Spatiotemporal Data Visualisation for Homecare Monitoring of Elderly People

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Abstract

Objective: Elderly people who live alone can be assisted by home monitoring systems that identify risk scenarios such as falls, fatigue symptoms or burglary. Given that these systems have to manage spatiotemporal data, human intervention is required to validate automatic alarms due to the high number of false positives and the need for context interpretation. The goal of this work was to provide tools to support human action, to identify such potential risk scenarios based on spatiotemporal data visualisation.

Methods and materials: We propose the multiple temporal axes (MTA) model, a visual representation of temporal information of the activity of a single person at different locations. The main goal of this model is to visualize the behaviour of a person in their home, facilitating the identification of health-risk scenarios and repetitive patterns. We evaluate the model's insight capacity compared with other models using a standard evaluation protocol. We also test its practical suitability by implementing a visualisation tool based on MTA and applied to a commercial home monitoring system.

Results: MTA proved to be more than 90% accurate in identify non-risk scenarios, independently of the length of the record visualised. When the spatial complexity was increased

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(e.g. number of rooms) the model provided good accuracy form up to 5 rooms. Moreover, it also gave high specificity levels (over 90%) for $5-8$ rooms. The MTA model outperformed the other models considered in identifying fall scenarios and was the second best for burglary and fatigue scenarios.

Conclusions: In home monitoring systems, spatiotemporal visualization is a useful tool for identifying risk and preventing home accidents in elderly people living alone. The MTA model helps the visualisation in different stages of the temporal data analysis process. In particular, its explicit representation of space and movement is useful for identifying potential scenarios of risk, while the spiral structure can be used for the identification of recurrent patterns. Experiences using the visualisation tool clearly illustrate the potential of the MTA model; for example, in practical scenarios, a visual mining tool to visualise daily or monthly activity.

Keywords:

Data visualisation; Visual mining; Temporal reasoning; Home monitoring; Ambient assisted living.

1 Introduction

Societies in developed countries are ageing due to increased life expectancy and low levels of fertility [1], and there are no signs of change in this tendency according to the World Health Organization (WHO) and the NIA/H (US National Institute of Aging/Health) [2]. This represents a great challenge for European society and for governments in general [3]. Some effects of this process include are the rising number of elderly living alone, the higher prevalence of dementia diseases and the overall increase in healthcare needs. The right to live independently supported by Information Technology (IT) and other new technologies is one of the pillars of European Union policy to guarantee the quality of life and the social inclusion of the elderly. Artificial Intelligence (AI) techniques will be essential for adapting home environments and enhancing healthcare services in this scenario.

Elder people who live alone are at risk of accidents at home as a consequence of three main factors: external, physical (due to age), or diseases (chronic or sudden). Loss of consciousness leading to a fall and aberrant behaviour associated with certain brain diseases (e.g. Frontotemporal dementia) are examples of possible risks.

In recent years, Ambient Assisted Living (AAL) systems have been proposed to deal with home risk detection [3]. AAL systems essentially acquire data from the environment (house) using a network of sensors, in order to provide a service to the user without involving direct interaction. One of the objectives of these systems is to detect a potential risk scenario and, if necessary, to raise the alarm. The most common risks are the following: (1) *Falls* which are one of the major causes of serious accidents for the elderly living alone, particularly in bathrooms and kitchens; (2) *burglary* and general home delinquency; (3) *fatigue*, one of the main effects of chronic cardiovascular diseases, characterised by physical weakness and slow activity especially at the end of the day; finally, (4) *aberrant behaviour*, which may be symptomatic of brain diseases like Frontotemporal Dementia (characterised by the involuntary repetition of movements).

AAL systems store a large amount of temporal data derived from a network of sensors, which describe the behaviour of an elderly person living alone. Most systems include a data-processing layer to abstract temporal information (from time points to intervals) and graphical visualisation layer for easier interpretation, usually as time lines or Gantt charts [4, 5, 6]. To act as automatic alarm, some authors propose AI techniques to provide an *a-priori* description of abnormal behaviour (risk scenario description) in the form of rules, temporal causal patterns or timed automata [7]. Due to false positives, these systems usually combine AI techniques with visualisation of the pieces of data that triggered the alarm.

The detection of risk scenarios based on these datasets is still a problem due to their nature (spatial-temporal data) and its domain context (behaviour of the elderly at home). As a consequence, this domain seems to call for powerful information visualisation solutions, which would allow easier and faster identification of risk scenarios in AAL systems, and provide a semiautomatic support to the online monitoring of elderly. Apart from scenario detection, visualisation techniques can also help in visual mining, that is, effectively analyse complex datasets and extract inherent structures form the spatiotemporal data [8].

In accordance with these considerations, we propose a new information visualisation model that allows visual data mining based on multiple temporal axes. Even though the information visualisation approach we propose is quite general and suitable for visually analyzing different healthcare temporal data, we will focus here on its use in the AAL context. In order to illustrate the suitability of our proposal, we have selected some of the most common risk scenarios (of different natures). This work is an extension of a previous paper appeared in [9].

This paper is structured as follows. In Section 2, we provide a review of works on spatiotemporal data visualization. Section 3 presents the formal framework used in the rest of the paper. In Section 4, we propose our visualisation model. The suitability of our proposal in a home monitoring environment is illustrated in Section 5. We evaluate the visualization capacities of our proposal in Section 6. Finally, Section 7 describes our conclusions and possible future works.

2 Related work

According to [10], the expressiveness and effectiveness of a temporal information display depends, among others, on the following key features: scale (discrete or continuous), scope (time point or interval events), arrangement (linear or cyclic) and viewpoint (single or multiple perspectives). In the following we will consider contributions dealing with the visualisation of sequences of time events (discrete).

The most simple and widely used solution is the timeline representation. In timelines, events are represented as geometric figures, arranged horizontally according to the time they occurred and displayed in one or multiple rows depending on their categories, as in Gantt charts [4, 5, 6]. In the medical domain, the visualisation of patient records can be done by events over the timeline as in LifeLines [11], KHOSPAD [12], KNAVEII[13], Care Vis [14], LifeFlow [15], and OutFlow [16]. However, in AAL systems, sensors register a large number of events and basic timeline-based representations are not effective. Some authors also suggest timeline visualisation methods, and considering temporal granularity and abstraction essential to the provision of suitable representations (e.g. abstracting time point events into interval-based events), such as the interactive ICU timeline visualisation tool proposed in [17] or Time Zoom [18].

The visualisation of temporal data to support the identification of recurrent health-risk scenarios requires the identification of patterns. Unlike timelines, we believe that the spiral arrangement helps to visualise the cyclic nature in which time is organised when patterns periodically occur (e.g. similar daily activity). The spiral proposals usually represent their rings as a fixed duration (like a clock). Carlis et al [19] propose a spiral layout to arrange an event sequence in 2 and 3 dimensions. The spiral time series model of [20] extends this idea by adjusting the length of its cycle and representing multiple records in different rings of the same spiral. SpiraClock has an interval sequence in the spiral, representing future and near past, simulating a clock [21]. Other authors also propose a spiral display to visualise spatiotemporal patterns of cartography in 3 dimensions [22]. However, in our domain, spatial data refer to a few locations visited frequently, and describe simpler spatiotemporal patterns.

Table 1: A comparative review of visual models

Models	Scale	Scope	Arrang.	Viewpoint
Timelines [4, 5, 6]	Continuous	Time Point	Linear	2D
[17]	Continuous	Intervals	Linear	2D
Gantt	Continuous	Interval/Relations	Linear	*2D*
Carlis [19]	Continuous	Not applicable	Cyclic	2D/3D
SpiraClock [21]	-	Intervals	Cyclic	Single
Hewagamage [22]	-	Not applicable	Cyclic	3D
PivotGraph [23]	-	Relations	Not applicable	Multivariate

Some efforts in AAL consider finite state machines for modelling elders' behaviour and patterns [7]. These approaches visualise patterns as state diagrams [24, 25]: a state diagram is graph where nodes are states and edges are transitions between them. Similar efforts have been done to visualise information in the form of graphs [26, 27, 23].

A comparative review of the aforementioned visualisation proposals is summarised in Table 1. In this review, we have adopted a selection of key features proposed in [10].

Despite the interest in home monitoring systems and efforts dedicated to temporal data visualisation, little attention has been paid to the graphical representation of the behaviour of people at home. We consider that such models should explicitly combine spatial and temporal visualisation in a simple and effective way in order to support the identification of periodic normal patterns but also scenarios of risk for health. To this end, the model should be expressive enough to represent the stay of the person in different locations, but also the action of moving from one room to another.

3 Formal framework

Temporal information plays an essential role when representing the behaviour of the elderly in AAL environments. On the one hand, general design decisions must be made for visualisation of this information, such as the types of temporal primitives (time points or intervals), the temporal relations between them, etc. On the other hand, the description of a risk scenario for elderly people also requires considering complex temporal information representing risk indicators, such as the sedentary nature (staying in the same location) or the levels of fatigue (decrease an activity). In the rest of the section we formally describe the idea of stay and activity.

3.1 Stay

Let L be the set of all possible locations of the house and T the time domain set. Formally,

Def. 1 Stay event: *The presence of a person in a given location for a certain period of time can be defined as a stay event as follows:* $s_i = (l_i, t_i^-, t_i^+)$*, where* $l_i \in L$ *is the location and* $t_i^-, t_i^+ \in T$ *are the starting and end time points of this presence, respectively* ($t_i^+ \geq t_i^-$).

