

A Customizable Approach for Monitoring Activities of Elderly Users in Their Homes

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Abstract. This paper presents an implemented context recognition system that enables caregivers to query and visualize daily activities of elderly who live in their own homes. The system currently serves several homes across Europe and provides caregivers with the ability to correlate activities with specific health indicators. The system also allows to define conditions under which alarms should be raised.

1 Introduction

Encouraging independent living as a way to promote a healthier society is a social and economic challenge. Elderly people wish to remain in their homes as long as possible as this gives them a richer social life and helps them maintain established habits. Enabling old people to do so is also positive from an economic perspective as the cost of home care is less than the cost of residential care. However, several issues need to be addressed in order to prolong independent living. An essential aspect among them is the early detection of possible deterioration of health so that problems can be remedied in an early stage and with the timely involvement of health care professionals and family.

A key enabler in this respect is automated behavior monitoring over time. Monitoring solutions must possess two key qualities: (**requirement 1**) the ability to selectively focus on different aspects of daily life depending on circumstances that are assessed by a physician or family member; and (**requirement 2**) the ability to trace these aspects over medium to long periods of time. To mention a few, interesting health-affecting behaviors can be; decrease of physical activity, irregularity in sleep, changes in cooking and eating habits and so on.

This paper presents a context recognition system that addresses the two requirements above. The system infers and records the activities and status of elderly over extended periods of time. The specific way in which behaviors are recognized are specified through *temporal models*, which can be defined, added or removed dynamically to a list of behaviors of interest. Caregivers, medical experts and family members (henceforth, *secondary users*) can search

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and inspect the recorded information through a versatile user interface which supports real time viewing of what is happening in the elderly person’s home. The interface also aggregates and provides tools to analyze data extending over long periods of time. The models used for behavior tracking are specified in the form of qualitative relations among sensor readings that are definable by secondary users.

The context recognition is part of a larger system called GiraffPlus [4] and is developed in an EU-FP7 funded project. The GiraffPlus system includes a network of sensors placed in the home or worn by the elderly. These include physiological sensors such as weight, blood pressure and pulse oxymetry, as well as environmental sensors like infrared motion, pressure, temperature, and electrical usage sensors. Data from these sensors are processed by the context recognition system through the qualitative models provided by secondary users. The GiraffPlus system is named after one of its components: the Giraff telepresence robot. The robot uses a Skype-like interface to allow caregivers to virtually visit an elderly person in the home. The Giraff telepresence robot is used as the primary means of communicating with the elderly; results of trend analysis, details of the models used for monitoring, and currently active sensors can all be accessed and/or manipulated on the Giraff robot’s interface.

In addition to providing behavioral traces for secondary users, the context recognition infrastructure also synthesizes appropriate action plans to aid the primary user when certain conditions hold on the recognized behaviors. Such enactments manifest themselves as proactive alerts, e.g. if the user is recognized as having altered sleep patterns over several days, appropriate physiological and activity-related information is presented to the caregivers upon contact through the Giraff telepresence robot. Each secondary user can select contexts of interest by using their personal interface to the GiraffPlus system.

2 Background

Current approaches to the problem of recognizing human activities can be roughly categorized as *data-driven* or *model-driven*. In data-driven approaches, models of human behavior are acquired from large volumes of data over time. Notable examples of this approach employ Dynamic Bayesian network (DBNs) in conjunction with learning techniques for inferring transition probabilities [14, 25]. Extensions of these approaches have been proposed for dealing with realistic features of the domain, such as interleaved activities [6, 12] and multiple persons [21].

Although highly effective in specific domains, such systems are typically brittle to changes in the nature and quantity of sensors, requiring significant re-training when the application context changes. This contrasts with the requirement that the criteria for context recognition can be specified on-line depending on circumstances assessed by secondary users and put to service immediately, without the need for re-training and model tuning (**requirement 1**). Liao et al. [10] have described an approach which partially overcomes these limitations using conditional random fields, showing that learned behavior models can be generalized

to different users. However, this has been empirically proved only for the specific context of activity recognition using GPS traces and location information, and does not address the problem of contextual recognition and planning/execution. A complementary approach is followed by Helaoui et al. [8] to overcome some of the limitations of purely data-driven techniques. Specifically, the authors incorporate modeling capabilities to capture features such as qualitative temporal relations which describe how events relate to each other. One of the key features of the approach is its capability to recognize interleaved activities. However, it is limited to detecting sensor context, and the applicability of the approach to a highly-dynamic context, like our use case, is untested.

Model-driven approaches to activity recognition follow a complementary strategy in which patterns of observations are modeled from first principles rather than learned or inferred from large quantities of data. Such approaches typically employ an abductive process, whereby sensor data is explained by hypothesizing the occurrence of specific human activities¹. Examples include work by Goultiaeva and Lespérance [7], where the Situation Calculus is used to specify very rich plans, as well as the work of Pinhanez and Bobick [16], Augusto and Nugent [2], Jakkula et al. [9], all of whom propose rich temporal representations to model the conditions under which patterns of human activities occur. Other techniques used to perform context recognition include ontological reasoning. For instance, Springer and Turhan [22] employ OWL-DL to specify models of complex situations, the argument being that the more complex the situation to recognize, the more sophisticated the behavior of the smart environment. However, time is considered only implicitly. Riboni and Bettini [19] combine ontological and statistical reasoning to reduce errors in context inference, albeit without addressing temporal relationships between activities.

