Implementation of Daily Functioning and Habits Building Reasoner Part of AAL Architecture

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Abstract. Individuals with Mild Cognitive Impairment (MCI) currently have few treatment options against memory loss. Solutions for caring for the elderly both efficacious and cost-effective are given by Ambient Assisted Living (AAL) architecture, promising the improvement of the Quality of Life (QoL) of patients. QoL factors that are important for the MCI patients include mood, pleasant engagements, physical mobility and health, and the ability to perform activities of daily living. In this paper, we propose a daily activity reasoner that monitors, measures and analyses in real time several everyday events for building habits diary and detecting abnormal behavior of the user, part of an effective AAL system. The proposed solution is based on a combination of mean shift clustering algorithm. The reasoner offers two primary functionalities: habits building and duration and frequency of events. The reasoner can predict the behavior and detect (slow or fast) changes that might indicate modification in the health status of the user.

Keywords: Daily activity monitoring · Habits measurement
Habit anomaly detection · GMM · K-means clustering

1 Introduction

Persons with mild cognitive impairment (MCI) experience declines in everyday functioning and cognitive performance greater than what is experienced in normal aging but less than that of dementia. Daily stress and daily memory complaints associated with cognitive deficits may contribute to greater psychological distress in the day-to-day experiences of people with MCI [1]. Supporting memory-related behavioral stability in MCI patients could help maintain their daily function and prolong the time before onset of dependency. According to [2] the decline in episodic memory is one of the defining features of MCI patients. Thus, early detection of cognitive dysfunction is of great importance in primary health care. In addition, assessment of everyday life activities should be performed in order to help medical personnel on when and how to intervene [3], and also for the affected to limit the effect of cognitive decline. According

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to [4], individuals with MCI, their family members, and their care providers have all identified "quality of life" (QoL) as a central goal in the treatment of dementia and MCI. QoL factors include mood, engagement in pleasant activities, physical mobility and health, and the ability to perform activities of daily living. After identifying the essential features of good QoL, the key question is: how can we use this information to improve the daily l of individuals suffering from these conditions?

To date, interventions aimed at extending functional capacity in MCI have been pharmacologic in nature. While medications may produce delays in the progression of cognitive difficulties, individuals with MCI are also interested in additional activities they can do to maintain and improve their QoL by managing their memory loss [5]. One such solution is offered by Ambient Assisted Living (AAL), an emerging multi-disciplinary field aiming at providing an ecosystem of different types of sensors, computers, mobile devices, wireless networks and software applications for personal healthcare monitoring systems [6]. One such AAL cloud-based service-oriented architecture was elaborated during the development of the eWALL project [7].

The main contribution of this paper is to present a daily activity reasoner part of the eWALL architecture that monitors, measures and analyses in real time several events for building habits log/diary and detecting abnormal behavior of the user.

We describe the daily functioning reasoner, used to build and measure the habits of the user, relying on statistical approaches such as Gaussian Mixture Model (GMM) and K-means and mean shift (MS) clustering algorithms (Sect. 2). Discussion of the experimental results and proof of our theoretical assumption on artificial data and the output of the reasoner is done in Sect. 3.

2 Daily Functioning Lifestyle Reasoner Description

eWALL is a platform providing dynamic environment for elderly patients with MCI for social interaction and continuous medical surveillance. The system offers personalized services such as daily activity monitoring, suitable exercises, reminders and others.

Lifestyle Reasoners (LR) within the eWALL are components that process and store long term data that follows certain patterns defining the lifestyle of the user. The aim of these components is to predict behavior and to detect (slow or fast) changes that might indicate a change in the user's health status. To do so, the LRs consume data from multiple sources and derive semantically meaningful patterns. The data is processed, stored, and compared data stored in the cloud and the reasoner determines e.g. whether a variation falls within the expected thresholds, or employs more complex methods to determine deviation. The reasoners make decisions about the short-, medium-, or long-term past. The eWALL system has 10 LR: Vital Signs, Daily Physical Activity, Mood, Sleep, Daily Functioning, Home Environment, Calendar, Physical Trainer, Cognitive Training, and eWALL interaction.

A block diagram describing the algorithm for the Daily Functioning LR is presented in Fig. 1. The input of the algorithm is a list of pairs formed by timestamp and activity. Each timestamp marks the time that a change of activity (or "state") was detected, while the activity value itself represents the new activity that was detected. The algorithm has two branches working in parallel.