The *duration of the stay* is denoted by $d(s_i) = t_i^+ - t_i^-$. Given a time interval (t_i, t_j), the *partial duration of a stay* s_k is the duration that this stay event occurs within the interval. Formally speaking, it is the duration of the intersection between the interval of s_k and the interval (t_i, t_j). That is:

$$d_{t_i}^{t_j}(s_k) = \begin{cases} 0 & \text{if } t_j \leq t_k^- \vee t_k^+ \leq t_i \\ min(t_j, t_k^+) - max(t_i, t_k^-) & \text{otherwise.} \end{cases} \tag{1}$$

The activity of a person in a house during a period of time can be expressed as a *stay sequence*. A sequence of n stay events is denoted by $S_s =< s_1, \dots, s_n >$, and an event s_k of S_s is expressed as $s_k \in S_s$. Note that a sequence of stay events formally corresponds to a sequence of partially ordered labeled time intervals.

Example

Let us consider a person moving in their 4 room house with: bedroom (B), bathroom (Ba), kitchen (K), and a corridor (C). This can be expressed as:

$L = \{B, Ba, C, K\}$
$T \in \mathbb{Z}$
$S_s =< (B, 0, 11), (Ba, 11, 14), (B, 14, 15), (C, 15, 18), (K, 18, 24), (C, 24, 25), (B, 25, 28) >.$
$s_1 = (B, 0, 11), \ldots, s_7 = (B, 25, 28)$

Most temporal visualisation metaphors used in AAL represent the stay events graphically, making explicit the stay of the person in each location for a certain period of time. In this sense, it is important to express the *degree of stay* of a person in the different locations during time. A function to measure the degree of stay, expressing the same idea, can be easily formalised.

Given a time interval (t_i, t_j), $t_j > t_i$, and a stay sequence S_s, we define a *density of stay (dos)* as follows:

$$dos : T \times T \to \mathbb{R}^+ \tag{2}$$

$$dos(t_i, t_j) = \frac{\sum\limits_{s_k \in S_s} d_{t_i}^{t_j}(s_k)}{t_j - t_i}. \tag{3}$$

Example

Let $S_s =< s_1, s_2, \ldots, s_7 >$ be the stay sequence previously introduced and let us suppose $(t_i, t_j) = (12, 18)$. The density of stay of S_s during this interval is:

$$dos(12, 18) = ((d_{12}^{18}(s_2) + d_{12}^{18}(s_3) + d_{12}^{18}(d_4))/(18 - 12) = (2 + 1 + 3)/6 = 1.$$

Moreover, in this example the density of stay of S_s is always 1 for any t_i and t_j within the duration of S_s since there are no gaps (no information about the presence) and stay events do not overlap (meaning that no more than one person is present in the house). Assuming that there is only one person at home, the domain of function dos is $(0, 1]$: in this case, $dos < 1$ means that information is missing (e.g. leaving the house). $dos > 1$ means that more than one person is at home.

In an AAL context, locations have different relevance according to their potential risk. For instance, the probability of having an accident in the kitchen or in the bathroom is higher than in the corridor. Therefore, the calculus of the density of stay for some particular locations is useful in this particular context.

Given a set of locations $L_a = \{l_1, \ldots, l_n\}$, a time interval (t_i, t_j), $t_j > t_i$, and a stay sequence $S_s =< s_1, \ldots, s_m >$, the located density of stay (dos') is defined as:

$$dos' : \wp(L) \times T \times T \to \mathbb{R}^+ \tag{4}$$

$$dos'(L_a, t_i, t_j) = \frac{\sum\limits_{s_k | l_k \in L_a} d_{t_i}^{t_j}(s_k)}{t_j - t_i}. \tag{5}$$

3.2 Activity

The activity of moving from one location to another is expressed by means of two consecutive stay events in a sequence.

Def. 2 Movement event: *Let $l_i, l_j \in L$ be two locations of the house. We define the* movement event *from l_i to l_j at time $t \in T$ as (l_i, l_j, t) or, in short, as $m_{l_i}^{l_j}(t)$.*

The movement event can also be inferred from two stay events as follows. Given two stay events $s_i = (l_i, t_i^-, t_i^+)$ and $s_j = (l_j, t_j^-, t_j^+)$, with $t_i^+ = t_j^-$, a movement event is defined as $m_{l_i}^{l_j}(t_i^+) = (l_i, l_j, t_i^+) = m_{l_i}^{l_j}(t_j^-)$.

Given a stay sequence, the *activity sequence* S_a is the sequence of movement events obtained by pairs of consecutive stay events.

Example

According to the previous example, we obtain the following activity sequence S_a from S_s:

$$S_a =< (m_B^{Ba}(11)), (m_{Ba}^B(14)), (m_B^C(15)), (m_C^K(18)), (m_K^C(24)), (m_C^B(25)) >.$$

Even in the stay event perspective, the measure of the degree of activity in a certain period is helpful in the AAL context, in order to analyse the behaviour of people at home.

Given a time interval (t_i, t_j), $t_j > t_i$ and a sequence of activity S_a, the *density of activity (doa)* is defined as follows:

$$doa : T \times T \to \mathbb{R}^+ \tag{6}$$

$$doa(t_i, t_j) = \frac{|\{m_a^b(t_k) \in S_a | t_k \in (t_i, t_j)\}|}{t_j - t_i}. \tag{7}$$

As before, the density of activity for some particular locations can be also defined for practical purposes.

Given a set of locations $L_a = \{l_1, \ldots, l_n\}$, a time interval (t_i, t_j) and a stay activity $S_a =< m_1, \ldots, m_m >$, the *located density of activity (doa')* is defined as:

$$doa' : \wp(L) \times T \times T \rightarrow \mathbb{R}^+ \quad (8)$$

$$doa'(L_a, t_i, t_j) = \frac{|\{m_a^b(t_k) \in S_a | a, b \in L_a \wedge t_k \in (t_i, t_j)\}|}{t_j - t_i}. \quad (9)$$

Example

Given the sequence of activity S_a defined in the previous example, we can calculate its doa and doa' for the interval $(12, 18)$, as follows:
$doa(12, 18) = |\{(m_{Ba}^B(14)), (m_B^C(15)), (m_C^K(18))\}|/(18 - 12) = 3/6 = 0.5.$

However, if we focus on the activity at some particular locations, like the bedroom or the bathroom, then $doa'(\{Ba, B\}, 12, 18) = |\{(m_{Ba}^B(14)), (m_B^C(15))\}|/6 = 0.333.$

Therefore, doa and dos are functions to measure and summarise the behaviour of people at home. The rest of this paper aims to describe a graphical metaphor for visualising both perspectives, stay and activity, in a manner suited to the AAL context.

3.3 Description of risk scenarios

Let us now focus on four main risk scenarios, related to fall, burglary, fatigue, and aberrant movements: all the corresponding patterns are quite common to the elderly people living alone and could produce emergency situations that need to be properly and quickly managed.

3.3.1 Fall scenario

In classical AAL systems, a fall alarm is traditionally defined as an unusual period where the person does not move from a given location for a certain period of time. According to the formal framework adopted, let $l_a \in L$ be the location of a possible fall and (t_i, t_j) an interval with a duration suitable for considering it as candidate period when a fall happens. A fall scenario alarm can be described as: $dos'(\{l_a\}, t_i, t_j) = 1$.

However, if a fall does not involve a loss of consciousness, people are able to slowly move from one location to neightbouring one. From the AAL system point of view, this is reflected by activation of sensors in both locations. In practice, due to the sampling constraints of the sensors, facts recorded in the log show a fast movement between rooms after a long period in one of them. Therefore, this fall scenario consists of two different stages (fall and fall recovery). Formally, we can define this *two-stage fall scenario* as:

$$dos'(\{l_a\}, t_i, t_j) = 1 \wedge doa'(\{l_a, l_b\}, t_j, t_k) > \epsilon^f, \tag{10}$$

where ϵ^f is a minimum temporal threshold of the fall recovery stage.

3.3.2 Burglary scenario

From an AAL system point of view, someone breaking into a house will mean two or more people inside.

From the stay perspective, a *burglary* scenario can be expressed by two or more stay events at the same time, that is:

$$\{s_i, s_j \in S_s | (t_i^-, t_i^+) \cancel{bm} (t_j^-, t_j^+)\} \neq \emptyset, \tag{11}$$

where $\cancel{bm}$ is a temporal relation between two intervals other than *before* or *meets* (or their inverse); that is: *overlaps*, *starts*, *during*, *finishes*, or *equal* (or their inverse) [28].

From the activity perspective, some different definitions can be provided. There is no strict equivalent description of the burglary scenario (previously defined) from the stay perspective in terms of movement events. However, a certain period of time when stay events occur at the same time at different locations will imply a frequent activity between these two location expressed as movement events. That is:

$$doa'(\{l_a, l_b\}, t_i, t_j) > \epsilon^b, \tag{12}$$

where l_a and l_b are locations where concurrent activity is identified, and ϵ^b is the minimum threshold for consideration as a burglary alarm. Finally, if we consider the semantics of location, we could also define a burglary scenario by the inconsistency of movement events. Due to the fact that two locations (l_a, l_b) are not physically connected, it is not possible to obtain a movement event $m_a^b(t)$ for any $t \in T$. Therefore the *burglary* scenario can be defined as:

$$\{m_a^b(t) \in S_a | \neg adjacent(l_a, l_b)\} \neq \emptyset, \tag{13}$$

where the adjacency of locations in a house is defined by its topology, as provided by its structure consisting of walls and doors.

