Pervasive and Mobile Computing 34 (2017) 157–167

Contents lists available at ScienceDirect

Pervasive and Mobile Computing

journal homepage: www.elsevier.com/locate/pmc

Unsupervised visit detection in smart homes

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ARTICLE INFO

Article history:
Available online 3 June 2016

Keywords:
Ambient Assisted Living (AAL)
Markov Modulated Poisson Process (MMPP)
Smart homes
Gerontechnology

ABSTRACT

Assistive technologies for elderly often use ambient sensor systems to infer activities of daily living (ADL). In general such systems assume that only a single person (the resident) is present in the home. However, in real world environments, it is common to have visits and it is crucial to know when the resident is alone or not. We deal with this challenge by presenting a novel method that models regular activity patterns and detects visits. Our method is based on the Markov modulated Poisson process (MMPP), but is extended to allow the incorporation of multiple feature streams. The results from the experiments on nine months of sensor data collected in two apartments show that our model significantly outperforms the standard MMPP. We validate the generalisation of the model using two new data sets collected from an other sensor network.

1. Introduction

Intelligent technology that supports elderly to live independently needs information about their activities. There is an increasing interest in networks of ambient sensors, such as motion detectors and door switches, for monitoring human activities [1–3]. Often the focus is on Activities of Daily Livings (ADLs), such as sleeping, toileting and cooking. ADLs are considered important indicators for the functional health status of older adults [4].

In our group, researchers from different disciplines (information technology, machine learning and occupational therapy) work together to develop monitoring systems for older adults. The objective of the research is to use pervasive technology to support older adults to independently live longer in their own homes and their familiar and safe environment. Currently our group monitors about 20 elderly living alone using sensor networks. For a correct health assessment it is important that we are sure that the data originates from the activities of the resident only and, therefore, that we know when there are visitors. Furthermore, the type and the frequency of visits are important indicators of the social participation of elderly. One solution to identify the visitors is using RFID tags [5], but this method has some practical disadvantages in real life situations such as the ease of forgetting to scan a visit. It is also possible to use a video sensor to count persons [6], but this is hard to realise in real life situations because of privacy reasons. An unobtrusive supervised method is used in [7]. A more holistic solution, multi-person activity recognition in smart homes, has been presented [8–11]. Hence simple sensors, both wearable and ambient, can be used for the detection and monitoring of multiple persons in smart homes. Unfortunately, these methods rely on large supervised data sets which bring the difficulty of collecting the ground truth data.

Because the number of apartments we are monitoring is large and future projects will involve even more apartments, we cannot rely on supervised learning methods to build accurate individual models for visit detection. In this paper we present an unsupervised method for visitor detection. The method specifically looks at transitions between sensors and models the

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http://dx.doi.org/10.1016/j.pmcj.2016.05.003
1574-1192/

regular pattern as a normal (non visitor) pattern. An anomaly in this pattern (for example non-modelled transitions between two distant sensors) may indicate that visitors may be present. A model that has been successfully applied for the detection of anomalous events using counts as features is the Markov Modulated non-homogeneous Poisson Process (MMPP) [12], which takes into account both the periodic and non-periodic influences present in the data. This fits our situation, assuming that the resident has periodic (daily and weekly) living patterns and non-periodic patterns such as a visit on an occasional basis. However, MMPPs are univariate, and as such cannot deal with the richer, multidimensional, data sets that are common to AAL.

In [13] we showed, on a single data set, that Markov Modulated Multidimensional non-homogeneous Poisson Process (M3P2) can be used for visit detection. The M3P2 model extends the MMPP by allowing the use of a multidimensional feature stream. In this paper we present a more extensive evaluation on a more elaborate data set. We studied the effect of feature selection, the assumption on periodicity of data and the generalisation to other sensor networks.

The contribution of our research is two-fold: (a) we show that properly designed unsupervised methods can be used to detect visits with networks of a small amount of simple sensors and (b) we show that M3P2, a novel model that deals with multiple data streams, is significantly better at this task than MMPP. Moreover, it allows us to distinguish between regular and non-regular visits automatically, and to have a model of daily and weekly cycles in the person's routine. We evaluate the performance of our model on real-life sensor data. We use two data sets, that we make public, consisting of nine months of sensor data collected in the apartment of two elderly persons. The results show that our model significantly (significance level, $p < 0.05$) outperforms the standard Markov Modulated Poisson Process (MMPP). Two additional data sets are used to evaluate the generalisation of the M3P2 model.

2. Related work

The issue of dealing with multiple persons in a smart home is an important problem that recently became the subject of extensive study. In his survey [14], Teixeira describes the ability to detect the presence, count, track and identify persons using different methods and sensor types. Binary sensors in a network are able to count and localise individuals with an accuracy that depends on the number of the nodes. Using a large number of sensors in a network, Singla et al. [11] described a method that focuses on the recognition of ADLs in multi-user contexts. Using the same dense sensor network, Crandall et al. applied standard supervised classification techniques, such as Naive Bayes and HMM, to identify and track multiple smart home residents [15–17]. Phua et al. [9] noted that standard supervised techniques yield high accuracies only if (a) the number of simple sensors is large, (b) the training data is accurately labelled and (c) the activities are simple and done in habitual way. These assumptions are unrealistic in real life situations. Using a small sensor network, comparable to our situation, Petersen et al. [7], applied Support Vector Machines to detect the presence of a visitor in a smart home during a period of 6 weeks. However, supervised techniques have the weakness that they assume that the activities do not evolve over time [9]. The collection of annotated data to train supervised classifiers is difficult and involves other (invasive) sensors or a strict administration from the elderly. Unsupervised methods for the detection of abnormal behaviour in smart homes have been presented in applications like fall detection or wandering. Clustering methods such as K-means are used for the identification and prediction of abnormal behaviour of elderly dementia sufferers, but these methods are not effective in the presence of visitors or pets [5].

