Journal of Ambient Intelligence and Smart Environments 1 (2012) 1–5
IOS Press

Analysis of Daily-Living Dynamics

Boštjan Kaluža [a,b,*], Matjaž Gams [a,b]
[a] *Department of Intelligent Systems, Jožef Stefan Institute, Ljubljana, Slovenia*
[b] *Jožef Stefan International Postgraduate School, Ljubljana, Slovenia*

Abstract. Analysis of daily-living behavior is an important approach to assess the wellbeing of an elderly person that lives at home alone. This paper presents an approach to monitoring an individual in the home environment by an ambient-intelligence system in order to detect anomalies in daily-living patterns. The proposed method is based on transforming the sequence of posture and spatial information using a novel matrix presentation to extract spatial-activity features. Then, an outlier-detection method is used for a classification of the individual's usual and unusual daily patterns regardless, of the cause of the problem, be it physical or mental. Experiments indicate that the proposed algorithm successfully discriminates between the daily behavior patterns of a healthy person and those with health problems.

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

1. Introduction

Recent years have seen an increase in interest with respect to the deployment of systems for ambient assisted living (AAL) [1], including remote eldercare [12], smart homes [5], biomonitoring [21], surveillance [8], etc. Whereas some of these systems can be tele-operated, the community strives to design systems that monitor a user autonomously and act in the case of an emergency, warning or suggestion, for example, fall detection [2,9,18]. Our study targets users in the home environment, a senior citizen, man or a woman, who does not need intensive care or assistance in day-to-day living, but accepts an ambient- intelligence (AmI) system to improve their health, safety, and wellbeing. The main issue we address is the detection of anomalies in the daily behavior of the monitored user.

A predominant approach consists of three components, i.e., a sensor system, an activity-recognition model and an analysis of daily behavior [4]. There are several challenges that must be addressed when constructing such a system. First, the user must be monitored with sensors that are not obtrusive, invasive or privacy-violating but yet precise enough to address the second challenge, which is an accurate activity-recognition model. An underlying recognition model needs to detect a wide variety of activities performed in many different manners under different environmental conditions and across many different individuals. Third, we have no knowledge about the exact plans and schedules a user may follow during the day. And finally, the system should adapt to each specific user and circumstances while it is deployed at the user's home.

In remote eldercare, the AAL systems use a wide variety of sensors such as vision systems [10], inertial sensors [2,9] and embedded sensors [16,20]. While some sensors might violate privacy issues (i.e., a camera), others do not provide (i) additional context in terms of location (i.e., inertial sensors) or (ii) rich information required for accurate activity and posture recognition (embedded sensors). The analysis of daily behavior usually focuses on recognizing or describing exact schedules and assumes that the person will follow them. Another approach relies on either observers, i.e., a nurse who periodically observes an elderly user, or on self-reporting, i.e., having people complete an activity report at the end of the day. Both ways of reporting have limited accuracy and usefulness due to the aggregation in time, forgetfulness and misreporting (intentional or unintentional).

*Corresponding author. E-mail: bostjan.kaluza@ijs.si

To remedy these shortcomings, this paper uses a localization system with body-worn wireless tags that do not violate privacy issues and cause an acceptable additional burden. The activity-recognition model based on the Random Forest classifier enables the detection of a wide range of activities. The main contribution of this paper is the third component, the analysis of daily movement patterns. The goal is to detect changes in behavior that indicate an early discovery of a potential health problem, for example, a person stops cooking at dinner time or skips meals in the morning. Unlike the related works, which try to recognize high-level activities or describe them, our proposed method focuses on the dynamics of activities and explores the relations between the spatial information and the 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 an outside cause, e.g., being locked in a room.

The central hypothesis is that daily movement patterns can be learned for a specific user and the anomalous behavior can be detected when compared to the learned patterns. We propose a presentation that aggregates a daily activity log into a *spatial-activity matrix*. It can be used to visualize the user's daily dynamics. For automatic detection with machine learning we propose a method for evaluating the behavior anomalousness based on principal component analysis (PCA) for feature extraction and the local outlier factor algorithm (LOF) [3] for detecting anomalous behavior patterns.

We deployed the system in a lab organized as a near-realistic home apartment of about 25 m^2 and equipped with the Ubisense localization system [25]. The activity-recognition model trained on several users was able to achieve a better than 87% accuracy in recognizing the activities of a new user [12]. We experimentally tested our new approach in multiple episodes with several users involving regular behavior and behavior when a user does not feel well. The experiments showed that the proposed method was able to discover all clearly deviating behavior patterns.

The rest of the paper is structured as follows. Section 2 reviews the related work and delimits this work. Next, Section 3 introduces the general structure of the system and describes the deployed sensors and activity recognition method. The main contribution of this work is presented in Section 4, where the method for analysis of daily-living dynamics is proposed. Section 5 presents the experimental setup and provides experimental evaluation, while Sections 6 and 7 close the paper with discussion and conclusion.