3.3.3 Fatigue scenario

In the AAL system, *fatigue* can be detected by a decreasing intensity of the activity of the person moving around the house. This can be expressed by the use of doa, if we consider it as a dynamic discrete function;

$$\frac{df_{doa}}{dt} < 0, \tag{14}$$

that is, a time derivate of f_{doa} which is a dynamic function of doa over time, describing discrete time domain.

3.3.4 Aberrant behaviour scenario

The *aberrant behaviour* in this context can be expressed as a high frequent movements between two locations. That is:

$$doa'(\{l_a, l_b\}, t_i, t_j) > \epsilon^a \tag{15}$$

where ϵ^a is the minimum threshold.

Unlike previous scenarios, clinical considerations must be taken into account. For example, some patient suffering from certain dementia (e.g., Frontotemporal dementia) could develop different behavioural deficits. In practice, the Alert Monitoring Center of an AAL system is limited to detecting simple symptoms of motor behaving if the diagnosis is known *a-priori*. In no case can this proposal be used to support or make decisions about the diagnosis.

Expressions 10-15 can be used to define alerts of potential risk scenarios. For example, rule-based approaches are a common and simple way to describe these alerts in the form of *if/then* clauses. However, threshold configuration is not a simple issue and, most often, human intervention is required in order to interpret the context.

4 Visualisation proposal: Multiple Temporal Axes model

In this work, we propose the Multiple Temporal Axes (MTA) model, a visual representation of temporal information of the activity of a single person in different locations. Even though this model is used for AAL decision support, it is generic enough to be applied for temporal visualisation in other domains.

The MTA model aims to cover the following needs:

- Visualisation of basic time primitive concepts: intervals and interval relations.

- Supporting stay view in order to provide the user with a clear and simple visualisation of the stay of someone at each location (*stay sequence*).
- Supporting activity view to clearly represent the movements between different locations (*activity sequence*).
- Visually identification of *densities*. That is, the model must highlight the intensity of the activity (dos and doa).

Moreover, since the MTA model is used in the AAL context, we also considered the following specific characteristics:

- Providing the user with a summary of movements in order to clearly visualise the general behavior for ing periods of time.
- Highlighting late afternoon and evening events, since most accidents in the house of elderly people occur during the last hours of the day.

In the following, we formally describe the MTA model as well as its main features.

4.1 MTA model description

MTA is a 2-dimensional (2-D) graphical model that visualises stay and activity events arranged according to several axes corresponding to locations where these events occur and considering time as the main parameter to visualise.

The first element of the MTA model is the *time origin* (t_0), which is graphically represented by $\bigcirc$. In the 2-D canvas, t_0 could be any point, but is generally located at the center.

An axis is used to express the evolution in time from t_0 of the presence at a particular location. Axes are represented by timelines, arranged in a radial configuration from t_0, with $\bigcirc$ the starting point of all axes.

Each axis represents both a spatial and a temporal perspective. The temporal information of the axis spans from its time origin to the time end, while the spatial aspect corresponds to the (possibly several) locations the axis refers to. That is, an axis x is defined by $x = (t_i, t_j, L_x)$, where $t_i, t_j \in T$ ($t_i < t_j$) and $L_x \in \wp(L)$, $|L_x| > 0$.

Formally, the model is defined according to the following definition:

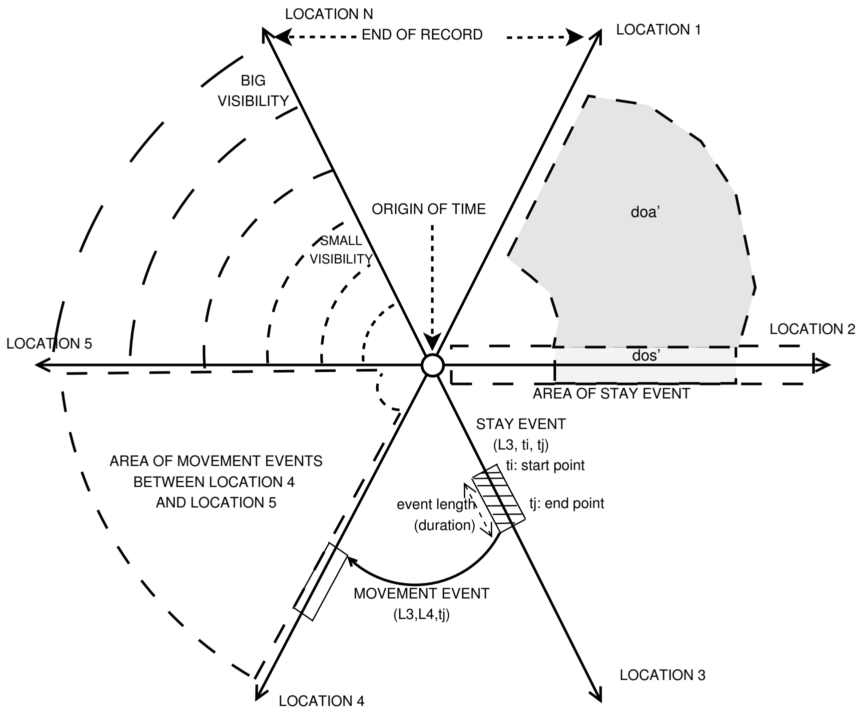

Figure 1: Description of Multiple Temporal Axes model.

Def. 3 Multiple Temporal Axes (MTA) model: *the MTA model is a triple* (S_s, S_a, X)*, where* S_s *and* S_a *are sequences of stays and activities, respectively, to be visualised, and* X *is the set of axes.*

The model is constrained by these three conditions:

1. Axis time origin: given (S_s, S_a, X), the time origin of all axes is t_0 and is defined as $t_0 = min(\{t_i \in T | (l, t_i, t_j) \in S_s\})$.

2. Referred events: each axis refers to those stay and activity events of the model that have the same locations. That is, given an MTA model (S_s, S_a, X) and an axis $x \in X$, $x = (t_0, t_e, L_x)$ where $L_x = \{l_1, \ldots, l_n\}$, x refers to the stay events $\{s = (l, t_i-, t_j) \in S_s | l \in L_x\}$ and to the movement events $\{m_{l_a}^{l_b}(t) \in S_s | l_a \vee l_b \in L_x\}$.

3. Axis time end: Given an axis $x = (t_0, t_e, L_x)$ of an MTA model ($x \in X$), its time end t_e depends on the referred stay events, that is, $t_e = max(\{t_j | (l_a, t_i, t_j) \in S_s \wedge l_a \in L_x\})$.

Figure 1 summarizes how the MTA model visually represents the information. From the visualisation point of view, stay events corresponding to an axis (i.e., corresponding to the same locations) are represented by rectangles along their timeline, the length of which depends on their duration. Since a movement event ($m_i^j(t)$) usually refers to two different axes, it is represented by an arc from the axis of location l_i at time t to axis l_j at time t. These arcs are graphically drawn using a Beizer curve line.

The later the activity events occur, the longer the arcs are. Due to the radial distribution of axes, the activity events located near the end of the axes show an arc (distance between starting and ending points) that is longer than the arc nearer the time origin. This feature provides the user with compact visualisation of early activities and a wider graphical representation of the later activities. Moreover, as the overall period of events to be visualised can be set by the user, it is possible to focus on movements of a single day, where late events are those in the evening, as well as on movements of a whole week, where the last days of the week are represented in a broader way.

Finally, collapsing axes is another important feature of the MTA. The action of collapsing axes means that two axes are combined to build a new axis as follows: $collapse((x_1, t_0, t_{e_i}), (x_2, t_0, t_{e_j}), MTA) = (x_1 \cup x_2, t_0, max(t_{e_i}, t_{e_j}))$.

In practice, users find it useful to collapse axes in order to summarise movements in the house (reducing the number of arcs). Axes are usually arranged according to the contiguity of corresponding locations. However, depending on the topology of the house, a movement event might cross axes.

Example

Figure 2 depicts different visualisations of the running example, introduced above, according to the MTA model. From a visual representation whereby each location corresponds to a single axis (Fig. 2-A), axes are progressively collapsed (Figure 2-B and C), until a single axis is left (Figure 2-D).

4.2 Visualising risk scenarios

Let us now focus on some specific visual patterns closely related to the four main risk scenarios. In the following we will consider the visual pattern corresponding to each of these risk scenarios.