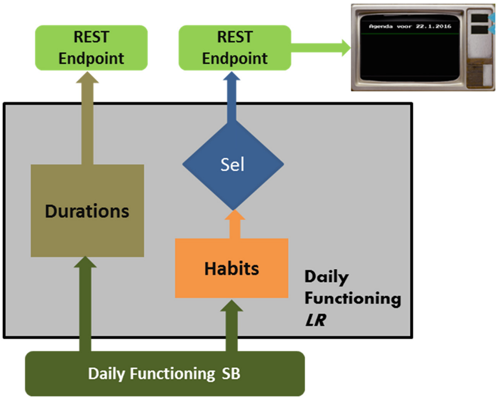

Fig. 1. Block diagram of Daily Functioning LR

The **Duration** branch collects all events for a monitoring period of 4 weeks. Using these events, duration of each one is calculated together with its statistical median value. The median value is preferred in order to avoid outliers which can introduce significant bias. The calculation of the averages is done only once a day. The monitoring period is tunable. The repetition of some of the daily functions is more important than their duration. Thus, this branch provides reasoning upon repetition of functions as well. Table 1 shows the types of activities and the performed reasoning.

Table 1. Types of daily activities

Activity	Estimate	Reasoning
Entertaining	Mean value	Abnormal if more than 3 h per day
Showering	Median value	Abnormal if less than two times a week
Outdoors	Median value	Abnormal if less than two times a week
Socializing	Median value	Abnormal if less than two times a week
Sleeping	Mean value	Abnormal if less than 7 h per day

The **Habits** branch involves more intelligent computing. It is using the low level information to build the habits of the user. Data for a monitoring period of 4 weeks is selected. It should be noted that the length of this period is a compromise between accuracy (larger interval) and responsiveness (smaller interval). The primary assumption is that the habits are repetitive activities, the start of each activity is within a certain time frame. Another assumption is that an activity can be repeated in the course of the week. All habits are built for a particular day of the week and are independent of the date or the day of the month. Once the habits are built, there is a further filtering by the block selection "Sel" (Fig. 1) based on the user's preferences about which of the habits he wants to be informed. The preferences are setup in the reasoner configuration. Every event received by the Habits reasoning is numbered and stamped with UTC time stamp in ms.

The analysis of the daily habits should be based on a statistical approach. One possibility is to estimate the Probability Density Function (PDF) by using a kernel method such as Kernel Density Estimation (KDE). A serious drawback of this approach is the need of further analysis in terms of detection of the modes and its parameters from the estimated PDF.

The other approach is to consider the task as clustering one. Every habit forms a cluster in the time and day of the week. The initial approach to address the clustering is the GMM [8]. In this model a PDF for a given habit can be approximated with arbitrary precision as superposition of Gaussian components. The estimation of parameters is typically done by the Expectation-Maximization (E-M) algorithm. The number of components (clusters) can be determined with Bayes Information Criterion (*BIC*). The optimal model is selected among many considering the insignificant decrease of *BIC* as a function of the number of components (*C*). The criterion is difficult to adjust, so the number of clusters is not always as expected. In addition sometimes a given cluster is incorrectly represented as a sum of two or more overlapped components. The GMM give an exact estimation of the mean and the standard deviation for a particular component, but any incorrect selection of *C* makes the data statistics hard for automated interpretation.

Since the GMM have not proved well in this particular application, the second technique that was used was the K-means clustering. The means and the standard deviations of the resulting clusters are close enough to those found with GMM and the robustness of the detection of the habits is superior to those of GMM estimation. The selection of the number of clusters is problematic since the algorithm is rough approximation of the GMM.

The MS clustering algorithm does not require a prior knowledge about the number of clusters and their shape. The calculation of the univariate kernel density estimate obtained with the radially symmetric kernels is described in [9]. Since the algorithm is intended to locate the modes in the histogram, it performs well in the described context. Using the priors (the number of elements in the cluster divided by the total number of observations) it is possible to retain only the significant clusters by appropriate threshold. Inappropriate bandwidth can cause modes to be merged, or generate additional "shallow" modes. A given habit can repeat few times daily and the histogram modes are spread apart from each other, so selecting lower values of the bandwidth and merging the adjacent clusters performed well in the experiments.

