An Approach to Analysis of Daily Living Dynamics

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Abstract— **This paper addresses a module within a care system based on daily human behavior extracted from localization data. The proposed method is based on transforming the sequence of posture and spatial information using novel matrix presentation to extract spatial-activity features. Then, outlier detection method is used for classification of individual's usual and unusual daily patterns regardless of the cause of the problem, be it physical or mental. Initial experiments show that the proposed algorithm successfully discriminates between daily behavior patterns of healthy person and those with health problems.**

Keywords: activities of daily living, daily dynamics, spatial-activity presentation, PCA, outlier detection

1 Introduction

Analysis of daily living behavior has been a popular research topic during the last decade since it can be used in several interesting applications such as smart environments, remote health care, ambient assisted living, security systems, surveillance, anomaly detection etc.

To make analysis of daily living behavior practical, an underlying recognition model needs to detect a wide variety of activities performed in many different manners under many different environmental conditions and across many different individuals. Hence, robust recognition across various activities, individuals and their variations is needed. Also, the system would better adapt to each specific user and circumstances.

The current approach relays on either observers, i.e. a nurse who periodically observes an elderly user, or on self-reporting, namely having people complete an activity report at the end of the day. However, these methods have significant deficiency in terms of accuracy, efficiency, cost, coverage and privacy. Observers are not constantly present and therefore their observations are sparse. Also, repetitive observation make this task boring, which may affect the accuracy of observations. Self-reporting has limited accuracy and usefulness due to forgetfulness and misreporting (intentional or unintentional). Automatic monitoring and analysis of daily living behavior would help not only to reduce the cost of paid observers, but also to improve the accuracy of observations compared to self-reporting and sparse observational sampling.

In this paper we present the Daily Living Dynamics module (DLD) as a part of the ongoing research at the EU project Confidence [3], which main objective is to build a care system for the elderly people based on localization sensors. The DLD module deals with one day as the default time unit. In that period, the person is observed by two already tested modules: the first is the micro module performing inside seconds and tens of seconds, discovering and reporting alarms mainly due to falls. The micro module adapts to each user, learns user postures and discovers context-aware falls, e.g., lying on the floor for a while causes an alarm while lying into a bed does not. The second module is mezzo module which deals with time span of minutes, tens of minutes and hours. It learns specific movements of each particular person, e.g., walking through gait analyses. If, for example, walking changes significantly, the system issues a warning to the user and caregivers. Within the DDL module we present a general method for detecting if unusual daily living behavior occurs. The main contributions of the paper are as follows. First, we define a presentation that aggregates an activity log into spatial-activity matrix, which can be used to visualize captured daily dynamics; and second, we propose a method for evaluating behavior anomalousness based on a PCA method for feature extraction and a LOF algorithm for detecting deviant behavior traces.

The reminder of this paper is organized as follows. In Section 2, we discuss related work that addresses the issues in analysis of daily living. Section 3 defines the spatial-activity matrix which is used to capture daily behavior, while Section 4 explains the procedure for detecting anomalous behavior. Section 5 represents the experiments and results. Finally, Section 6 gives some conclusions and outlines the future work.

2 Activites of Daily Living

Activities of Daily Living (ADL) is a term used in medicine and nursing, especially in the care of the el-

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derly. It describes the things we normally do during a day. Manual assessment (by observer or self-reporting) helps practitioners determine how independent persons are and what skills they can accomplish on their own, for example, driving, cleaning, cooking, shopping, bathing, dressing, feeding, toileting etc. The evaluator scores various activities in each category to determine the person's skill. The score is compared to the score of the previous visit, which leads to a decision whether supervision or assistance is needed [2].

Many researchers contributed their work in automated activity recognition. Typically, an automated system for daily living analysis has three main components: (i) a sensing hardware that gathers relevant information about activities (e.g., a video camera, a marker-based motion capture, accelerometers, gyroscopes, a localization system etc); (ii) low-level activity recognition that discriminates sensed postures (e.g., walking, sitting, lying etc); and (iii) high-level activity analysis or recognition of activity patterns or daily behavior (preparing meal, shopping, daily dynamics etc). Choudhury et al. [2] reviewed several approaches identifying rich sensors (camera, microphone), personalized sensors (attached to a person – accelerometers, location tags) and dense sensors (attached to objects – RFID) as the most common sensing component, while methods used in the second and the third component can be divided to generative (Naïve Bayesian model, Hidden Markov models, Dynamic Bayesian networks etc.) and discriminative (support vector machines, logistic regression, conditional random fields etc.).