Figure 3 shows a realistic scenario of a fall corresponding to a two-stage fall description, using the MTA model. In this example, the model shows regular activity until the person fall

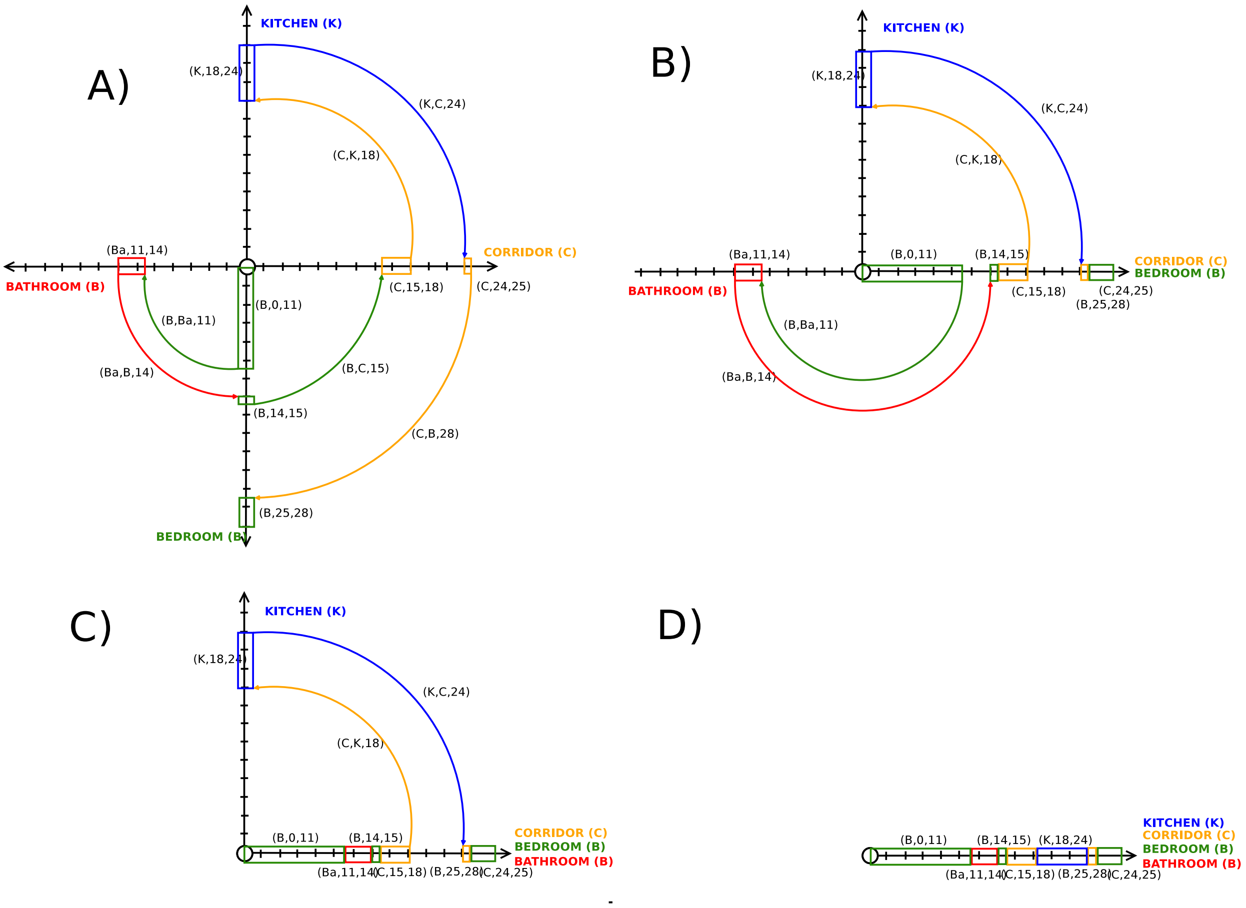

Figure 2: Multiple Temporal Axes Model: collapsing axes.

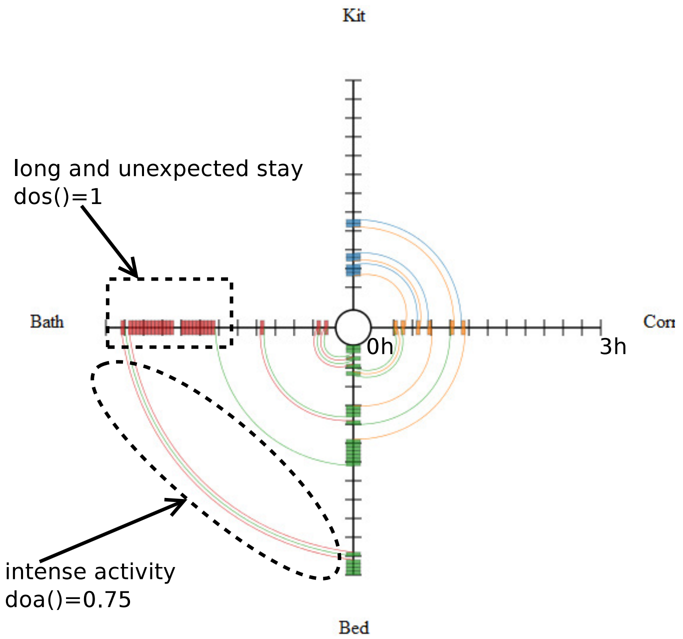

Figure 3: Multi-temporal axes model: example of a fall.

in the bathroom (fall stage), represented by a long stay event on the Bath axis. After that, the model shows frequent arcs between two axes, corresponding to a slow movement/transition between the bathroom and the bedroom (recovery stage). According to the formal framework, $dos'(\{Bath\}, 31, 53) \approx 1$, $doa'(\{Bath, Bed\}, 54, 58) = 0.75$ and $\epsilon^f = 0.6$. Note that, in real-world logs, errors in the sensors recording movement imply gaps between the stay events of the MTA model. However, in this example, the two-stage formal description provided is still valid since the fall stage can match the stay event after the gap.

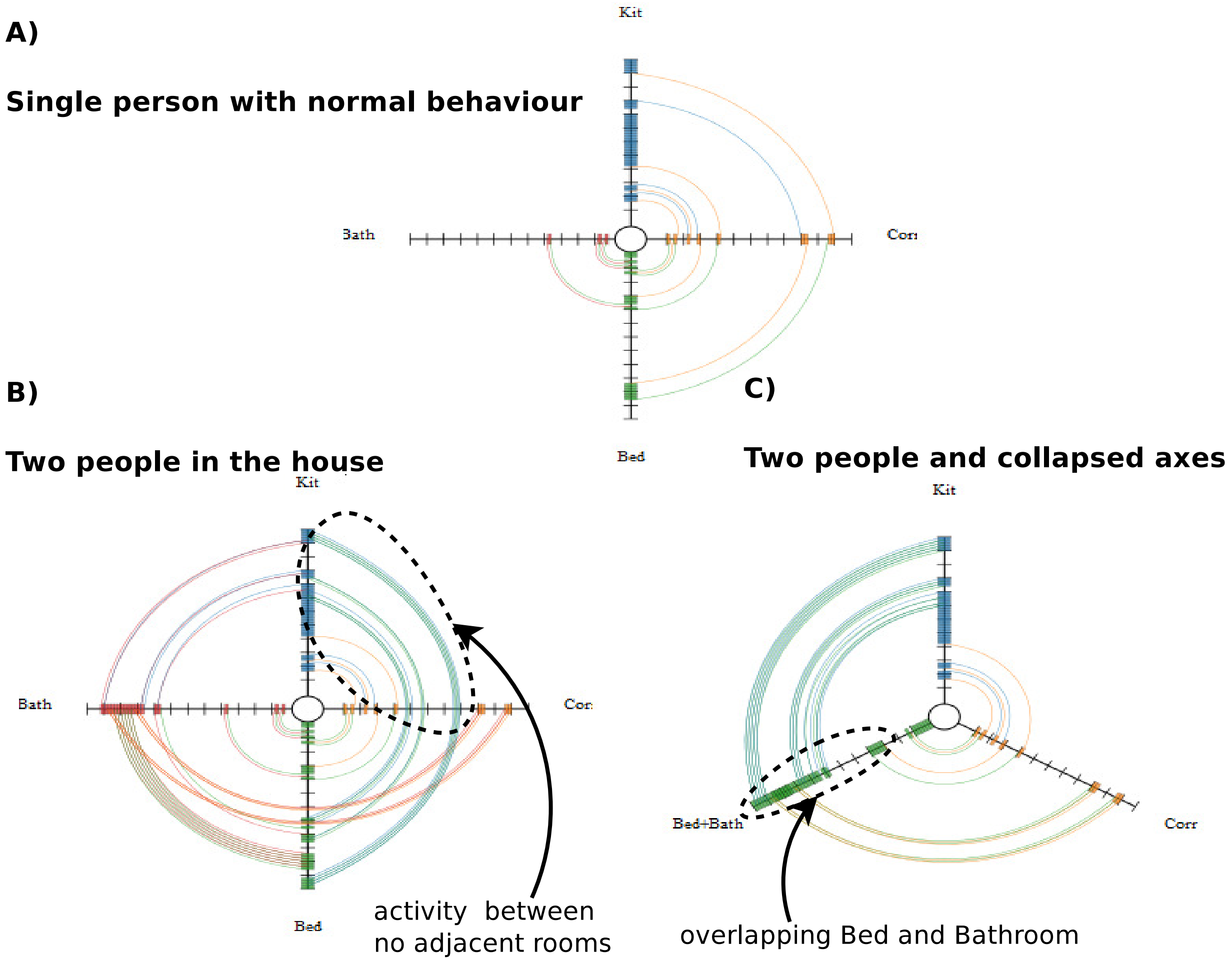

Figure 4: Multiple temporal axes model: burglary.