MMPPs [18], as unsupervised methods, are widely applied for the detection of anomalous events in various areas: to detect intrusions in a telephone network, Scott [19] introduced the non-homogeneous MMPPs, which take into account the natural cyclic nature of the variations in telephone traffic. A similar model was used by Hutchins et al. [20] to model the occupancy in a building and by Scott et al. [12] to model web traffic data. These models are all univariate, and as such cannot deal with the richer data sets that are common to AAL. Multivariate MMPPs have been described in detail in [21] for the homogeneous case, but lack the capacity of non-homogeneous MMPPs to model regular variations.

3. Sensor data

We have collected multiple data sets, in several ambient assisted living apartments, for a duration of up to more than a year. Different sensor networks were used to collect data as described in Section 6. These sensor networks consist of off-the-shelf binary sensors that measure motion, pressure on the bed, toilet flush and the opening and closing of cabinets and doors. An overview of the location of the sensors in the apartment of one resident is shown in Fig. 1. The elderly are living their routine life and are not told to modify their behaviour in any way. The location of the sensors is chosen so that all the important rooms in the apartment are covered and so that the network does not affect the elderly's daily life. For instance, the pressure sensor for the bed is installed under the mattress and sensors in the kitchen are installed above the stove, under the freezer, etc. A detailed description is provided in [13,10].

4. Features: description and extraction

The binary sensors generate a continuous stream of sensor-events. Our experience is that sensor-transitions are better than the number of sensor-events in the measurement of ADLs. Two consecutive sensor events are referred to as a sensor-transition. The number of these sensor-transitions during some time slice is likely to be smaller when there is only one

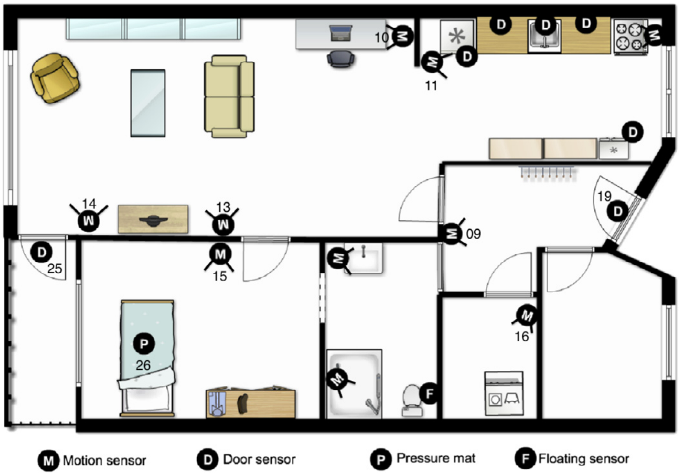


Fig. 1. A map of the apartment of volunteer *A* equipped with sensors. The number of used sensors, their types and their position do not differ a lot between the different apartments.

person in the house (i.e. the resident) than when there is more than one person in the house (i.e. a visitor). Therefore, the number of all possible sensor-transitions, referred to as $N(t)$, can be considered as a feature to detect visits.

When the resident is alone at home, we can assume that $N(t)$ only consists of sensor-transitions from *topologically connected* sensors, i.e., sensors that the resident can activate in sequence without tripping a third sensor in between. A graph representing the sensors that are topologically connected in the apartment of volunteer *A* is given in Fig. 2. The node identities in this figure correspond to the sensors shown in Fig. 1. An example of a sensor-transition of not-topologically connected sensors is the sensor-transition coming from the front-door sensor followed by the living-room sensor (edge 19 → 13). It is unlikely that this transition is generated by the resident alone, because he/she must go through the hall-sensor resulting in two transitions (edges 19 → 09 and 09 → 13). To detect visits, the number of sensor-transitions for which the sensors are *not* topologically connected, referred as $N^{\overline{C}}(t)$, can also be considered as a feature. Because a visitor always enters and leaves the apartment through the front-door, a third feature $N^D(t)$ can also be considered and used with the M3P2 model described in Section 5.3. $N^D(t)$ is defined as the number of sensor-transitions during time slice t, for which one of the sensor readings originates from the front-door sensor. For a formal definition of the features, we define a sensor-transition $\tau_{ij}^{(t_n)}$ between the sensors i and j starting at time stamp t_n by:

$$\tau_{ij}^{(t_n)} = \begin{cases} 1 & \text{if sensor } i \text{ fires at } t_n \text{ and sensor } j \text{ fires at } t_{n+1} \\ 0 & \text{otherwise.} \end{cases} \quad (1)$$

The feature $N(t)$ can then be expressed as:

$$N(t) = \sum_{\substack{b(t) \le t_n < e(t) \\ i,j \in S}} \tau_{ij}^{(t_n)} \quad (2)$$

where S is the set of all sensors and the function $b(t)$ (respectively $e(t)$) returns de beginning (respectively the end) of the time slice containing t_n.

Similar equations hold for $N^{\overline{C}}(t)$ and $N^D(t)$ by redefining S to be the subset of the topologically not-connected sensor tuples and the subset of the tuples where the front-door sensor is involved, respectively.