3 Experimental Results

For testing of the algorithms, the artificial data for a habit is generated as superposition of a uniformly distributed background of 30 events plus three components of ten events with normal distribution. The means are 20×106, 40×106 and 70×106 ms. The standard deviations are 0.6×106, 1.2.106 and 2.4×106 ms. On Fig. 2(a) are illustrated the results of modes detection using GMM. The optimal number of clusters is chosen with *BIC* (Fig. 2(b)).

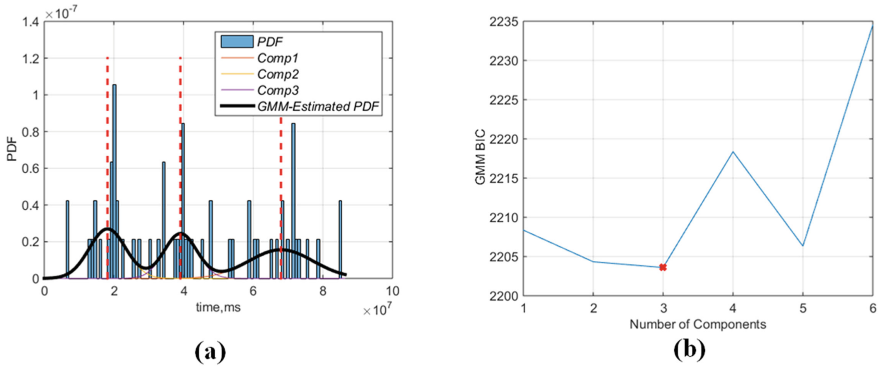

Fig. 2. **(a)** Daily habit estimation using GMM; **(b)** Number of components selection using *BIC*

For the same data a clustering using K-means is also performed (Fig. 3(a)). The best result in terms of background rejection and precision of the modes position is achieved with MS algorithm (Fig. 3(b)). The selected bandwidth is 5 × 106 ms.

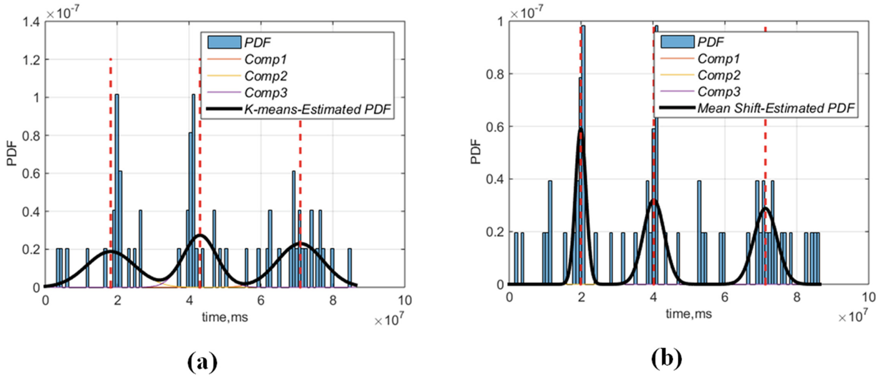

Fig. 3. **(a)** An example of daily habit estimation using K-means; **(b)** using mean shift

As can be seen from the figures, the clustering algorithm based on MS delivers promising results comparing to the others. This algorithm is working in a natural way with the data. The reasoner provides two endpoints of type GET returning data only upon request. Retrieving the habits is done by the method **habits** and its response is a list of the estimated habits. The parameters for each habit are described in Table 2.

Both methods don't have input parameters and the estimated values delivered by each are done based on an optimal time interval determined in the experiments.

Table 2. Parameters measured for habits

Habits	
Habit	"Entertaining", "showering" etc.
Dayofweek	"Sunday", "monday" etc.
Timeofday	HH:mm:ss.SSSZ, local time zone of the user when the habit is done

4 Conclusion

In this paper we present a daily activity LR intended to reason upon user's activities to be used as an automated diary. When analyzing these activities, patterns are formed based on which the reasoner estimates the user's behavior and assists him if necessary. The LR implements two primary functionalities: habits building and duration and frequency of events. It searches for repeating activities based on which it forms habits by taking into account the natural variations introduced by user's behavior. By reasoning upon the duration or frequency of different functionalities, for example, if the user is spending too much time watching TV, we can encourage him/her to do other activities and try to break down this habit.

The design and implementation of most of eWALL software components including the lifestyle reasoners are operational and currently are in the phase of end-user testing.

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