2. Related Work

Activities of Daily Living (ADL) is a term used in medicine and nursing, especially in the care of the elderly. It describes the things we normally do during a day. Manual assessment by an 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, and toileting. 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 as to whether supervision or assistance is needed [2].

Many researchers have contributed to automated activity recognition. Typically, an automated system for daily-living analysis has three main components: (i) sensing hardware that gathers relevant information about activities (e.g., a video camera, a marker-based motion capture, accelerometers, gyroscopes, a localization system); (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 (e.g., preparing a meal, shopping, daily dynamics). Choudhury et al. [4] 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 components can be divided into generative (naïve Bayesian model, hidden Markov models, dynamic Bayesian networks) and discriminative (support vector machines, logistic regression, conditional random fields).

Muncaster [19] 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 the activities at different granularities. In the test scenario the system was able to distinguish a person entering, leaving or passing the shop. Storf et al. [24] studied recognition of ADLs from sensors embedded in the environment. They introduced a mutliagent approach that uses an event-driven activity recognition language to compose atomic activities into high-level activities. The authors report accuracy of higher than 80%. In a similar setting Cook and Holder [6] applied hidden Markov models for recognition of ADLs and varied the number of sensors used for recognition. The achieved accuracy ranged between 80% and 90%, and dropped below 75% when significant number of sensors was removed. Huỳnh et al. [11] presented an approach for recognizing daily activities. The movement was sensed by three body-worn accelerometers, while the recognition of 15 low-level and three high-level activities was performed using four approaches: k-means clustering, support vector machine, nearest neighbor classifier, and hidden Markov models. In the experimental setting the system achieved an accuracy of $69 - 80\%$ 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. [14] proposed a fuzzy-association analysis of an individual's daily patterns based on an infrared location sensor and groups of activity sensors (e.g., sleeping, eating, leisure sensor group). They defined two fuzzy membership functions: start time (e.g., dawn, morning) and duration (e.g., short, medium), and transformed a sequence of activities using these two functions to categorical attributes. Afterwards, the Apriori algorithm was applied to the dataset, searching for activity patterns. The authors suggest that the changes in behavioral patterns indicate that the person is not well.

In this paper the system uses 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. These two modules were developed within the Confidence system [7]. The focus of this paper is on the third component, the analysis of daily patterns that aims to detect changes in behavior that indicate an early discovery of a potential health problem, for example, a person visits a toilet unusually often. In contrast to related work, which mainly dealt with a description of high-level activities, our method focuses on the dynamics of activities, and in addition on Markov models, for exploring the relations between spatial information and activities.

Lymberopoulos et al. [16] proposed a system for the automatic extraction of the spatial-temporal patterns of a user from the sensor network deployed inside her home. The proposed method, based on location, time and duration, was able to extract frequent patterns using the Apriori algorithm and to encode the most frequent patterns in the form of a Markov chain, while our work uses the location and the activity performed by the user to build a model of normal behavior and detect anomalous behavior patterns. Monekosso and Remagnino [20] used embedded sensors and also addressed the problem of anomalous behavior detection. The output of the sensors was directly used to train a HMM model based on normal observations. If the likelihood that a new observation was generated by the trained model was low, the behavior was considered abnormal. Our work first recognizes the user's activities from sensor data and then combines them with spatial information. Compared to HMMs, it does not require an estimation of the parameters in the learning phase.

3. System Architecture

The general structure of the system presented in Figure1 consists of the learning (left-hand side) and recognizing (right-hand size) phases. Both phases, however, share some steps. Firstly, raw sensor readings are obtained from the environment and prepocessed in order to (i) reduce the amount of noise and (ii) compute additional features. Next, an activity-recognition algorithm is applied to classify the current data configuration into one of the activities an individual can perform, e.g., walking, sitting, lying. The output is a behavior sequence that consists of activities and places where they were performed. The rest of the steps are different. In the learning phase, patterns are discovered by converting the behavior sequence to a novel matrix presentation (introduced in Sec. 4.1) and applying principal value decomposition. In the recognition phase, a new sequence is matched against existing behavior patterns and the degree of outlierness is computed.