5. Models

5.1. Markov Modulated non-homogeneous Poisson Process (MMPP)

A Markov modulated Poisson process is a widely used stochastic process for modelling counts of random events that occur during a sequence of time intervals, in which different Poisson processes are switched between by an underlying Markov chain. The probability density for every Poisson process is given by a Poisson distribution:

$$\mathrm{Pois}(N = n; \lambda) = \frac{\lambda^n}{n!} e^{-\lambda}. \quad (3)$$

In [19], a MMPP was introduced, where the rate $\lambda(t)$ of the count data $N(t)$ varies over time. We follow [22], where both the periodic and the non-periodic influences on the count data are modelled. The periodic aspects (in this case, weekly and

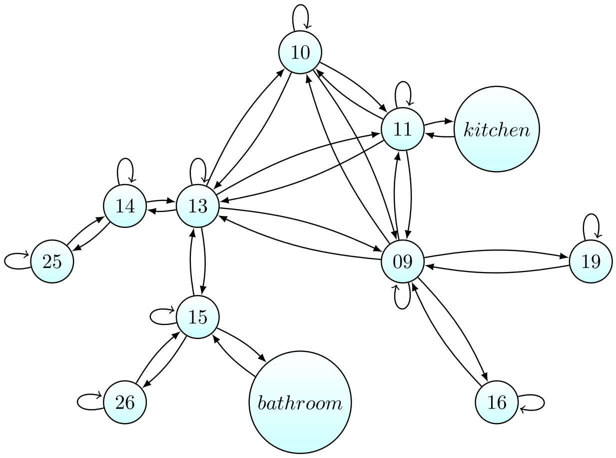


Fig. 2. A graph indicating the sensors that are topologically connected to each other. The node id's correspond to the sensor id's depicted in Fig. 1. The node bathroom (resp. kitchen) consists of six (resp. three) sensors that are topologically connected to each other. These sensors are omitted to keep the overview of the graph clear.

daily cycles) are modelled by decomposing the rate $\lambda(t)$ as follows:

$$\lambda(t) = \lambda_0 \cdot \delta_{d(t)} \cdot \eta_{d(t),h(t)} \tag{4}$$

where $d(t) \in \{1, \ldots, 7\}$ indicates the day of week in which t falls, and $h(t) \in \{1, \ldots, K\}$ indicates the time interval of a day in which t falls. δ_j represents the effect of the day j of the week and $\eta_{j,i}$ represents the effect of the time interval i given day j of the week. These effects are normalised by requiring that $\sum_{j=1}^{7} \delta_j = 7$ and $\sum_{i=1}^{K} \eta_{j,i} = K\ \forall j$. For example, $\delta_6 = 2$ would imply that the counts on Friday are twice λ_0. Fig. 4 illustrates the overall average λ_0, the effect of the day of week, δ_j, and the effect of the time of day, $\eta_{j,i}$.

We learn the model parameters using Maximum a Posteriori optimisation, using Gamma and Dirichlet distributions as conjugate priors for the model parameters λ_0, δ and η, following [22,10].

$$\begin{aligned} \lambda_0 &\sim \mathrm{Gamma}(a^L, b^L) \\ \frac{1}{7}[\delta_1, \ldots, \delta_7] &\sim \mathrm{Dir}(\alpha_1^d, \ldots, \alpha_7^d) \\ \frac{1}{D}[\eta_{j,1}, \ldots, \eta_{j,D}] &\sim \mathrm{Dir}(\eta_1^h, \ldots, \eta_D^h) \quad \forall j \in \{1, \ldots, 7\}. \end{aligned} \tag{5}$$

The presence of anomalies in the counts is modelled with the latent variables $z(t)$, which form a Markov chain with transition probabilities $m_{zz'}$ of the transition matrix M. Anomalies are modelled as resulting in an increase (positive anomaly) or decrease (negative anomaly) of the observed counts. The values of the hidden states $z(t)$ are as follows:

$$z(t) = \begin{cases} 0 & \text{no anomaly in time slice } t \\ 1 & \text{anomalous count increase in time slice } t \\ -1 & \text{anomalous count decrease in time slice } t. \end{cases} \tag{6}$$

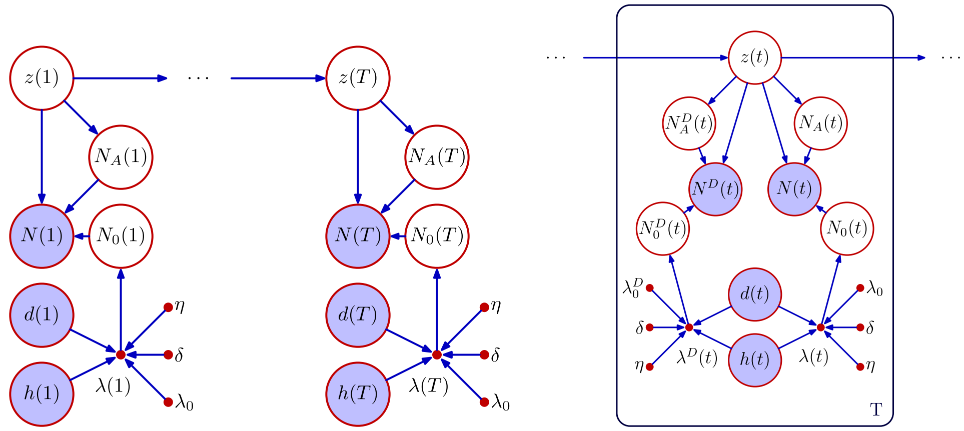
In our case, a positive anomaly corresponds to a visit, while a negative anomaly may correspond to either the absence of the resident or the absence of a regular visit. In both cases, they correspond to deviations from the regular pattern. We expand on these concepts in Section 5.2. We model the event counts $N(t)$ as:

$$N(t) = N_0(t) + N_A(t), \tag{7}$$

the sum of $N_0(t)$, the number of "normal" events, and, $N_A(t)$, the anomalous counts for that time period. Both of these are Poisson-distributed, and $N_A(t)$ is conditioned on $z(t)$. We use conjugate priors for the model parameters:

$$\begin{aligned} N_0(t) &\sim \mathrm{Pois}(\lambda(t)) \\ z(t)\, N_A(t) &\sim \mathrm{Pois}\left(\lambda_A\left(z(t)\right)\right) \\ \lambda_A(z(t)) &\sim \mathrm{Gamma}(a^A, b^A) \\ (m_{s0}, m_{s1}, m_{s,-1}) &\sim \mathrm{Dir}(\alpha_{s0}, \alpha_{s1}, \alpha_{s,-1}) \quad \forall s \in \{0, 1, -1\}. \end{aligned}$$

Notice that in this formulation λ_A is state-specific, meaning that the expected count increase ($z(t) = 1$) does not necessarily follow the same distribution as the count decrease ($z(t) = -1$). In the experimental section, we show that this extra flexibility is important to our application.



(a) MMPP. (b) M3P2.

Fig. 3. Graphical model for different distributions and variables defining the MMPP and the M3P2 models. The shaded nodes are observed and the small solid nodes indicate deterministic parameters. The directed edges indicate conditional dependence of the nodes. $\lambda(t)$ depends on the parameters λ_0, δ, η, $d(t)$ and $h(t)$, while $N(t)$ depends on $N_0(t)$, $N_A(t)$ and $z(t)$.

Our model is unsupervised: during training we jointly optimise the model parameters and the latent states using the EM algorithm. We use Markov Chain Monte Carlo (MCMC) sampling from the posterior of the latent state to estimate the parameters of the posterior Dirichlet distributions [22].

5.2. Regular visits, irregular visits and long-term temporal variations

The periodic effects in the MMPP model are governed by $\delta_{d(t)}$ and $\eta_{d(t),h(t)}$. Because of our choices for these parameters, anomalies are defined with respect to the weekly patterns. A visit that occurs at a specific time at a specific day in the week (for example the cleaner that comes on Friday) is not considered as anomaly, but is learned as a regular pattern, or *regular visit*. A visit that does not follow such a periodic behaviour is detected as *irregular visit*. If we choose another setting for these parameters we can modify the period with which we model effects. For example, if we do not learn the δ from the data but set $\delta_i = 1\ \forall i$, we assume that every day of the week follows the same pattern. In that case the cleaner that comes every week on Friday will be detected an anomaly. We can also use prior knowledge to set some parameters, for example η can be set to model daytime or night cycles.

The MMPP learns the characteristic activity pattern and the anomalies from a data set that spans some time period W. During that time period we assume that there are no other effects than the effects captured by our model. However, long term effects, which are not modelled, may occur. In the experiment section we study how far this assumption is warranted.

5.3. Markov Modulated Multidimensional non-homogeneous Poisson Process (M3P2)

An important limitation on the above-described MMPP is that the model is restricted to one-dimensional observations. In our application, detecting the presence of multiple persons, we are dealing with more than one feature that is informative. Although multivariate MMPP has been analysed before [21], this does not extend to non-homogeneous MMPP. We therefore extend the model to multiple simultaneous count features, resulting in the Multidimensional MMPP, abbreviated as M3P2 in the remainder of this text. A graphical representation of the M3P2 is given in Fig. 3(b). We define the M3P2 similarly to the MMPP, where the observation streams are assumed to be independent. Let $N^i(t)$ denote the ith observation stream at time t. Similar to the MMPP, define

$$N^i(t) = N_0^i(t) + N_A^i(z(t)) \tag{8}$$

and $p(N^1(t), N^2(t), \ldots) = \prod_i p(N^i(t))$.

As a consequence of the increased expressiveness of the M3P2, it is advantageous to increase the cardinality of the latent states $z(t)$. In particular, in our application we explicitly model the usage of the front door. Since a visitor cannot enter or leave the house without making use of the door, we introduce a new state that models the entering or leaving of the house. The states are now:

$$z(t) = \begin{cases} -1 & \text{irregular absence of a visit} \\ 0 & \text{Normal situation} \\ 1 & \text{irregular visit} \\ 2 & \text{irregular door activity.} \end{cases} \tag{9}$$