Muncaster [8] presented a framework for hierarchical activity recognition, where a moving object was first extracted from a video stream and then a dynamic Bayesian network was applied to model activities at different granularities. In the test scenario the system was able to distinguish a person entering, leaving or passing the shop. Huỳnh et al. [7] presented an approach for recognizing daily activities. Movement was sensed by three body-worn accelerometers, while recognition of 15 low-level and three high-level activities were performed by four approaches: k-means clustering, support vector machine, nearest neighbor classifier, and hidden Markov models. In the experimental setting the system achieved accuracy between $69-80\%$ for low-level (e.g, sit, eat, walk, ...) and $83-92\%$ for high-level (preparing for work, shopping, housework) activities. In addition, Lee et al. [5] proposed a fuzzy-association analysis of individual's daily patterns based on infrared location sensor and groups of activity sensors (e.g, sleeping, eating, leisure sensor group). They defined two fuzzy membership functions: start time (dawn, morning etc) and duration (short, medium etc), and transformed a sequence of activities using this two functions to categorical attributes. Afterwards, Apriori algorithm was applied on the dataset searching for activity patterns. The authors suggest that the changes in behavioral patterns indicate the person wellbeing.

In this paper, the system is using a localization system (in other publications, accelerometers are more often used) with body-worn wireless tags (described in Section 5), while low-level activity recognition is performed with a Random Forest classifier. The focus of this paper is on the third component, the analysis of daily patterns. The goal is to detect changes in behavior that indicate early discovery of a potential health problem, for example, a person stops cooking at dinner time and skips meals in the morning. Unlike the related works, which try to recognize high-level activities or describe them, our proposed method focuses on dynamics of activities, and in addition to Markov models, it further explores relations between spatial information and activities. The method is general in the sense that it detects unusual behavior regardless of the cause, be it illness of any kind, any physical or mental degradation or even outside cause, e.g., being locked in a room.

3 Spatial-activity Matrix

3.1 Definition

Behavior can be represented as a trajectory through action/state space that we will refer to as a behavior trace. A behavior trace is a sequence of tuples $B = ((a,s)_1, (a,s)_2, ..., (a,s)_n)$ in which each tuple $(a,s)_i$ indicates environmental state s and activity being performed a at i^{th} sampling point.

Suppose there are m predefined activities $a_1, a_2, ..., a_m$ and n areas where the person can be present $s_1, s_2, ..., s_n$. Let v denote a spatial-activity vector:

$$v = [a_1, a_2, ..., a_m, s_1, s_2, ..., s_n]^T$$

If a tuple of person's behavior at point t is $(a = a_j, s = s_j)_t$, $k = 1...m$, $j = 1...n$, we assign a spatial-activity vector v_t to a tuple, where each element $v(i) \in v_t$ is defined as:

$$v_t(i) = \begin{cases} 1 & ; i \in \{j, k\} \\ 0 & ; \text{otherwise} \end{cases} \quad (1)$$

Let $t_{a,b}$ denotes transition vector from spatial-activity vector v_a to v_b as an indication of change constrained by $\|t_{a,b}\| = 1$:

$$t_{a,b} = \neg(v_b \rightarrow v_a) \quad (2)$$

Suppose we want to describe a behavior trace $B = ((a,s)_1, (a,s)_2, ..., (a,s)_n)$. Then we assign a new vector v_i for each tuple $(a,s)_i$. Let $M(B)$ denote spatial-activity matrix, where dynamics of a person in the given behavior trace B is captured:

$$M(t) = v_1 * {v_1}^T + \sum_{i \in [2,...,n]} (v_i * {v_i}^T + t_{i-1,i} * {t_{i,i-1}}^T) \quad (3)$$