3.1. Sensors and Data

For the sensing component we selected a commercially available localization system called Ubisense [23, 25]. Ubisense is based on ultra-wideband (UWB) technology and allows local positioning by tracking a set of tags that 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. In practice, however, the accuracy occasionally drops significantly. The tags were placed at the following locations on the body, as shown in Figure 2: chest, belt, left and right ankle. The data can be captured in an on-line fashion and processed immediately or collected off-line for training purposes. Each sequence contains trajectories

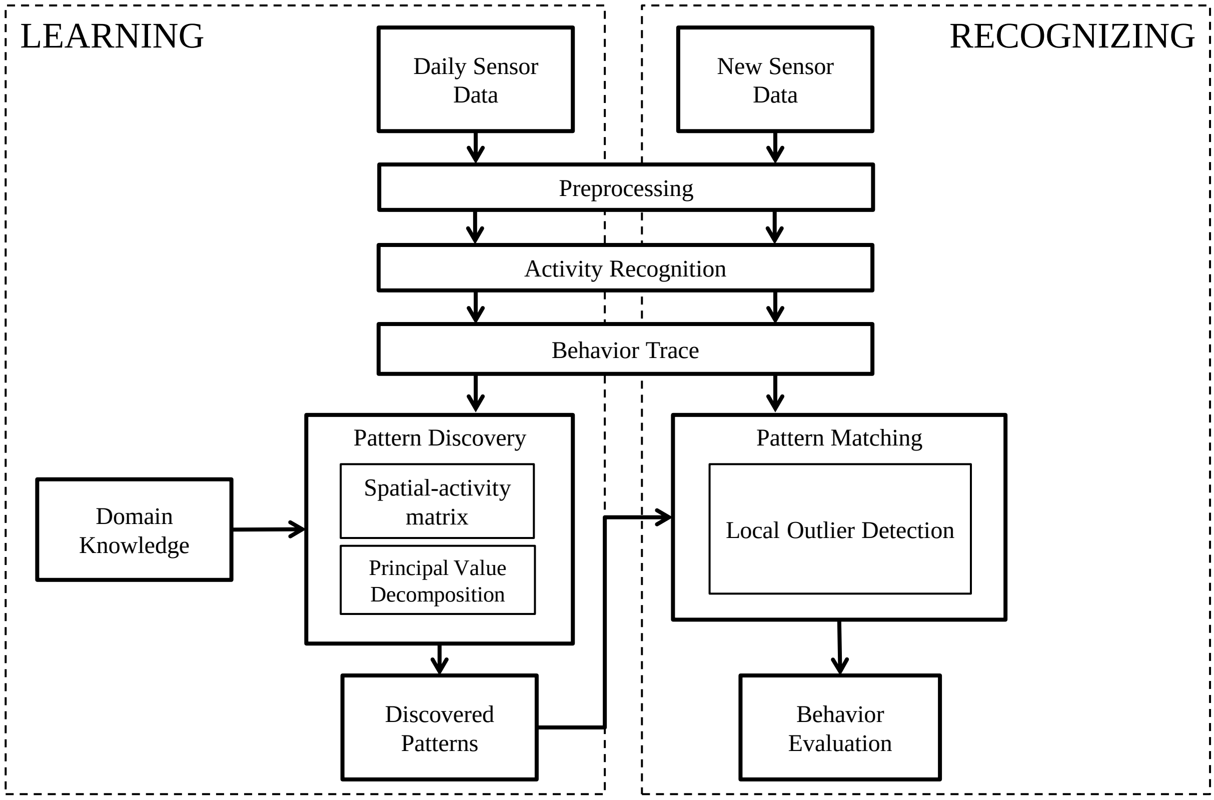


Fig. 1. General scheme for the analysis of daily-living dynamics.

for the x, y and z coordinates. Part of the data has been included in the UCI machine-learning repository [15].

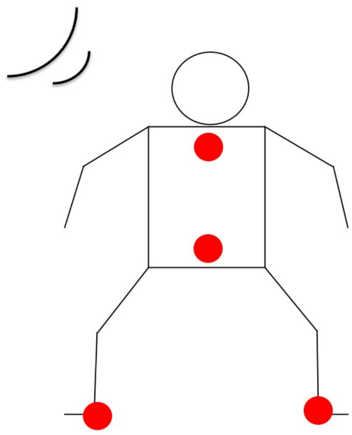


Fig. 2. Ubisense tag placement.

The raw sensor data are further processed using several filters. First, we apply a median filter to remove the impulsive noise. Next a method that enforces human body constraints between the measured positions of the tags is applied. It uses iterative constraint satisfaction to match the measurements to a valid body configuration. Finally, we apply Kalman's filter to estimate additional parameters, such as the velocity of a tag.

3.2. Activity Recognition

The activity recognition is performed in three steps. First, we extract the attributes from the tags, 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 are omitted for activity recognition because from the activity-classification point of view the location where an activity takes place is not important. However, the x and y coordinates are essential for any analysis of daily-living patterns.

Second, the user postures are classified into 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 classification for each point in time. We have tested a variety of machine-learning algorithms [17], including C4.5 decision trees, Naïve Bayes, Support Vector Machine, k-NN, Bagging, AdaBoost etc., with Random Forest (RF) offering the highest classification accuracy.