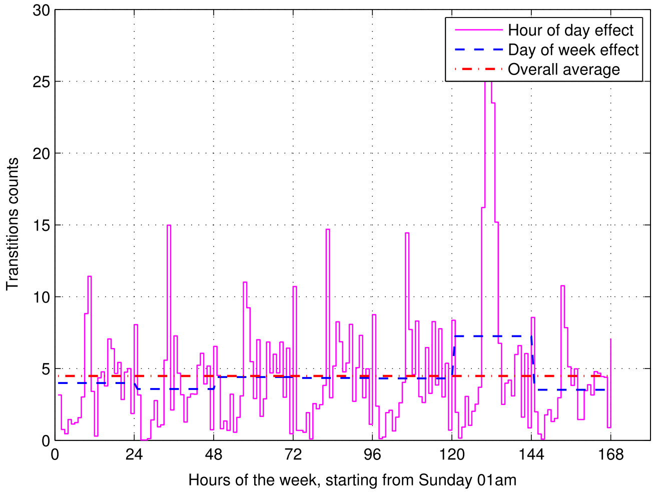


Fig. 4. An illustration of the overall average (λ_0), the day of week effect combined with λ_0 ($\lambda_0\delta_{d(t)}$) and the effect of the hour of the day of the week combined with λ_0 ($\lambda_0\delta_{d(t)}\eta_{d(t),h(t)}$). The effect of $\eta_{d(t),h(t)}$ during the night is clearly lower than the day. The effect of Friday is higher than the other days. The morning rhythm is also clearly visible.

The state $z(t) = 2$ acts as a *gating* state without which it is impossible to transition from the absence of an irregular visit to its presence, and vice-versa. We encode our knowledge that it is impossible for visitors to enter or leave without using the door in the priors, setting $\alpha_{0,1}$, $\alpha_{-1,1}$, $\alpha_{1,-1}$ and $\alpha_{1,0}$ to 0.

In case we are dealing with two data streams (e.g. $N(t)$ and $N^D(t)$), the calculation of the posterior probability $p(z(t)|N(t), N^D(t))$ is also done using the MCMC sampling method. We consider $N(t)$ and $N^D(t)$ to be independent given $z(t)$, so that $p(N(t), N^D(t)|z(t)) = p(N(t)|z(t))p(N^D(t)|z(t))$.

In the first part of each MCMC-iteration, the hidden states $z(t)$ of the Markov chain are sampled by iteratively computing the conditional distribution $p(z(t), N(1 \ldots t), N^D(1 \ldots t))$ in a forward step, as follows:

$$\alpha_t(s) = p(z(t) = s, N(1 \ldots t), N^D(1 \ldots t)) = p(N(t)|s)p(N^D(t)|s) \sum_r M_z(r, s)\alpha_{t-1}(r). \tag{10}$$

Define f_+ (respectively f_-) to be the probability of $N(t)|z(t)$ in case there is a positive (respectively a negative) anomaly, which is computed by marginalising out both the number of additional (respectively, missing) events, $N_A(t)$, and the actual parameters of the distribution for the anomaly, giving rise to:

$$f_+(t) := \sum_i \text{Pois}(N(t) - i; \lambda(t)) \, \text{NB}\left(i; a^A, \frac{b^A}{1 + b^A}\right) \tag{11}$$

$$f_-(t) := \sum_i \text{Pois}(N(t) + i; \lambda(t)) \, \text{NB}\left(i; a^A, \frac{b^A}{1 + b^A}\right) \tag{12}$$

where NB indicates the Negative Binomial distribution.

Defining f_+^D and f_-^D on the same way for the second data stream N_A^D, the likelihood functions $p(N(t), N^D(t)|z(t))$ can be expressed as given in Eq. (13). Note that an irregular visit, $z(t) = 1$, is mainly caused by an increase of visit transition counts, while an increase of the door counts will cause an irregular visit coming in or leaving.

$$p(N(t), N^D(t)|z(t)) = \begin{cases} \text{Pois}(N(t); \lambda) \cdot \text{Pois}(N^D(t); \lambda^D) & \text{if } z(t) = 0 \\ f_+(t) \cdot \text{Pois}(N^D(t); \lambda^D) & \text{if } z(t) = 1 \\ f_-(t) \cdot f_-^D(t) & \text{if } z(t) = -1 \\ \text{Pois}(N(t); \lambda) \cdot f_+^D(t) & \text{if } z(t) = 2. \end{cases} \tag{13}$$

The model parameters are then updated using the samples obtained using Eq. (10) as for a standard MMPP, following [22].

6. Experiments

6.1. Objectives

A set of six experiments is conducted to evaluate the performance of the models. In the first experiment, we studied the effect of the time discretisation: the duration of the time-slice in which we count the transitions. If this is too small we may

Table 1
A summary of which data set is used for which experiment(s).

Data set	Volunteer	Period	Experiment(s)
A	M, 84	Apr 2013–Dec 2013	1, 2 and 3
B	F, 80	Oct 2013–Jun 2014	4 and 5
C	M, 84	Jul 2012–Sep 2102	6
D	F, 87	Jul 2012–Sep 2102	6

have too few counts to make a good model. If it is too large we lose resolution and will miss information as the duration of a visit may vary from few minutes to several hours. The second experiment is conducted to select the most relevant feature: are the general sensor-transitions sufficient, or are the more specific sensor-transitions (these involving the topologically not-connected sensors) more informative for the visit detection? A third experiment was carried out to investigate how well the model performs in the face of slow changes in the patterns over long periods of time. For example, do we need to take any influence of meteorological seasons into account or not? In the fourth experiment, we compared our model, the M3P2, with the baseline, the standard MMPP model: does the incorporation of a second data feature stream, $N^D(t)$, result in better performance or is one feature stream, $N(t)$, sufficient. The fifth experiment is conducted to evaluate how regular and irregular visits are detected when different periodicities are considered. The last experiment is conducted to test the generalisation of our model. The M3P2 model is applied to two new data sets collected using a different sensor network.