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Define $norm(M)$ as an operation which normalizes values of the matrix M to the interval $[0,1]$. The $norm(M)$ is defined for an element $M(i,j) \in M$ by expression

$$M(i,j) = \begin{cases} \frac{M(i,j)}{\sum_{k=1}^{m} M(k,k)} & ; i = j \wedge i \leq m \\ \frac{M(i,j)}{\sum_{k=m+1}^{m+n} M(k,k)} & ; i = j \wedge i > m \\ \frac{M(i,j)}{\sum_{\substack{k=1 \\ l=1 \\ l \neq k}}^{m} m(k,l)} & ; i \neq j \wedge i \leq m \wedge j \leq m \\ \frac{M(i,j)}{\sum_{\substack{k=m+1 \\ l=m+1 \\ l \neq k}}^{m+n} m(k,l)} & ; i \neq j \wedge i > m \wedge j > m \\ \frac{M(i,j)}{\sum_{k=m+1}^{m+n} M(i,k)} & ; i \leq m \wedge j > m \\ \frac{M(i,j)}{\sum_{k=1}^{m} M(i,k)} & ; i > m \wedge j \leq m \end{cases} \tag{4}$$

Intuitively, the matrix $M(t)$ consists of four regions

$$M(t) = \begin{bmatrix} M_{aa} & M_{as} \\ M_{sa} & M_{ss} \end{bmatrix}.$$

The interpretation of the regions is as follows: the spatial-spatial part M_{ss} includes the shares of time spent in the particular states and the transition distribution between different states; the activity-activity part M_{aa} includes the shares of time spent performing particular activities and the transition distribution between activities; the spatial-activity part M_{sa} describes distribution of activities over states; and the activity-spatial part M_{as} describes the distribution of states over activities.

The complete procedure in described in Algorithm 1. The input is a behavior trace B. Each tuple $(a,s)_i$ of the behavioral trace B is first transformed to the spatial-activity vector v_i using Eq. 1 and added to a set of vectors V. The set V is then used to compute the spatial-activity matrix M using Eq. 3. Finally, the matrix M is normalized by Eq. 4.

Require: behavior trace $B = \{(a,s)_1, (a,s)_2, ..., (a,s)_n\}$
Ensure: normalized matrix $M(B)$
  $V \leftarrow \{\}$
  for $e \in S$ **do**
    $v \leftarrow sa\_vector(e)$
    $V \leftarrow V \cup v$
  end for
  $M \leftarrow v_1 * {v_1}^T$
  for $v_i \in V$, $i > 1$ **do**
    $M \leftarrow M + v_i * {v_i}^T + t_{i-1,i} * {t_{i,i-1}}^T$
  end for
  $norm(M)$

Algorithm 1: Spatial-activity matrix.

3.2 Visualization

Since the matrix M is normalized to the interval $[0,1]$ it can be directly visualized by mapping the table values with a color map. Fig. 1 represents an example of such visualization of the matrix M where a warmer color represents higher intensity (see legend on the left side).

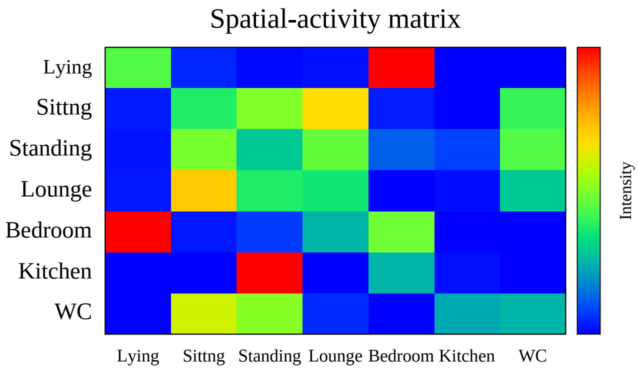

Figure 1: Visualization of the spatial-activity matrix. Warmer color represents higher value.

The matrix normalization has another positive impact to the visualization – small change, for example, in ratio between sleeping in the bed (being ill) and walking around apartment (healthy person), is rapidly propagated through the spatial-activity matrix and therefore, one can quickly notice the change and the type of change at the same time. Visualization is especially useful in comparison of multiple behavior traces (see Fig. 2).

4 Deviation-detection method

4.1 Feature extraction

Principal component analysis (PCA) is an orthogonal linear transformation that transforms a number of possibly correlated variables onto a subspace. The choice of the k-dimensional projection subspace is made in such a way that the distances in the projection have a minimal deformation: squares of the distances in the projection of k-dimensional subspace are as big as possible. By projecting the data to the new coordinate system the greatest variance emerge on the first coordinate (called the first principal component), the second greatest variance on the second coordinate, and so on.