Third, the activity-recognition model still produces some false classifications in theory and practice. Usually, it misclassifies single moments or short intervals of an activity more often than longer intervals, e.g., the user's activity cannot switch between walking and sitting down every tenth of a second. Such transitions between activities that do not occur in reality, but are caused by misclassifications, are considered to be spurious. To reduce the number of spurious state transitions we filter the activities returned by RF using the hidden Markov model (HMM) [22] as follows. Classified activities are considered as observation symbols, while true labels are considered as hidden states. The parameters of the model are learned on manually labeled sequences using the Baum-Welch method [22]. The most likely path of state transitions for a given sequence of observations is computed using the Viterbi algorithm [22]. This approach reduces the classification error and the number of spurious state transitions.

4. Behavior Analysis

4.1. Spatial-Activity Matrix

Behavior can be represented as a trajectory through an 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 the environmental state s and the activity a being performed at the i^{th} sampling point. Note, that given a sampling frequency, the length of the behavior trace $n = |B|$ implicitly defines the duration of the recorded behavior.

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 us v denote a spatial-activity vector:

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

If a tuple of a 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:

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

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

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

Suppose we want to describe the 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 the spatial-activity matrix, where the dynamics of a person in the given behavior trace B is captured:

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

Define $norm(M)$ as an operation that normalizes the values of the matrix M to the interval $[0,1]$. The $norm(M)$ is defined for an element $M(i,j) \in M$ by the 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 the time spent performing particular activities and the transition distribution between activities; the spatial-activity part M_{sa} describes the distribution of activities over states; and the activity-spatial part M_{as} describes the distribution of states over activities.

The procedure is described in Algorithm 1. The input is a behavior trace B. Each tuple $(a, s)_i$ of the behavioral trace B is first transformed into 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: Create spatial-activity matrix.

4.2. 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. 3 represents an example of such a visualization of the matrix M where a warmer color represents a higher intensity (see the legend on the left-hand side).

The matrix normalization has another positive impact on the visualization – a small change, for example, in the 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. This visualization is especially useful in a comparison of multiple behavior traces (see Fig. 4).

4.3. 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 the k-dimensional subspace are as large as possible. By projecting the data onto the new coordinate system the greatest variance emerges on the first coordinate (called the first principal component), the second greatest variance on the second coordinate, and so on.

Implementing PCA is the equivalent of applying Singular Value Decomposition (SVD) to the covariance matrix. A spatial-activity matrix M_i (for a day) is unrolled into a vector. Then we construct a matrix $\mathbf{M}$, which consists of n vectors each unrolled from M_i, $i = 1...n$. The PCA proceeds as follows. First, we subtract the mean μ_i, $i = 1...n$ (Eq. 5) from the $\mathbf{M}$ so that a matrix $\mathbf{M_z}$ with zero mean is obtained (Eq. 6). Next, a matrix $\mathbf{C}$ of variances and covariances is computed (Eq. 7) where the diagonal elements $i = j$ are variances σ_{ij}^2 and the non-diagonal elements $i \neq j$ are covariances $\sigma_i \sigma_j$. C is now decomposed into three matrices with SVD (Eq. 8). $\mathbf{S}$ is a diagonal matrix that stores singular values $\lambda_1, \lambda_2, ..., \lambda_n$. $\mathbf{U}$ and $\mathbf{V}$ are orthogonal matrices, while their column vectors are the so-called left and right eigenvectors of $\mathbf{C}$. When these eigenvectors multiply$\mathbf{M_z}$, the coordinates are shifted and rotated until they end up aligned with vectors, now termed basis vectors. Note that PCA now re-expresses the data as a linear combination of its basis vectors, $\mathbf{M_z V}$. $\mathbf{V}$ columns are found to produce the desired linear combinations. The first column of $\mathbf{V}$ 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.

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

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

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

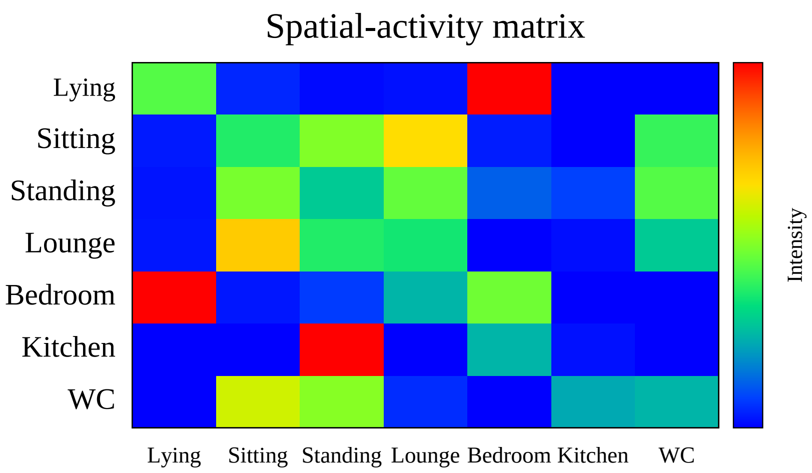


Fig. 3. Visualization of the spatial-activity matrix of one person for one day. The warmer color represents a higher value.