Figure 4 illustrates an example of the detected presence of an intruder. Figure 4-A shows the behaviour of a single person in her house using the MTA model. Figure 4-B shows the same activity when a second person is also in the house. Activity events connecting no adjacent rooms (e.g., Kit and Bath axes) highlight the possibility of intruders in the house. In this case, $m_{Kit}^{Bath}(38)$, $m_{Bath}^{Kit}(40)$, or $m_{Bath}^{Kit}(45)$ are present. Note that, this visual feature is only possible when the house has a reduced number of rooms. However, another effect of the presence of a second person is an increase in the number of activity events. Figure 4-C shows the same scenario when Bed and Bath axes are collapsed. This provides clear visualisation of this incident since the model highlight the contrast between the period of normal behaviour and the detection of two people in the house (sudden high values of doa).

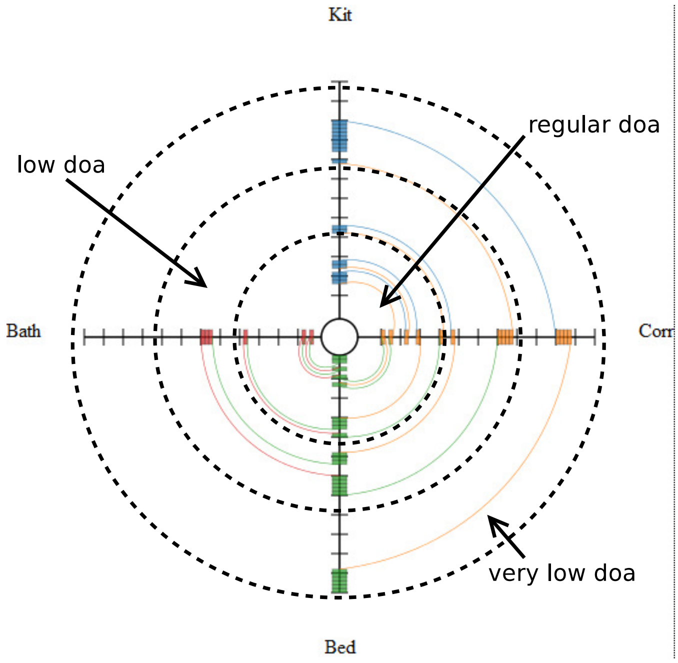

Figure 5: Multiple temporal axes model: example of fatigue.

Figure 5 shows a scenario of fatigue using the MTA model. In this example, the decreasing intensity of activity is easily detected by a gradual reduction in the number of movement events with time. According to the formal framework, we can see that $doa(0, 20) = 0.9$, $doa(20, 40) = 0.4$, and $doa(40, 50) = 0.2$.

Figure 6 illustrates a scenario of aberrant behaviour. In this example, the abnormal behaviour is the uncommon activity between the kitchen and the corridor, expressed as $doa'(\{Kit, Corr\}, 42, 48) = 0.83$, that is, a high density of activity between the Kit and Corr axes.

5 Case study

5.1 AAL system

The MTA has been tested using logs from a real AAL system called $proDIA$ [29], a home monitoring system for detecting scenarios of risk for elderly people living alone. The system

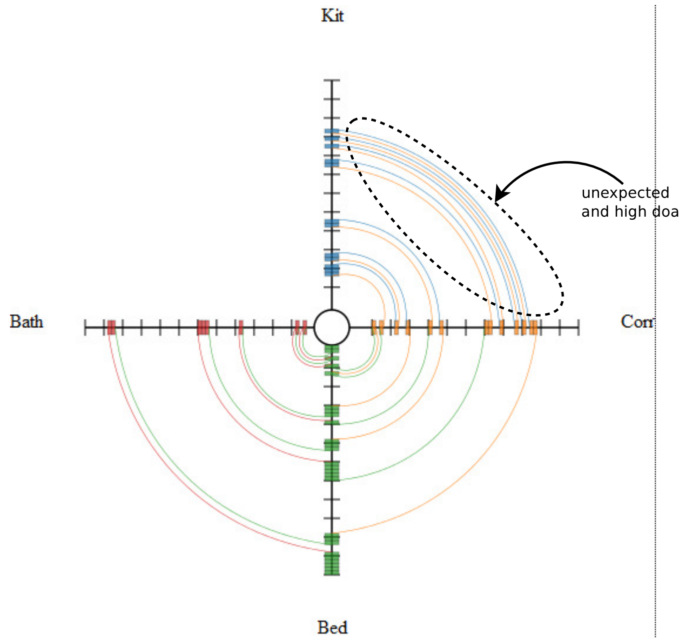

Figure 6: Multiple temporal axes model: example of aberrant behaviour.

is based on the assumption that no intrusive monitoring is acceptable (i.e. no cameras and no wearable sensors) and the use of low-cost technology is suitable and appropriate. A prototype of this AAL system has been installed in around 100 houses in the province of Murcia, Spain.

The home monitoring system is composed of the sensor level, the communication level and the data processing level (see Figure 7):

- The sensor-data acquisition is the first level of the system architecture. The network of sensors consists of: infrared motion sensors installed in each room of the house; pressure sensors installed in the bed and on the sofa; and a magnetic sensor, to check the entrance door.

- From the communication point of view, data from sensors are collected in a home-station (mini-PC) using IEEE-802.15.4 communication standard. Then, sensor data are sent to the Alarm Monitoring Center (Central Station) using 3G telecommunication technology.

- At the data processing level, the location of the person is identified, and a log describing activities in the house is recorded. This log is human-supervised in order to identify possible scenarios of risk, supported by a rule-based alert system.

In order to support of the human supervision, we extended the home monitoring system by including a visualisation tool called $8VISU$ tool.

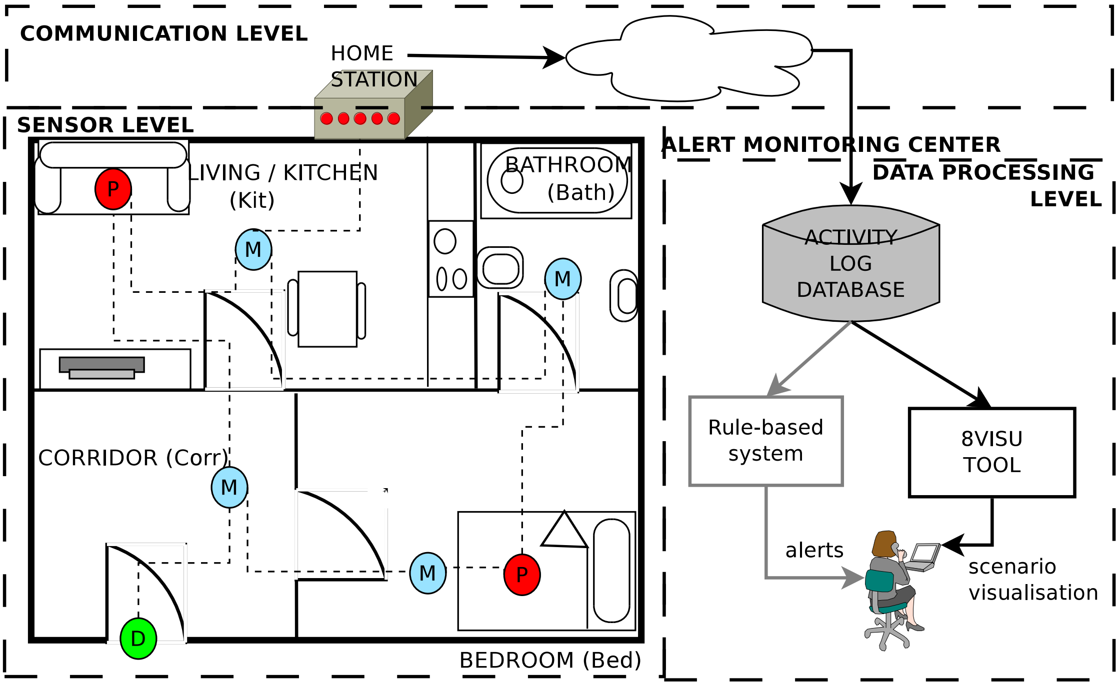

Figure 7: AAL environment: sensor-data acquisition layer composed of infrared motion sensors (M), pressure sensors (P) and a magnetic sensor at the door (D).

5.2 8Visu tool

8Visu tool is a visualisation tool specifically implemented to support the identification of risk scenarios of AAL systems. This tool is a two-step log visualisation. The first step consists of data abstraction. This process involves removing artifacts and data abstraction, that is, transforming time point records of sensors into intervals of presence (stay events). The second step is to graphically display the data processed by use of a visualisation engine, which consists of a web application based on the open source JavaScript library $D3$ [30]. The engine displays data using four different visualisation models: timelines, Gantt diagrams, spiral and MTA. This tool provides key functionalities, such as zoom, multiple-log/ multiple-model display, highlight room activity or axes collapse among others. In Figure 8, screenshots of 8Visu tool are depicted to illustrate this functionality.