Implementing PCA is equivalent of applying Singular Value Decomposition (SVD) on the covariance matrix. Assume that M is a spatial-activity $n \times n$ matrix. First, we subtract the mean μ_i, $i = 1...n$ (Eq. 5) from the M so that a matrix M_z with zero mean is obtained (Eq. 6). Next, a matrix C of variances and covariances is computed (Eq. 7) where diagonal elements $i = j$ are variances σ_{ij}^2 and non-diagonal elements $i \neq j$ are covariances $\sigma_i \sigma_j$. C is now decomposed into three matrices with SVD (Eq. 8). S is a diagonal matrix that stores singular values $\lambda_1, \lambda_2, ..., \lambda_n$. U and V are orthogonal matrices, while

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their column vectors are so-called left and right eigenvectors of C. When these eigenvectors multiply M_z, coordinates are shifted and rotated until they end up aligned with vectors, termed now basis vectors. Note that PCA now reexpresses the data as a linear combination of its basis vectors, M_zV. V columns are found to produce the desired linear combinations. The first column of V corresponds to the largest principal component, the second column corresponds to the second largest, and so on. These define the direction in which the variability of the original data set is maximized.

$$\mu_i = \frac{1}{n}\sum_{k=1}^{n} M(i,k) \tag{5}$$

$$M_z = M - I\mu \tag{6}$$

$$C = \frac{1}{n}M_z^T M_z \tag{7}$$

$$C = USV^T \tag{8}$$

The transformed data now enable use of machine learning or data mining methods.

4.2 Outlier Detection

LOF (Local Outlier Factor) [1] is an outlier detection algorithm based on computing densities of local neighborhoods. The main idea of the LOF algorithm is to assign to each vector a degree of being an outlier. This degree is called the local outlier factor (LOF) of a vector. Vectors with high LOF have local densities smaller than their neighborhood and typically represent stronger outliers, unlike vectors belonging to uniform clusters that usually tend to have lower LOF values.

Assume that A is a set of daily behavior traces $A = B_1, B_2, ..., B_n$. To detect an anomalous behavior trace we apply the procedure described in Algorithm 2. First, for each behavioral trace B_i compute spatial-activity matrix M_i using Algorithm 1, then compute a vector p_i of principal components (Eq. 5-8), and add a vector p_i to the new dataset A'. Next, for each vector p_i compute k_dist_i as distance to the k^{th} nearest neighbor of p_i, compute reachability distance for each vector p_i with respect to the vector p_j, where $d(p_i, p_j)$ is Euclidean distance from p_i to p_j, and compute local reachability density lrd_i of the vector p_i as inverse of the average reachability distance based on the k nearest neighbors of the vector p_i. Finally, compute LOF_i of the vector p_i as ratio of average local reachability density of p_i's k nearest neighbors and local reachability density of the vector p_i.

Require: set of behavior traces $A = B_1, B_2, ..., B_n$, number of k nearest neighbors
Ensure: outlier degree for each behavior trace LOF_i
  $A' \leftarrow \{\}$
  for $B_i \in A$ **do**
    $M_i \leftarrow sa\_matrix(B_i)$
    $p_i \leftarrow PCA(M_i)$
    $A' \leftarrow A' \cup p_i$
  end for
  for $p_i \in A'$ **do**
    $k\_dist_i \leftarrow k\_distance(p_i)$
    for $p_j \in A', p_j \neq p_i$ **do**
      $r\_dist_{i,j} \leftarrow max(d(p_i, p_j), k\_dist_j))$
    end for
    $lrd_i = \frac{k}{\sum_{p_j \in kNN(p_i)} r\_dist_{i,j}}$
    $LOF_i \leftarrow \frac{\frac{1}{k}\sum_{p_j \in kNN(p_i)} lrd_j}{lrd_i}$
  end for

Algorithm 2: Anomaly detection.

5 Experiments

5.1 Testing Environment

For the prototype deployment we have organized a room as a near-realistic home apartment, in the range of about 25 m^2. The apartment was equipped with a bed, a few chairs and tables, and divided into four logical areas: a kitchen, where a person can prepare a meal; a sleeping area, devoted to sleeping; a lounge, where a person can eat a meal, watch TV, write a letter etc.; and a toilet.

For the sensing component we selected a commercially available localization system Ubisense [9]. Ubisense, which is based on ultra-wideband (UWB) technology, allows local positioning by tracking a set of tags, which are attached to a person. A sampling frequency of around 10 Hz can be achieved with four tags attached to a person simultaneously. In a typical open environment, a location accuracy of about 15 cm can be achieved across 95% of the readings. The tags were placed at the following locations on the body: chest, belt, left and right ankle.