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

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

4.4. Anomalous Behavior Detection

The LOF (Local Outlier Factor) [3] is an outlier-detection algorithm based on computing the 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 a 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 the spatial-activity matrix M_i using Algorithm 1, then compute the vector p_i of the principal components (Eq. 5-8), and add vector p_i to the new dataset A'. Next, for each vector p_i compute the k_dist_i as the distance to the k^{th} nearest neighbor of p_i, compute the reachability distance for each vector p_i with respect to the vector p_j, where $d(p_i, p_j)$ is the Euclidean distance from p_i to p_j, and compute the local reachability density lrd_i of the vector p_i as the inverse of the average reachability distance based on the k nearest neighbors of the vector p_i. Finally, compute the LOF_i of the vector p_i as the ratio of the average local reachability density of p_i's k nearest neighbors and the 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. Experimental Evaluation

5.1. Experimental Setup

For the prototype deployment we organized a room as a near-realistic home apartment 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.

5.2. Activity Recognition

To build an activity-recognition model we recorded five members of our department aged between 25 and 32 years. Each participant was recorded when performing various activities in three episodes lasting approximately 15-20min each. In total there were around 4 hours of recordings. The scenario details are available in [12].

The confusion matrix of the activity recognition presented in Table 1 was obtained with a leave-one-person-out validation. The left-hand column shows the label of the correct activities, and the top row shows the assigned label. The overall classification accuracy is 87.52 %.

Table 1
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. Anomalous Behavior Detection

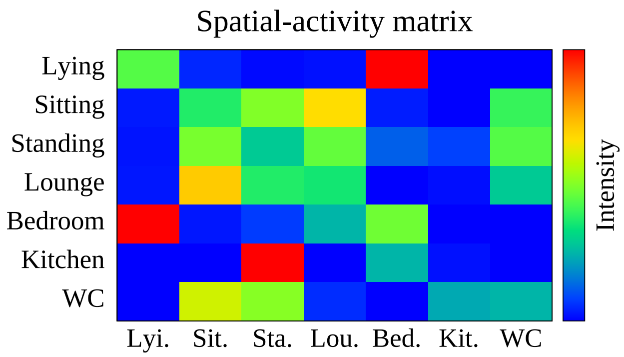
We performed two test as follows. In the first test we condensed a full day of activities into scenarios that last around half an hour each. In the second test we recorded a user in the office for a period of one month.

The first experiments proceeded as follows. The measurements were performed on four people aged between 25 and 57 years, all members of our department. However, the dataset shown 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, heart failure or several other general health problems, be it physical or mental. In the third scenario the user is limping, e.g., due to hip pain. 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 sits more than usual. Each user was given a loose daily scenario and an approximate timing for 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 the recordings varied between 25 and 40 minutes. Each recording/day was represented with one behavior trace.

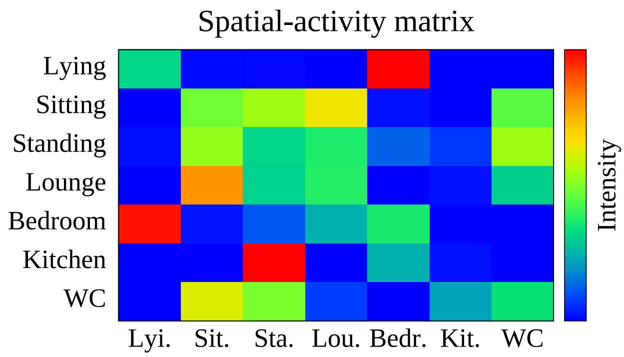
In the experiment we compared the behavior traces of the usual-day scenario with the slow-day and the limping-day scenarios. Fig. 4 represents a visualization of the spatial-activity matrix computed from the behavior traces of one person for the four usual days (4a-4d) and two deviant days (4e, 4e). The spatial-activity matrixes plotted in figures 4a-4d captured more or less the same daily dynamics with small variations, for example, there was slightly more standing in the toilet in day 4 (4d) than in day 1 (4a). The slow day (4e) has a distribution of activities over rooms (part M_{sa}) that is quite different compared to the normal days. The most significant feature is an additional red square which means that there was more sitting in the lounge. The distribution also deviates during a slow day (4f) where, e.g., the share of standing is higher than in normal days. The difference is even more obvious when PCA is applied. Fig. 5 shows the first three PCA components of the behavior traces plotted in Fig. 4. The four circles '$\bullet$' represent the usual days, while the other days are represented by crosses '$\times$'.