6.2. Sensor data

For the first three experiments, a data set collected during 9 months between April 2013 and December 2013 in the apartment of a volunteer *A* is used. This resident, a male of 84 years old, received visits from a caregiver every day around 8:30 in the morning and around 9:00 in the evening and weekly visits of a cleaner every Friday between 9 and 12 in the morning. The resident also occasionally got visits from his children. For the fourth and fifth experiments we used two data sets: (a) the same data set used for the first three experiments and (b) an extra data set collected in the apartment of a volunteer *B* during 9 months between October 2013 and June 2014. This resident, a female of 80 years old, rarely got visits, except a visit of the cleaner twice a month. For generalisation experiment (last experiment), we used two data sets collected using a different sensor network. This sensor network, described in [23], consists of simple binary sensors communicating with a receiver using RFM DM nodes. The data set *C* was collected between July 2012 and September 2012 in the apartment of volunteer *A*, while the data set *D* is collected in the same period in the apartment of a different volunteer: a female of 87 years old. A summary of which data sets is used for which experiment is given in Table 1.

6.3. Annotation and performance measure

To measure the performance of the model we used annotated data. The annotation of the data is done using self report and by visually inspecting the raw sensor data. The volunteers are asked to register some information about the visits they received during at least two weeks. A special form was designed to make the registration easy for them. After the period of annotation, an interview with the elderly took place to clarify the annotations. The start and end time of the visits registered by the elderly seemed to be approximate times. For this reason the exact time generated by the front- and back-door sensors are used for the annotation instead of the times filled in by the elderly.

In order to map the ground truth into discrete time slices, we decided to label all the time slices that are fully or partially covered by a non-regular visit as a positive class ($z = 1$). For example, a non-regular visit on Friday September, 13 between 18:55 and 20:04 lasted one hour and 9 min, but spans 3 time slices (respectively 4 time slices) in the annotation when $D = 24$ (respectively $D = 48$) is used. These 3 (respectively 4 time slices) are labelled as a positive anomaly class. The same procedure holds for the irregular absence of visit ($z = -1$). The precision, recall and the F-value are computed separately for the two states ($z = 1$ and $z = -1$). The values stated in Section 7 are obtained by calculating the average of at least 10 experiment repetitions. A non-regular visit lasting more than one time slice is defined to be correctly detected if at least one time slice of this irregular visit is correctly detected by the classifier.

7. Results

7.1. Effect of time discretisation

We varied the number of time slices in a day $K \in \{8, 12, 24, 48, 96\}$, corresponding to time slice length of $\{3, 2, 1, 1/2, 1/4\}$ hours. The reason to limit to only these values is because most non-regular visits have a duration of 3 h or less. A 3-fold cross validation is used to determine the best model parameters (*e.g.* λ_0 and λ_A) during the training phase. The results, listed in Table 2, are obtained by taking the average of 10 repetitions when MMPP is applied on $N(t)$. The results show that the highest F-value is obtained when $K = 24$. The results also show that the precision increases with K. This can be explained by the fact that increasing K, which is equivalent to decreasing the time slice length, will decrease the number of observation per

Table 2
Precision, recall and F-value of MMPP applied on $N(t)$ using different K's.

K	Slice length (h)	Non-regular visits ($z = 1$)		
		Precision	Recall	F-value
8	3	0.661	0.667	0.661
12	2	0.653	0.854	0.728
24	1	0.735	0.792	0.762
48	1/2	0.750	0.752	0.750
96	1/4	0.858	0.664	0.743

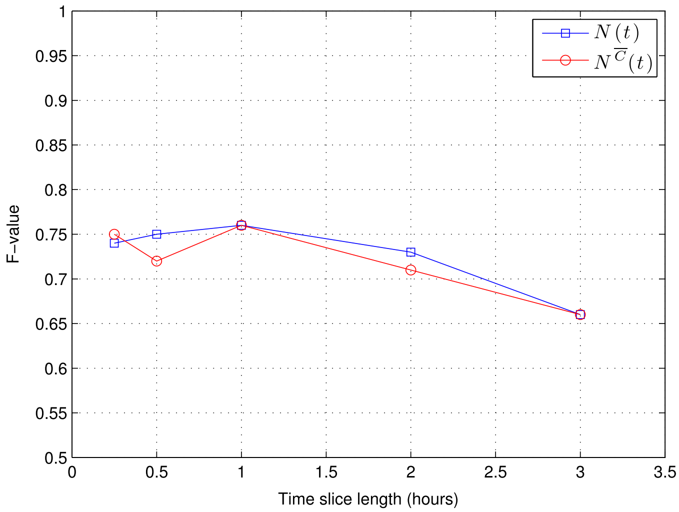


Fig. 5. The F-value obtained when MMPP is applied on $N(t)$ and $N^{\overline{C}}(t)$ using different time slices. The standard deviation varies between 0.03 and 0.1 in all cases after 10 repetitions.

time slice, which will increase the variance. As a consequence, the number of false positives will increase, which decreases the precision. The results of the irregular absence of visits ($z = -1$) are not reported because of lack of data, resulting in a very large standard deviation of the F-value. The first fold (calendar weeks 14–27) and the third fold (calendar weeks 40–53) have only one or two 'irregular absences of visits', while all the other 'irregular absences' lie in the second fold. In our case, the recall was almost always equal to 1 (respectively equal to 0) when testing with the first fold (respectively the third fold). For this reason, we omit absence of visit for the rest of our experiments. Unless mentioned otherwise, we chose for $K = 24$ in the following experiments because it gives the best compromise between the performance and the practical usage.