8Visu tool is also designed for off-line monitoring, in order to retrospectively evaluate the behaviour of a person in the house. For example, the human supervisor can identify patterns in the daily routine of the monitored person. Figure 9 shows how 8Visu tool is used to analyse the activity of a person during a 31 day period using the AAL system. According to Figure 9-A, most of the activity is focused in certain rooms. Days 1,8, 15, 19 and 20 were similar,

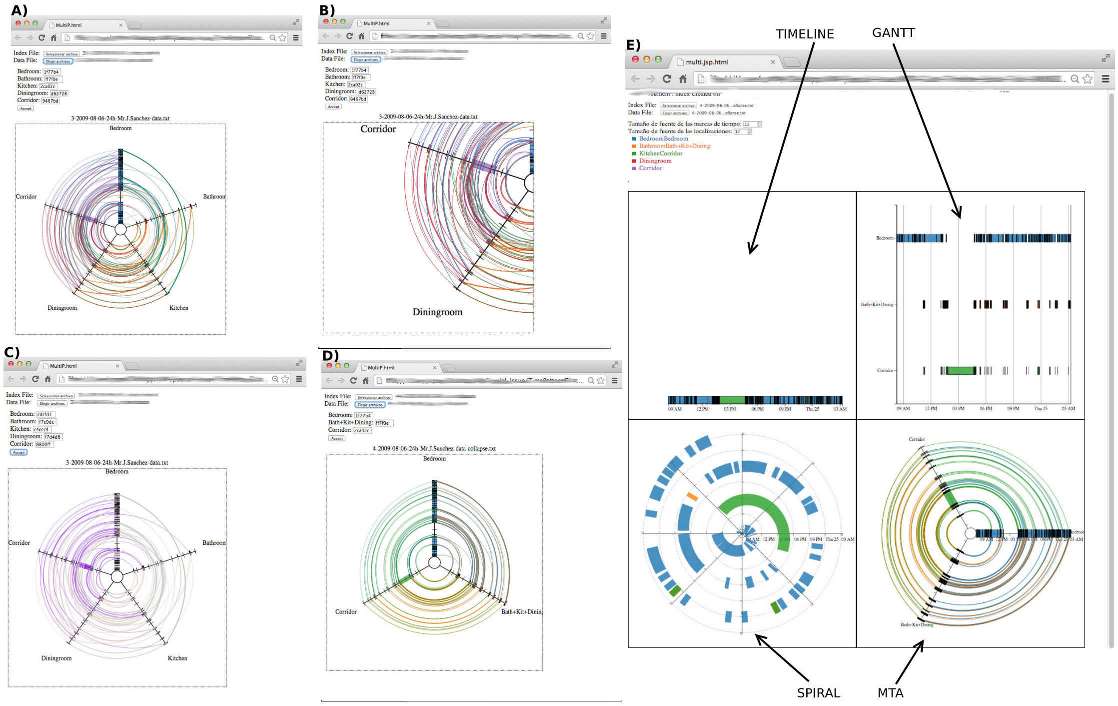

Figure 8: Functionality of 8VISU tool in: (A)1 day visualization, (B) log zoom, (C) activity focus, (D) axes collapse, and (E) multiple model view.

as observed in Figure 9-B, since one of the room sensors collapses producing a continuous presence in one room. However, the person is more active on Tuesdays than on Wednesdays but acts similarly.

6 Experiments

In this section, we evaluate the MTA model, analysing its insight capacity to support scenarios of risk and providing a comparative study with other proposals: timelines, Gantt diagram and spiral visualisation.

6.1 Experiment design

There is a wealth of methodologies to evaluate the effectiveness of visualisation [31, 32]. For the sake of objectivity, we adopt the scenario-based framework proposed in [33] for empirical studies in information visualisation methods. According to this framework, we consider the following dimensions of analysis: *user performance*, *user experience* and *visual analytics*. *User performance* refers to how specific features objectively affect time and task accuracy (e.g. to

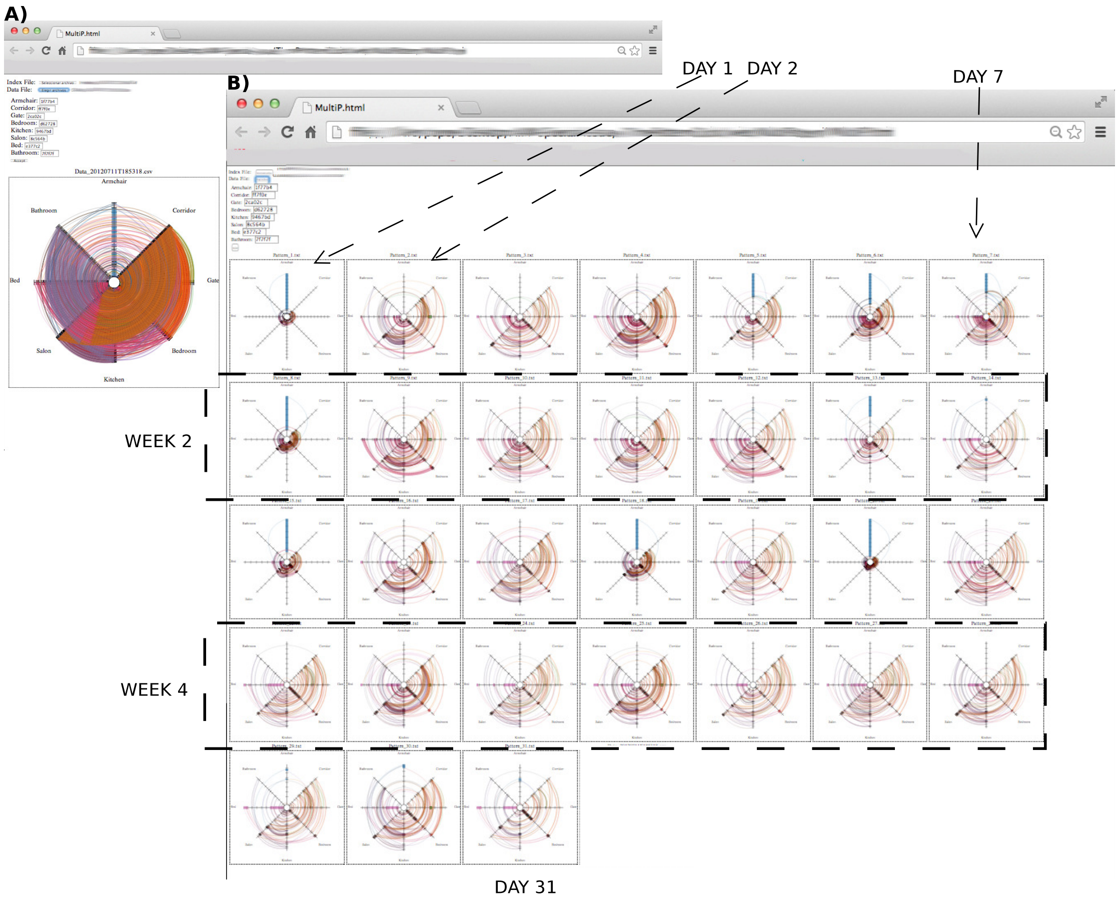

Figure 9: Example of visual mining for 31 days of activity.

identify a scenario of risk). On the other hand, *user experience* gathers the subjective opinion about the visualisation, particularly the perceived efficiency, correctness and understanding. Finally, *visual analytics* measure how visualisation tools support the generation of relevant knowledge (e.g. propose/reject hypotheses and decision making). These three dimensions of analysis can be evaluated combining elements of controlled experiments (simplified real problems) and usability testing methodologies in the form of task-solving questionnaires.

6.2 Protocol and participants

As in [34], in this experiment we consider two independent variables: the datasets (17 types of scenario) and the visualisation methods (MTA, timeline, Gantt and spiral). Table 2 summarises the datasets used (in the form of logs), describing different simplified scenarios of risk.

Participants were given a 3 minute tutorial regarding the problem and the visualisation methods before the test started. They were not allowed to ask the test administrator questions. The test consists of 43 questionnaires grouped to these three topics: log matching (choosing the

Table 2: Type of datasets used in the experiment.

Risk scenario	Num. Events	$dos(t_0, t_{end})$	$doa(t_0, t_{end})$	# Rooms	Duration (secs)
Normal	28	1.0	0.210	4	1680
Normal	28	0.98	0.320	4	1680
Aberrant	52	0.95	0.700	4	3600
Burglary	59	1.03	0.080	4	3600
Burglary	86	1.41	0.430	4	3600
Fall	38	1.0	0.180	4	3600
Fatigue	61	1.0	0.080	4	3600
Normal	28	1.0	0.275	3	1740
Normal	28	1.0	0.285	3	1680
Normal	28	1.0	0.285	5	1680
Normal	28	1.0	0.392	5	1680
Normal	28	1.0	0.321	6	1680
Normal	28	1.0	0.357	6	1680
Normal	28	1.0	0.285	7	1680
Normal	28	1.0	0.392	7	1680
Normal	28	1.0	0.357	8	1680
Normal	28	1.0	0.392	8	1680

correct visualisation picture from a given log), risk scenario identification, and subjective perception (selecting the best visualisation model given a scenario). As in the studies proposed in [34], we adopted the following measures:

- Total time spent to reach the insight (average of the overall test).
- Correctness: accuracy, specificity and sensitivity of the test.
- Domain value: importance of the insight.

Ten volunteers from the University of Murcia were selected. All participants have followed computer science studies, are familiar with the AAL problem, but had never used visualisation methods to analyse scenarios of risk. The demographics are the following: 29.5 years old (average); 60% undergraduate and 10% master students; 30% faculty members.

