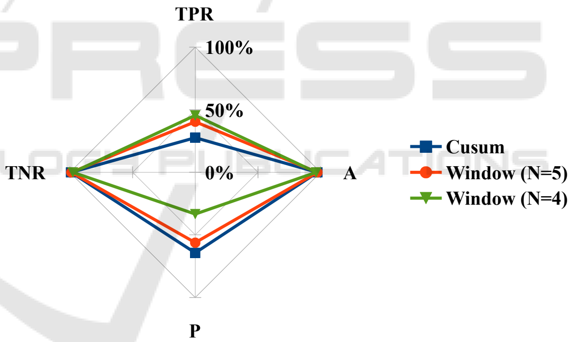

Figure 4: Comparison of Cusum-based and Window-based Algorithms to CPA Tool.

We are working on improving our behavior change detection in the context of the European project City4Age (City4Age, 2016). The City4Age project target using data generated by technologies deployed in urban areas, in order to provide new adaptable services for elderly people. These services target capturing frailty of elderly people, and provisioning subsequent individualized interventions.

Further technologies are investigated for more diversified analysis of behavior; e.g., bed sensors can be used for sleep period and vital sign recognition, kinect sensors enable more accurate monitoring of walking activity, and beacon sensors with smart phones allow more precise understanding of outdoor activities.

New reasoning techniques are studied to correlate identified statistical changes with overall changes in behavior toward better adaptation of provided services; e.g., decrease in weight indicates negative nutritional change and triggers sending of personalized notifications to improve nutritional status.

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