5.2 Activity Recognition

From the localization data we have extracted attributes such as the z coordinates, the velocities of all the tags, the absolute distances and the distances in the z direction between all the pairs of tags. The x and y coordinates were omitted for activity recognition because from the posture classification point of view the location where an activity takes place is not important. However, the x and y coordinates are essential for the daily living dynamics.

User postures were classified in one of the following activities: walking, sitting, and lying. Let F_i denote a set of features that are computed at a point in time t_i. The attribute vector, which is then used for the classification, is composed of $F_1, F_2, ..., F_n$ successive sets from the time interval $t_1, t_2, ..., t_n$ and labeled with the activity that occurs most often in the given time interval. A new attribute vector is then obtained after every update, thus overlapping with the previous one and provides instant

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classification for each point in time.

We have tested a variety of machine-learning algorithms [6], including C4.5 decision trees, Naïve Bayes, Support Vector Machine, k-NN, Bagging, AdaBoost etc., with Random Forest (RF) offering the highest classification accuracy.

The confusion matrix of the activity recognition is presented in Table I. The left column shows the label of the correct postures, and the top row shows the assigned label. The overall classification accuracy is 87.52 %.

Table I: Confusion matrix for activity recognition. The overall accuracy is 87.52 %.

true / labeled [%]	Lying	Sitting	Standing
Lying	98.99	0.93	0.08
Sitting	1.67	67.71	30.62
Standing	0.85	3.27	95.88

5.3 Daily Living Dynamics

The testing of this approach requires many days of recordings of daily activities. Such tests are currently in progress, but initially we condensed a full day of activities into scenarios that last around half an hour each. The spatial-activity matrix captures behavior of daily living and aggregates it over a specific time period.

The dataset consists of three different days performed by two users. Each day corresponds to a particular scenario, basically the same for each of the users. The first, usual day represents a typical daily routine for an elderly person. It consists of sleeping, morning routine, breakfast, using toilet/household chores/reading newspaper, preparing and eating lunch, going out/watching TV/household chores/resting, dinner, watching TV/reading, and sleep. In the second, slow day, the scenario is that the user is not feeling well and as a consequence is moving slowly and rests a lot. Such a behavior could occur if he/she had flu or any other general health problem, be it physical or mental. In the third scenario the user is limping. As a consequence, the user is also moving slowly and does not stand a lot. The user is not lying as much as on the previous day, but is sitting more than normal. Each user was given the scenario and an approximate timing of each activity, but performed it on her/his own.

The scenarios were performed and recorded 12 times in total consisting of eight normal days and four days where the user was not healthy. The length of recordings varied between 25 and 40 minutes. Each recording/day was represented with one behavior trace.

In the experiment we compared behavior traces of the usual-day scenario to the slow-day and the limping-day scenarios. Fig. 2 represents visualization of spatial-activity matrix computed from behavior traces of one person the four usual days (2a-2d) and two deviant days (2e, 2e). Spatial-activity matrixes plotted in figures 2a-2d captured more or less the same daily dynamics with small variations, for example, there was slightly more standing in toilet in day 4 (2d) than in day 1 (2a). The slow day (2e) has the distribution of activities over rooms (part M_{sa}) quite different compared to the normal days. Most significant is an additional red square which means that there was more sitting in the lounge. Distribution also deviates in slow day (2f) where, e.g., the share of standing is higher than in normal days.

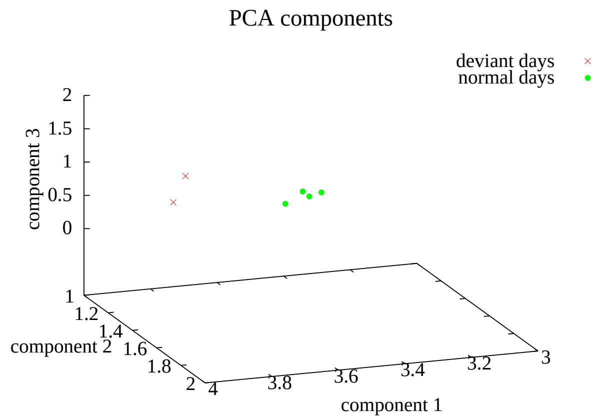

Figure 3: Visualization of principal components computed from matrices showed in Fig. 2. Normal days are presented with green circles, deviation days with red crosses.