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

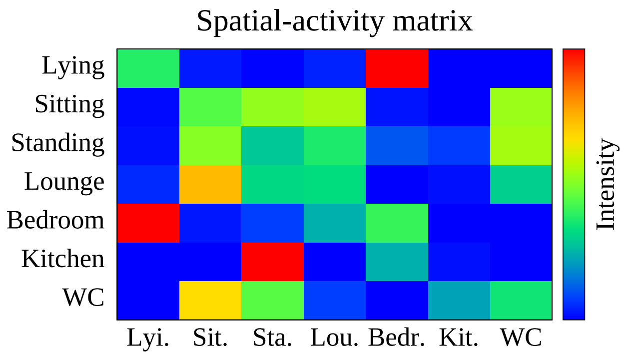
In the second experiment we recorded a member of our department for a period of one month. The user was recorded during working hours, approximately eight hours/day. In this experiment, the user wore only



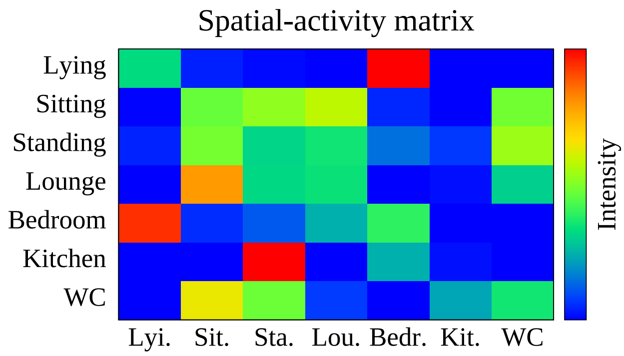
(a) Normal day 1



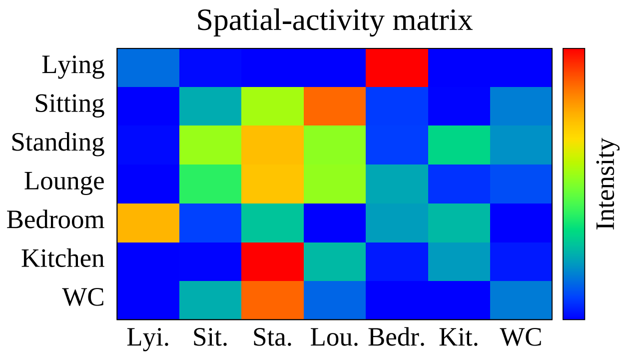
(b) Normal day 2



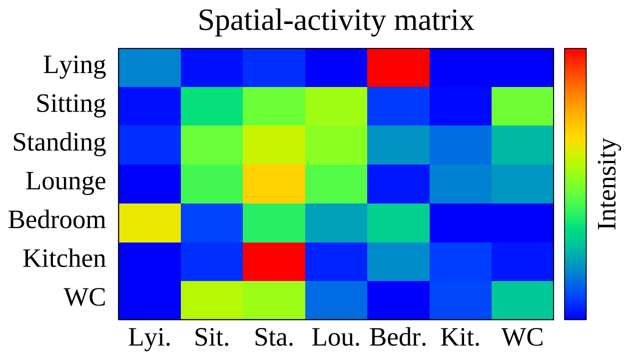
(c) Normal day 3



(d) Normal day 4



(e) Slow day



(f) Limping day

Fig. 4. Visualization of four normal (4a, 4b, 4c, 4d) and two deviant days (4e, 4f) of one person.