7.2. Feature selection

To investigate the value of topological connected sensors, the MMPP is applied using the features $N(t)$ and $N^{\overline{C}}(t)$ described in Section 4. Similar to the first experiment, a 3-fold cross validation is used during the training phase. Fig. 5 shows the F-values when MMPP is applied to these features using different time slice lengths. The results show that the F-values corresponding to the features $N(t)$ and $N^{\overline{C}}(t)$ do not differ a lot from each other and confirms that different features do not affect which time discretisation is optimal. This means that the use of the general sensor-transition counts, $N(t)$, is sufficient for the detection of the visits.

7.3. Temporal variations

For this experiment, we varied the number of weeks, W, during which we assume that the resident's behaviour does not change. Using the feature and time slice duration found above, we varied W between 4 and 39 weeks. Setting $W = 4$ assumes there are 'monthly' variations in the behaviour, while setting $W = 39$ assumes there were no variations for the whole duration of the data collection. The results, given in Table 3, are obtained by taking the average of 10 repetitions of MMPP for each value of W. The results show that the best performance is obtained when using a period of 13 weeks long. This is remarkably close to the duration of a meteorological season, and it seems very plausible that there is a seasonal effect in the data. It will be fascinating, in future work, to incorporate this in the model and evaluate it on multi-year data. Note that the computational time to build such model is less than 10 min.

Table 3
Precision, recall and F-value obtained when MMPP is applied on $N(t)$ using $D = 24$ and different values for the period W.

W (weeks)	Non-regular visits ($z = 1$)			std dev
	Precision	Recall	F-value	F-value
4	0.511	0.670	0.579	0.15
6	0.636	0.626	0.630	0.10
8	0.826	0.690	0.752	0.05
13	0.749	0.784	0.765	0.04
39	0.748	0.749	0.748	0.01

Table 4
Precision, recall and F-value obtained when MMPP (resp. M3P2) is applied on $N(t)$ (resp. $N^D(t)$) using one hour as time slice length (*i.e.* $D = 24$) and a season as a temporal variation (*i.e.* $W = 13$). The data set A (resp. B) corresponds to the volunteer A (resp. B).

Model (MMPP/M3P2)	Data set	Non-regular visits ($z = 1$)		
		Precision	Recall	F-value
MMPP	A	0.749	0.784	0.765
M3P2	A	0.856	0.800	0.827
MMPP	B	0.842	0.800	0.821
M3P2	B	0.849	0.854	0.851

7.4. Comparison between M3P2 and MMPP

In this experiment, we investigate whether the M3P2, using an additional feature stream, outperforms the MMPP. We do this by combining the $N(t)$ feature used by the MMPP with the $N^D(t)$ feature, the number of front-door transitions, and keep $K = 24$ and $W = 13$ as found above. The results of this experiment, listed in Table 4, show that the M3P2 results in significantly higher F-values than the MMPP. The significance is tested using the two-sample t-test using a threshold level $\alpha = 0.05$. The normality assumption is tested using the Kolmogorov–Smirnov test using the same threshold level. The better precision of M3P2 compared to MMPP reflects the lower number of false positives obtained by the M3P2. Most of the false positives are caused by slight temporal shifts of the nurse's daily visits. An earlier (respectively later) visit of the nurse results in a higher value of $N(t)$ in the preceding (respectively following) time slice than the one in which the visit normally takes place. Another reason for false positives, in both models, is the lack of an accurate annotation for such large data sets. As mentioned earlier, the annotation is based on visual inspection of the raw sensor data combined with several interviews with the residents. Time slices that are detected as visits by the model and that cannot be clarified by the resident may result in erroneous false positives. We think that these false positives correspond to unexpected visits which the resident cannot remember.

7.5. Periodicity

In previous experiments we have considered visits as a deviation from the normal patterns for the resident within their weekly cycle. Such anomalies depend on how the cycle is defined, however, and it is therefore useful to evaluate how visits are detected when a different periodicity is considered. In particular, we experimented with the following 4 periodicities:

- a periodicity 'day/night', meaning that we assume that every day has a day cycle (08:00–00:59) and a night cycle (01:00–07:59) and that all the days of the week are the same. All hours of the day cycle, respectively night cycle, are the same. Furthermore, all the days of the week are the same.
- A periodicity of a day, meaning that we assume that every day is the same, but the hours of the day are not. Visits that do not have a periodicity of 24 h are detected as an anomaly.
- A periodicity 'weekday/weekend', meaning that we assume that the weekdays (Monday–Friday) are the same and that the weekends are the same. Weekly visits are considered as an anomaly and are detected.
- A periodicity of a week, meaning that we assume that only the weeks are the same. The days of the week and the hours of the day are assumed to be different. Visits that do not have a periodicity of one week are detected as an anomaly. This is our setting for the first four experiments.

The periodicity of a day, for example, is obtained by setting $\delta_j = 1\ \forall j \in \{1, \ldots, 7\}$. For this experiment, we use the optimal values of $K = 24$ and $W = 13$, as found before, and use the M3P2 model with the features $N(t)$ and $N^D(t)$ described above. The results of this experiment, listed in Fig. 6, show that the best performance of the model M3P2 is obtained with the periodicity of a week. This is to conform with our assumption that the residents have daily and weekly living patterns. The standard deviation of the F-values is large for both the two data-sets in the case of periodicity 'day/night' because the assumption that the residents have a constant behaviour throughout the day (08:00–24:00) is not warranted. The large standard deviation in case of data set B is due to a long visit period (guest) lasting more than three days between December 31 and January 3.