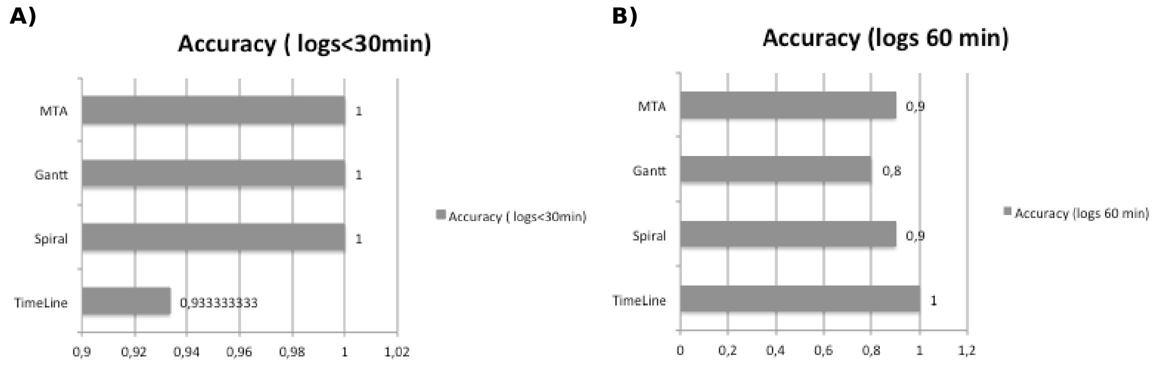

Figure 10: User performance: comparative study considering time as a variable.

6.3 Results

Participants needed 39.82 minutes, in average, to solve the test (minimum=31 minutes 44 seconds and maximum = 50 minutes). It means that each questionnaire took 55.5 seconds and each participant spent about 18 seconds to analyse each visualisation figure on average.

One key aspect in evaluating the capacity of the visualisation models is their capacity to represent the correct insight into different datasets (scenarios). Since space and time are explicitly represented in logs, they must be considered variables in our study. Temporal variable is defined as the amount of data (length of the log) that must be visualised; therefore, the longer the log, the more complex the scenarios. Figure 10 depicts the accuracy of the participants using different methods to solve log-matching problems. According to our experience in AAL domains, we group logs according its length. We consider short logs those that record less than 30 minutes of activity while longer scenarios are those that record about 60 minutes.

Unlike timeline, Gantt and spiral, the MTA explicitly display space and movement. Therefore, the spatial variable of study is the number of rooms of the log. Figure 11 shows the correctness of participants to understand temporal data when the number of rooms increases (from 3 to 8 rooms). The correctness is measured according to accuracy, specificity and sensitivity rates.

User experience is the second dimension considered in this study. Again, perceived correctness of the visualisation models depends on the spatial and temporal variables. In this case, we evaluate both variables simultaneously, considering simple logs (length$<$ 30 events, $dos(t_0, t_{end}) = 1$, $doa(t_0, t_{end}) < 0.2$), regular logs (length$\in$ $[30, 60]$ events, $dos(t_0, t_{end}) = 1$, $doa(t_0, t_{end}) \leq 0.3$) and complex logs (length$>$ 60 events, $dos(t_0, t_{end}) \geq 1$, $doa(t_0, t_{end}) > 0.3$). Figure 12 summarises the results obtained regarding perceived correctness of the visuali-

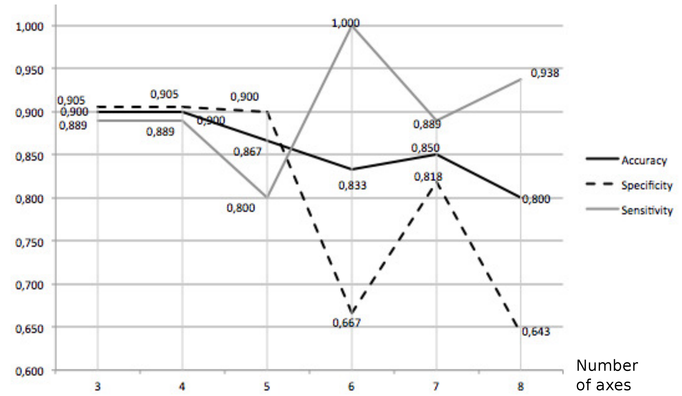

Figure 11: User performance: MTA correctness variating the number of rooms (displayed axes).

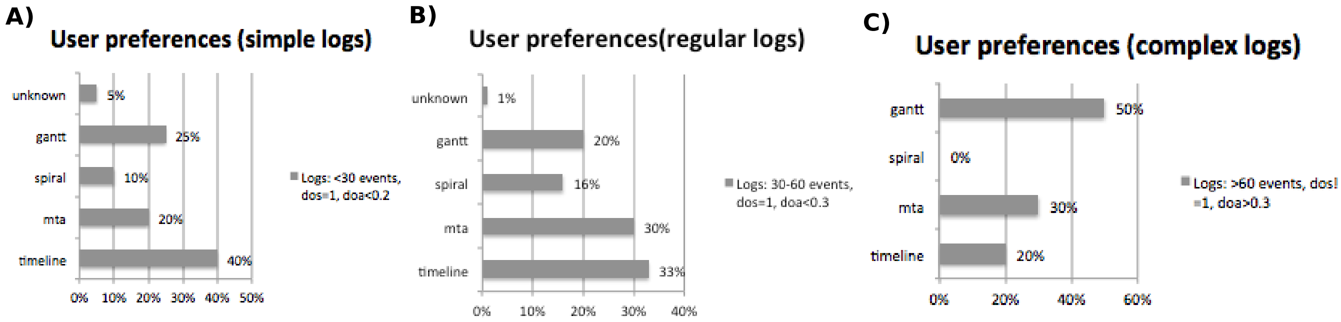

Figure 12: User experience: preferences according to the duration of the log.

sation models.

Finally, we also study how visualisation methods support the identification scenarios of risk. Figure 13 provides a summary of this visual analytics study, representing the method chosen used to correctly identify a scenario of risk. For instance, Figure 13-D is interpreted as follows: spiral model was chosen 90% of the times by participants when a fatigue scenario was correctly identified.

6.4 Discussion

Regarding *user performance*, the expressivity capacity of all models is acceptable in simple scenarios, even when the length of the log increases, as shown in Figure 10. All models provided similar results even for long logs (> 60 minutes). Therefore, the time variable is not the only aspect to consider in order to identify the best visualisation model.

On the other hand, study of the MTA model according to the spatial dimension (Figure 11) shows that in houses consisting of 5 to 8 rooms, participant accuracy clearly decreases.

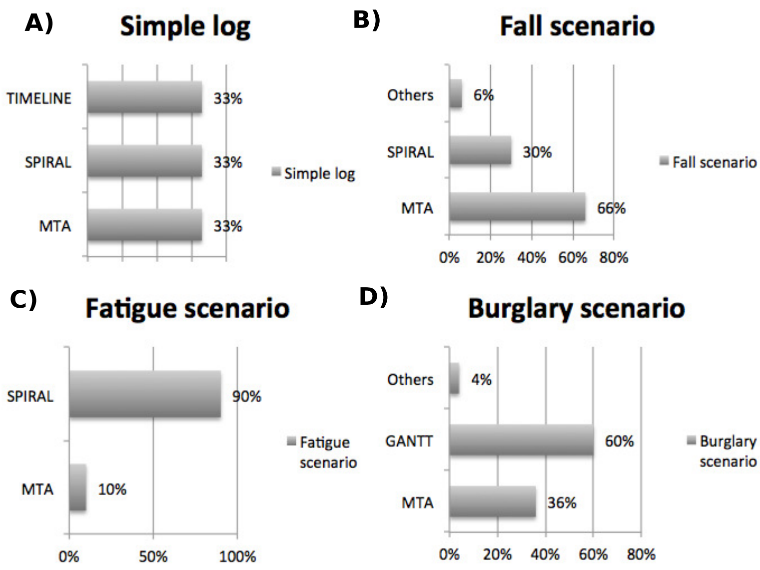

Figure 13: Visual analytics: correctness according to risk scenarios.

However, unlike accuracy, sensitivity surprisingly improves when the number of rooms is more than 5. This result means that any participant can identify acceptably no-risk scenarios even when the number of rooms is high.

According to *user experience*, the Gantt model is preferred when the complexity of the scenario increases (see Figure 12-C). However, as can be observed in Figure 10-B, the user performance results show that the Gantt model is the least accurate for large logs. In our opinion, the preference for Gantt was due to the fact that this model is widely known by the participants, since there is no correlation at all with the accuracy of the results obtained.

We highlight the fact that the *user preference* for the MTA model is constant even when the complexity increases (Figures 12-A, B and C), and its accuracy for small or big logs (Figure 10) is between 0.9 and 1. Therefore, user preferences and user performance seem to be balanced.

From a *visual analytics* point of view, according to Figure 13-A, all models permit the identification of non-risk scenarios, since all of them obtained acceptable and quite accurate results.

As mentioned in Section 1, fall is the most recurrent incident for elderly people. According to Figure 13-B, the MTA model clearly outperforms the rest of models. Figure 13-D also confirms the hypothesis that cyclic models are the most suitable for fatigue scenarios, the Spiral and MTA models obtaining most positive identifications.

According to the four study scenarios of study of Figure 13, MTA obtained the best results for two of them, and was second best for the others.

7 Conclusions

In this work, we described a formalism for the visual analysis and mining in AAL. More precisely, we propose a visualisation model (MTA) based on multiple temporal axes. On the one hand, we evaluated the MTA model using a controlled experiment approach, and, on the other hand, we demonstrate its suitability by implementing it in a tool (called 8VISU) used in a real-world AAL system for elderly people living alone.