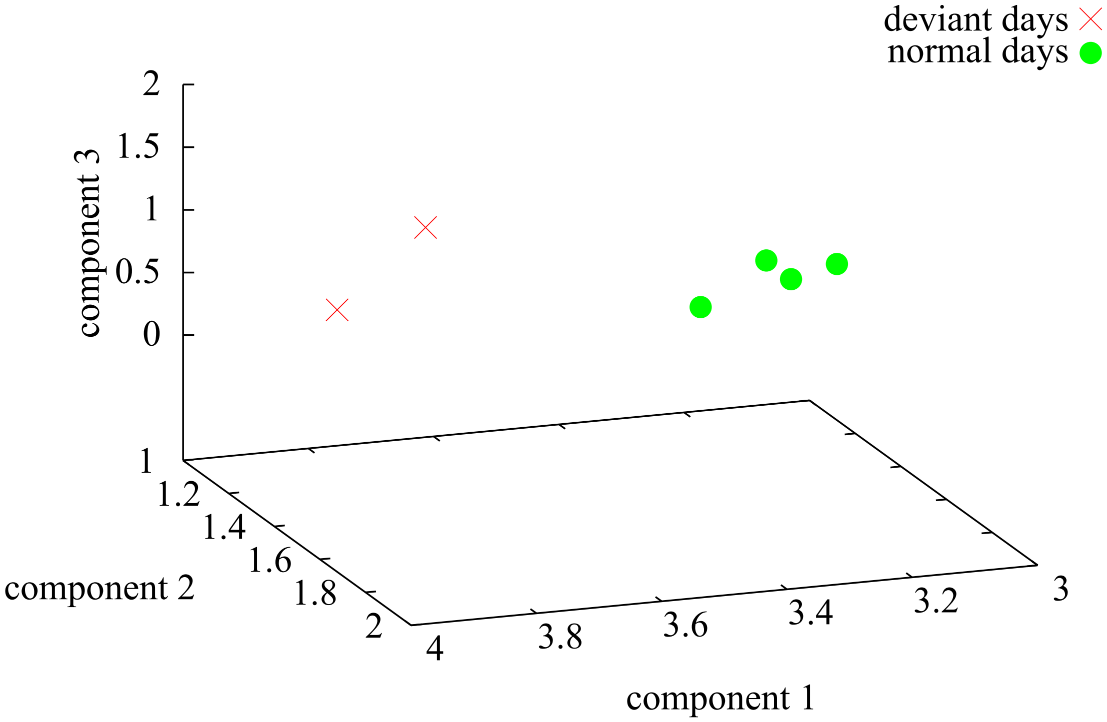


Fig. 5. Visualization of principal components computed from the matrices shown in Fig. 4. Normal days are presented with circles, deviation days with crosses.

Table 2

LOF values of the behavior traces. A higher value represents a 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

one Ubisense tag on the chest. The first 10 days were used for training, while the next five days were used for evaluation. Additionally, we recorded three days when the user was experiencing some difficulties: limping day, where the user limps while he walks; agitation day, where user occasionally walks around the office for half a minute; and urinary tract infection day, where the user visits toilets more than usual. In total there was 18 working days resulting in over 90 hours of recordings.

The results for five regular and three anomalous days are presented in Table 3 for $k = 2, 3, 4$. The normal-working days have LOF values lower than 1 except on the third day, while the days, when the user experienced some kind of difficulties, have significantly higher LOF values.

Table 3

LOF values of the long-term test. A higher value represents a higher outlierness of a behavior trace.

Day	k=1	k=2	k=3
Regular day 1	0.737	0.784	0.684
Regular day 2	0.803	0.698	0.594
Regular day 3	1.618	1.579	1.281
Regular day 4	0.840	0.866	0.738
Regular day 5	0.767	0.916	0.881
Limping	3.706	4.820	6.216
Agitation	7.110	8.987	12.960
Urinary infection	14.405	18.052	19.869

6. Discussion

In these experiments we selected one day as a default unit, but in general, the approach can be applied to periods of various length. Furthermore, monitoring the behavior with different granularities by using different periods simultaneously, e.g., half a day, a day, a week, a month, would allow us to detect changes in behavior that occur with different pace.

It should be noted that the task is based on combining activities and spatial information, thus applying a uniform method such as HMMs is not feasible. The novel method provides an essential explanation of the two concepts by combining several existing algorithms, specializing them for the particular task. In addition, HMMs must estimate the model parameters in the learning phase, whose quality depends on the amount of labeled data [22].

The visualization of the spatial-activity matrix can be used in two ways. Firstly, it enables human detection of anomalous behavior; by examining the matrices one can notice changes in behavior dynamics. Secondly, it provides an explanation in the case that the automatic procedure detects anomalous behavior patterns.

The final remark concerns the type of sensors used in the experiments. Even though our approach was evaluated with wireless location sensors (i.e., Ubisense), it can be applied to any type of sensors from which it is possible to provide location and recognize activities, for example, one can use embedded sensors as shown in [6,24]. In fact, our future plans include an extensive experiment in environment with embedded sensors.

7. Conclusion

The main goal of this paper was to deliver a solution whereby a caregiver can constantly observe the daily behavior of a person remotely in an efficient and unobtrusive 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 a visualization and explanation of deviations from normal behavior.

We proposed a method for the automatic discovery of anomalous 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 information that the dynamics of the user has changed significantly and an explanation as to how. The experimental results showed that the proposed approach is successful in discriminating the behavior traces of normal days and days where the user's wellbeing is affected.

The method has not been tested thoroughly yet. More realistic, long-term tests with the target group 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.

Acknowledgments

This work was partly supported by the Slovenian Research Agency under the Research Programme P2-0209 Artificial Intelligence and Intelligent Systems, and partly from the European Community's Framework Programme FP7/2007-2013 under grant agreement No. 214986. We would like to thank Mitja Luštrek, Erik Dovgan, Boža Cvetković, Violeta Mirchevska for suggestions, discussions and help with the programming.

References

[1] J.C. Augusto, M. Huch, A. Kameas, J. Maitland, P.J. McCullagh, J. Roberts, A. Sixsmith, R. Wichert: *Handbook of Ambient Assisted Living - Technology for Healthcare, Rehabilitation and Well-being*, IOS Press, 2012.