The difference is even more obvious when PCA is applied. Fig. 3 shows the first three PCA components of the behavior traces plotted in Fig. 2. Four green circles '•' represents the usual days, while the other days are presented with red crosses '×'.

Anomalous behavioral traces were computed using Algorithm 2. Table II shows the LOF values for different values of $k = \{2, 3\}$ for all recordings of both users. Normal days have $LOF < 1$ in all cases, while deviant days have LOF value significantly higher than 1.

Table II: LOF values of the behavior traces. Higher value represents higher outlierness of a behavior trace.

scenario	k=2 user 1	k=2 user 2	k=3 user 1	k=3 user 2
normal day 1	0.619	0.615	0.887	0.963
normal day 2	0.694	0.613	0.904	0.766
normal day 3	0.652	0.639	0.843	0.797
normal day 4	0.601	0.743	0.832	0.841
limping day	2.369	4.270	4.519	6.465
slow day	3.274	2.358	5.451	4.227

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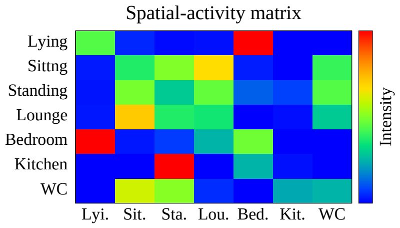
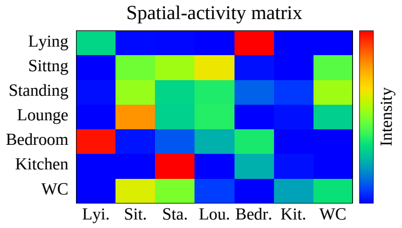
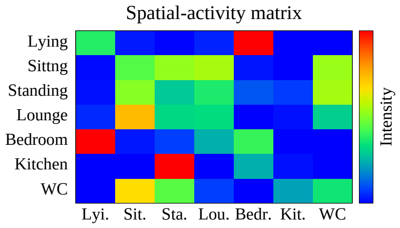


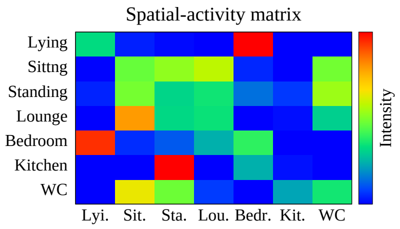
(a) Normal day 1



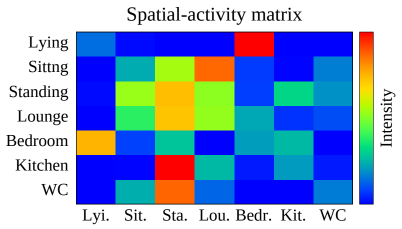
(b) Normal day 2



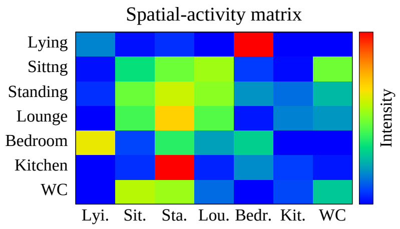
(c) Normal day 3



(d) Normal day 4



(e) Slow day



(f) Limping day

Figure 2: Visualization of four normal (2a, 2b, 2c, 2d) and two deviant days (2e, 2f).

6 Conclusions and Future Work

The main goal of this paper was to deliver a solution whereby a caregiver can constantly observe daily behavior of a person remotely in a more efficient and less intrusive manner. We presented an approach for transforming behavior traces (sequence of posture and spatial information) into a spatial-activity matrix, which captures daily behavior and already on its own presents visualization and explanation of derivations from normal behavior. Also, we proposed a method for automatic discovery of deviant daily behavior, which consists of feature extraction based on PCA, and outlier detection implemented with the LOF algorithm. The output can be directly used to signal a warning to the user and caregivers, providing an information that the dynamics of the user has significantly changed and an explanation how.

Preliminary results showed that proposed methods are successful in discriminating the behavior traces of normal days and days where user's wellbeing is affected. The method has not been tested thoroughly yet - only on 12 days, where each day was represented as an around half an hour predefined scenario. More realistic tests are needed to verify the performance of the newly designed method, and further improve it. However, the first results are quite promising and with further modifications the novel method for daily living dynamics might prove as useful as indicated.

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