The MTA model helps visualisation in different stages of the AAL process. It combines the advantages of timelines [4, 5, 6], providing a clear representation of home activity (movement and activity events) categorized by locations. The spiral-based layout highlights temporal recurrent patterns and the later activities of the day when one day log is visualised. As in SpirаClock in the tunnel model [35], the outer rings in our proposal represent the most recent time. The spatial dimension, unlike in [19, 20, 35], it is also an essential feature of the MTA model, using a radial axis for each spatial category (i.e., room location). Spatial features are useful for identifying unusual behaviour and potential scenarios of risk. Finally, there are some analogies between graph-based approaches and the MTA model [26, 27, 23]. Indeed, each axis could be considered as a state (i.e., being in particular room or, more generally, in a set of rooms) and arcs between time axes correspond to edges, i.e. transitions from one room to another.

Our experience in AAL was also promising. Implementation of the 8VISU tool clearly illustrates the practical use of the MTA model, as shown in Section 5.2. In particular, the visualisation of 24 hours of activity can be easily displayed using MTA. Moreover, it can be used for visual mining purposes since 8VISU can easily show the activity of 31 days in order to identify day-activity patterns.

The results of the experiments show the advantages of the MTA model over other models (timeline, Gantt, spiral) in different scenarios (normal behaviour, fall, burglary and fatigue). It obtained the best results in two of the four scenarios under study and was the second best in the rest. Moreover, the experiments confirm that: (1) cyclic models are useful for representing certain scenarios (such as fall and fatigue) and (2) the explicit representation of space and movements helps to identify recurrent behaviour patterns (monthly visualisation).

Our studies also identify two limitations to our proposal. First, the amount of temporal data visualised make it difficult to interpret them. However, this difficulty is the same in all visualisation models under study. Second, a high number of displayed axes (corresponding to the number of rooms of the house) negatively affects the accuracy when a risk scenario is to be identified. On the one hand, the results highlight that, even in these cases, the specificity is very high. On the other hand, the user can reduce the number of axes by using the axis collapse functionality, considered in the formal model and implemented in the visualisation tool.

Future work will focus on the extension of the MTA model to other care-providing domains and a study of temporal data visualisation in clinical domains.

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References

[1] Eurostat. *Older, more numerous and diverse Europeans*. Commission Staff Working Document. Demography Report, 2011.

[2] WHO, NIA, and NIH. *Global health and ageing*. NIH Publications. WHO, 2011.

[3] Ger Van Den Broek, Filippo Cavallo, and Christian Wehrmann. *AALiance Ambient Assisted Living Roadmap*. IOS press, 2010.

[4] Steve B. Cousins and Michael G. Kahn. The visual display of temporal information. *Artificial Intelligence in Medicine*, 3(6):341–357, 1991.

[5] Beverly Harrison, Russel Owen, and Ronald Baecker. Timelines an interactive system for the collection and visualization of temporal data, 1994.

[6] Catherine Plaisant, Brett Milash, Anne Rose, Seth Widoff, and Ben Shneiderman. Lifelines: Visualizing personal histories. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*, pages 221–227, 1996.

[7] Isabel Navarrete, José A. Rubio, Juan A. Botía, José T. Palma, and Francisco Campuzano. Modeling a risk detection system for elderly's home-care with a network of timed automata. In *IWAAL*, pages 82–89, 2012.

[8] Hans-Jörg Schulz, Thomas Nocke, and Heidrun Schumann. A framework for visual data mining of structures. In *Proceedings of the 29th Australasian Computer Science Conference - Volume 48*, ACSC '06, pages 157–166. Australian Computer Society, Inc., 2006.

[9] J.M. Juarez, J.M. Ochotorena, M. Campos, and C. Combi. Multiple temporal axes for visualising the behaviour of elders living alone. In *Healthcare Informatics (ICHI), 2013 IEEE International Conference on*, pages 387–395, 2013.

[10] Wolfgang Aigner, Silvia Miksch, Heidrun Schumann, and Christian Tominski. *Visualization of Time-Oriented Data*. Human-Computer Interaction Series. Springer, 2011.

[11] Catherine Plaisant Phd, Catherine Plaisant, Richard Mushlin, Aaron Snyder, Jia Li, Dan Heller, Ben Shneiderman, and Kaiser Permanente Colorado. Lifelines: Using visualization to enhance navigation and analysis of patient records. In *In Proceedings of the 1998 American Medical Informatic Association Annual Fall Symposium*, pages 76–80, 1998.

[12] Carlo Combi, Luisa Portoni, and Francesco Pinciroli. Visualizing temporal clinical data on the www. In *Proceedings of the Joint European Conference on Artificial Intelligence in Medicine and Medical Decision Making*, AIMDM '99, pages 301–314, London, UK, UK, 1999. Springer-Verlag.

[13] Yuval Shahar, Dina Goren-Bar, David Boaz, and Gil Tahan. Distributed, intelligent, interactive visualization and exploration of time-oriented clinical data and their abstractions. *Artif. Intell. Med.*, 38(2):115–135, 2006.

[14] Wolfgang Aigner and Silvia Miksch. Carevis: Integrated visualization of computerized protocols and temporal patient data. *Artif. Intell. Med.*, 37(3):203–218, July 2006.

[15] Krist Wongsuphasawat, John Alexis Guerra Gómez, Catherine Plaisant, Taowei David Wang, Meirav Taieb-Maimon, and Ben Shneiderman. Lifeflow: Visualizing an overview of event sequences. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*, CHI '11, pages 1747–1756, New York, NY, USA, 2011. ACM.

[16] Krist Wongsuphasawat and David Gotz. Outflow: Visualizing patient flow by symptoms and outcome. In *IEEE VisWeek Workshop on Visual Analytics in Healthcare, Providence, Rhode Island, USA*, pages 25–28, 2011.

[17] Ragnar Bade, Stefan Schlechtweg, and Silvia Miksch. Connecting time-oriented data and information to a coherent interactive visualization. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*, pages 105–112, 2004.

[18] Raimund Dachselt and Markus Weiland. Timezoom: a flexible detail and context timeline. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*, 2006.

[19] John V. Carlis and Joseph A. Konstan. Interactive visualization of serial periodic data. In *ACM Symposium on User Interface Software and Technology*, pages 29–38, 1998.

[20] Marc Weber, Marc Alexa, and Wolfgang Müller. Visualizing time-series on spirals. In *INFOVIS*, pages 7–14, 2001.

[21] Pierre Dragicevic and Stéphane Huot. Spiraclock: a continuous and non-intrusive display for upcoming events. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*, pages 604–605, 2002.

[22] K. Priyantha Hewagamage, Masahito Hirakawa, and Tadao Ichikawa. Interactive visualization of spatiotemporal patterns using spirals on a geographical map. In *Proceedings of the IEEE Symposium on Visual Languages*, pages 296–. IEEE Computer Society, 1999.

[23] Martin Wattenberg. Visual exploration of multivariate graphs. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*, CHI ’06, pages 811–819, New York, NY, USA, 2006. ACM.

[24] Jorik Blaas, Charl P. Botha, Edward Grundy, Mark W. Jones, Robert S. Laramee, and Frits H. Post. Smooth graphs for visual exploration of higher-order state transitions. *IEEE Trans. Vis. Comput. Graph.*, 15(6):969–976, 2009.

[25] John E. Hopcroft, Rajeev Motwani, and Jeffrey D. Ullman. *Introduction to automata theory, languages, and computation - international edition (3. ed)*. Addison-Wesley, 2008.

[26] A. Johannes Pretorius and Jarke J. van Wijk. Visual inspection of multivariate graphs. *Comput. Graph. Forum*, 27(3):967–974, 2008.

[27] Bas Ploeger and Carst Tankink. Improving an interactive visualization of transition systems. In *Proceedings of the 4th ACM symposium on Software visualization*, SoftVis '08, pages 115–124, New York, NY, USA, 2008. ACM.

[28] J. F. Allen. Maintaining knowledge about temporal intervals. *Communications of the ACM*, 26:832–843, 1983.

[29] Juan A. Botía, Ana Villa, and José T. Palma. Ambient assisted living system for in-home monitoring of healthy independent elders. *Expert Systems with Applications*, 39(9):8136–8148, 2012.

[30] Michael Bostock, Vadim Ogievetsky, and Jeffrey Heer. D3 data-driven documents. *IEEE Transactions on Visualization and Computer Graphics*, 17(12):2301–2309, December 2011.

[31] Chaomei Chen and Mary P. Czerwinski. Empirical evaluation of information visualizations: An introduction. *Int. J. Hum.-Comput. Stud.*, 53(5):631–635, 2000.

[32] Chaomei Chen and Yue Yu. Empirical studies of information visualization: a meta-analysis. *International Journal of Human-Computer Studies*, 53(5):851 – 866, 2000.

[33] H. Lam, E. Bertini, P. Isenberg, C. Plaisant, and S. Carpendale. Empirical studies in information visualization: Seven scenarios. *IEEE Transactions on Visualization and Computer Graphics*, 18(9):1520–1536, 2012.

[34] Purviben Bharatkumar Saraiya. *Insight-Based Studies for Pathway and Microarray Visualization Tools*. PhD thesis, Department of Computer Science, VirginiaTech, Virginia, 2006.

[35] Martin Suntinger, Hannes Obweger, Josef Schiefer, and M. Eduard Gröller. Event tunnel: Exploring event-driven business processes. *IEEE Computer Graphics and Applications*, 28(5):46–55, 2008.