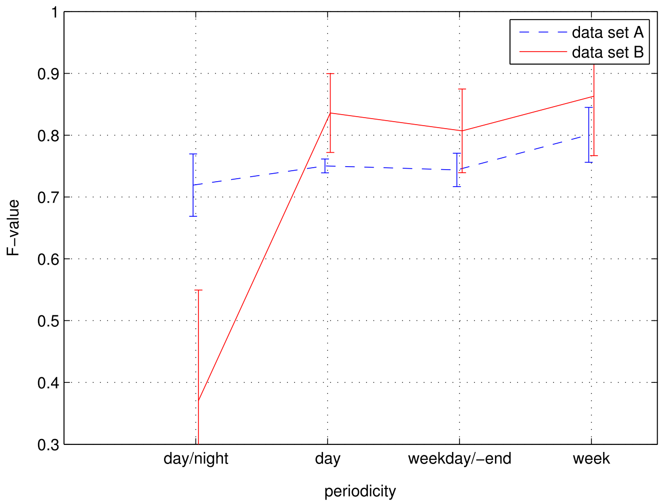


Fig. 6. The F-value with the corresponding standard deviation, obtained when M3P2 is applied on $N(t)$ and $N^D(t)$ using different periodicities.

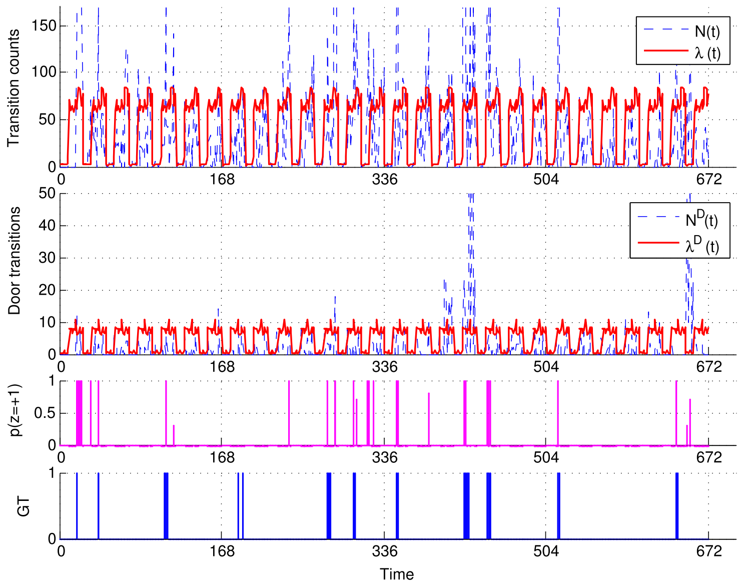


Fig. 7. Feature data streams $N(t)$ and $N^D(t)$ along with $\lambda(t)$, the corresponding posterior probability of non-regular visits ($p(z = +1)$) and the ground truth (GT).

7.6. Generalisation

With this last experiment, we confirm that our model is not specific to our particular data set and generalises well, both to different people and to different types of sensor network. To achieve this, we use two new data sets which are different from the data sets used in the previous experiments: (1) they use fewer sensors, and of a different type, (2) the data sets were collected at different times of the year (3) the sleep time of the sensors is much smaller, resulting in numerically very different data, and (4) one of the data sets is from a new, previously unseen volunteer. The results, listed in Table 5 and Fig. 7, are obtained using the optimal values of the parameters found from the previous experiments. Hence, $W = 13, D = 24$ and the periodicity is set to a day to capture the weekly visits. The results show that the performance of our model on the new two data sets is comparable to the performance on the data sets A and B.

8. Conclusions

We presented an unsupervised method for the detection of visits in the home of older adults living alone. A Markov modulated multidimensional non-homogeneous Poisson process (M3P2) is described, which allows us to incorporate multiple feature streams. The non-homogeneous property allows us to model weekly and daily cycles. As features we

Table 5
Precision, recall and F-value obtained when M3P2 is applied on $N(t)$ and $N^D(t)$ using one hour as time slice length and a season as a temporal variation. The values are averages of 10 repetitions with a corresponding standard deviation smaller than 0.015.

Data set	# weeks	Non-regular visits ($z = 1$)		
	Annotated	Precision	Recall	F-value
C	4	0.686	0.917	0.785
D	1	0.611	1.000	0.759

looked at transitions between sensors, both general transitions and transitions with knowledge on the sensor placement. The M3P2 is tested on two real-life data sets collected between April 2013 and June 2014 in the apartment of two older adults living alone. The study has shown that M3P2 is able to detect visits with a significantly ($p < 0.05$) higher F-value than the traditional MMPP. In particular, the reduced number of false positives, reflected in the much higher precision, is of great practical importance in care environments. In addition, the approach is able to model daily and weekly characteristics, and can distinguish between regular and irregular visits. The conducted experiments show that the (a) the simple sensor-transitions are sufficient for the detection of visits; (b) the meteorological seasons and the weekly patterns are reflected in the parameters of the model and (c) the proposed model can deal with the different lifestyles of different people and different types of sensor networks.

Detecting and analysing visits gives us an insight in the social life of the resident, and allows for a more accurate automatic activity recognition in general. These can allow the elderly to live in their own home for longer, with better monitoring and improved security.

Acknowledgements

This work is part of the SIA-raak Smart Systems for Smart Services, Health-lab and COMMIT. The authors would like to thank all the research participants.

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