[2] A.K. Bourke and G.M. Lyons: A threshold-based fall-detection algorithm using a bi-axial gyroscope sensor, *Medical Engineering & Physics*, **30**(1), 84 – 90, 2008.

[3] M.M. Breunig, H.P. Kriegel, R.T. Ng, and J. Sander: *LOF: Identifying density based local outliers*, In Proceedings of the ACM SIGMOD Conference, Dallas, TX, May 2000.

[4] T. Choudhury, M. Philipose, D. Wyatt, and J. Lester: Towards activity databases: Using sensors and statistical models to summarize people's lives, *IEEE Data Eng. Bull* **29**, 2006.

[5] D.J. Cook: Multi-agent smart environments, *Journal of Ambient Intelligence and Smart Environments* **1**(1), 51–55, 2009.

[6] D.J. Cook, L.B. Holder: Sensor Selection to Support Practical Use of Health-Monitoring Smart Environments. *Handbook of Ambient Assisted Living*, 434-450, IOS Press, 2012.

[7] Confidence Project, http://www.confidence-eu.org.

[8] A. Dore, M. Pinasco, L. Ciardelli, and C. Regazzoni: A bio-inspired system model for interactive surveillance applications, *Journal of Ambient Intelligence and Smart Environments* **3**(2), 147–163, 2011.

[9] K. Doughty, R. Lewis, and A. McIntosh: The design of a practical and reliable fall detector for community and institutional telecare. *Journal of Telemedicine and Telecare* **6**, 150–154, 2000.

[10] F. Cardinaux, D. Bhowmik, C. Abhayaratne, and M.S. Hawley: Video based technology for ambient assisted living: A review of the literature, *Journal of Ambient Intelligence and Smart Environments*, **3**(3), 253–269, 2011.

[11] T. Huynh, U. Blanke, and B. Schiele: *Scalable recognition of daily activities with wearable sensors*, In Proceedings of LoCA 2007, LNCS, vol. 4718, pp. 50–67, 2007.

[12] B. Kaluza, V. Mirchevska, E. Dovgan, M. Lustrek, and M. Gams: *An agent-based approach to care in independent living*, In Proceedings of International Joint Conference on Ambient Intelligence (AmI 2010), 2010.

[13] K. Krapp and G. Cengage: Activities of daily living evaluation, *Encyclopedia of Nursing & Allied Health*, eNotes.com, 2006.

[14] B.S. Lee, T.P. Martin, N.P. Clarke, B. Majeed, and D. Nauck: Dynamic daily-living patterns and association analyses in telecare systems, In Proceedings of the Fourth IEEE International Conference on Data Mining, pp. 447–450, 2004.

[15] Localization data for person activity dataset, http://archive.ics.uci.edu/ml/datasets/Localization+Data+for+Person+Activity.

[16] D. Lymberopoulos, A. Bamis, and A. Savvides: Extracting spatiotemporal human activity patterns in assisted living using a home sensor network. In Proceedings of PETRA, Athens, Greece, 2008.

[17] M. Lustrek and B. Kaluza: Fall detection and activity recognition with machine learning, *Informatica* **33**(2), 197–204, 2009

[18] M. Lustrek, B. Kaluza, E. Dovgan, B. Pogorelc, and M. Gams: Behavior analysis based on coordinates of body tags, In Proceedings of the European Conference on Ambient Intelligence (AmI 2009), pp. 14–23, Salzburg, Austria, 2009.

[19] J. Muncaster and Y. Ma: Hierarchical model-based activity recognition with automatic low-level state discovery, *Journal of Multimedia* **5**, 66–76, 2007.

[20] D.N. Monekosso and P. Remagnino: Behavior analysis for assisted living, *IEEE Transactions on Automation Science and Engineering*, **7**(4), 879–886, 2010.

[21] B. O'Flynn, P. Angove, J. Barton, A. Gonzalez, J. O'Donoghue, and J. Herbert: Wireless biomonitor for ambient assisted living, In Proceedings of IEEE International Conference on Signals and Electronic Systems (ICSES), 2006.

[22] L.R. Rabiner: A tutorial on hidden Markov models and selected applications in speech recognition. In Proceedings of the IEEE **77**(2): 257-Ű286, 1989.

[23] P. Steggles and S. Gschwind: Ubisense – a smart space platform, Technical report, Ubisense, 2005.

[24] H. Storf, T. Kleinberger, M. Becker, M. Schmitt, F. Bomarius, and S. Prueckner: An event-driven approach to activity recognition in ambient assisted living, In Proceedings of the European Conference on Ambient Intelligence (AmI 2009), *LNCS*, volume 5859/2009, 123-132, 2009.

[25] Ubisense. http://www.ubisense.net.

[26] S.A. Wallace: Behavior bounding: An efficient method for high-level behavior comparison, *Journal of Artificial Intelligence Research* **34**, 165–208, 2009.