Data- and model-driven approaches have complementary strengths and weaknesses: the former provide an effective way to recognize elementary activities from large amounts of continuous data – relying, however, on the availability of accurately annotated datasets for training; conversely, model-driven approaches provide a means to easily customize the system to different operational conditions and users through expressive modeling languages – which, though, is based on the ability of a domain modeler to identify criteria for recognition appropriately from first principles.

Constraint-based modeling and inference have been employed to perform schedule execution monitoring for domestic activities. Two notable representatives of this direction are described by Pollack et al. [17] and Cesta et al. [3]. These systems differ from our work in that they employ pre-compiled (albeit highly flexible) schedules as models for human behavior.

The context recognition engine used in the GiraffPlus system is mostly related to temporal constraint-based approaches such as SAM [15] and constraint-based chronicle recognition [5]. These approaches employ temporal reasoning techniques to perform on-line recognition of temporal patterns of sensory events. An approach based on evidence theory augmented with temporal features presented

¹ An approach similar to the work of [20] on deducing context in a robot’s environment.

by Mckeever et al. [11] underscores the advantage of explicitly accounting for activity durations. Our work introduces a key novelty in temporal constraint-based context recognition, namely the ability to take temporal uncertainty in the sensor readings [24] into account. This capability is an important enabler of configurable (**requirement 1**) and continuous (**requirement 2**) recognition, as this allows us to interpret the output in time of sensors in ways that fit high-level, user-defined models of behavior, and possesses the necessary good performance to be used on-line.

In summary, GiraffPlus extends the state-of-the-art in context recognition in terms of (1) models of human behaviors that are instantiated on-line, (2) generalization of activity recognition to context recognition by taking multiple sources of physiological and environmental data into account, and (3) applicability to real world scenarios.

3 The GiraffPlus System

The GiraffPlus system integrates components for environmental sensing, physiological sensing, context recognition, data visualization and storage. In this section we briefly present the components of the system and how they are integrated in order to provide a better understanding of the role and place of the context recognition in the overall architecture. Figure 1 shows how the components of the system interacts with the services and hardware used in the project, the main components are as follows:

Physical Environment. The home of the end-user contains several sensors which are wirelessly connected to an Asus EEE Box PC which in turn is connected to Internet.

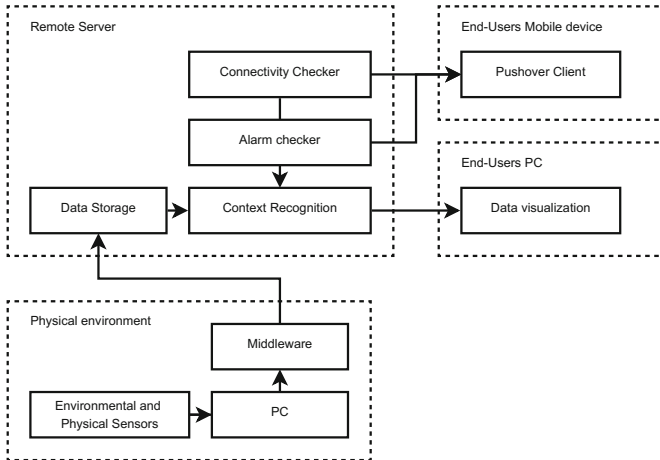


Fig. 1. A high level overview of the relationship between the context recognition and the other components in the GiraffPlus system.

Environmental and Physical sensors. The environmental sensors that are used include motion sensors, pressure sensors (to detect the presence of the inhabitant in the bed for instance), electrical usage sensors, reed-switch sensors (to detect open doors etc.), smoke alarms, flood detectors and more. All environmental sensors are provided by Tunstall, whereas the physiological sensors are provided by Intellicare. The latter measures physiological parameters such as blood pressure, heart rate and body weight. However, unless told otherwise, the end user takes these measurements whenever he or she so wishes, and the data these sensors provide are useful as-is to a caregiver and thus not deemed very interesting from a context recognition perspective. Therefore, the context recognition has focused on using the environmental sensors (although there is no limitation on this, both types of data are handled equally).

PC. The PC an Asus EEE Box PC, originally intended to be used as a media center, this computer is suitable to be used in homes due to its small form factor, low noise and power efficiency. The PC is connected to the Internet, either via a 3G router or directly depending on the available options at each test site. Furthermore, it is connected to a Tunstall Connect+ gateway which enables it to receive and forward data from the environmental sensors.

Middleware. The middleware that runs on the PC is partially derived from the PERSONA project [23] and handles forwarding of sensor data to the remote database server. It also handles buffering of data in case the Internet connection is temporarily lost or congested, thus data that can not be submitted are queued for later transmission. A detailed description of the middleware can be found in [13].

Remote Server. The remote server hosts a database and several Java-servlets running on a Tomcat web server. This means that all connections to the server are done by Representational State Transfer (REST) HTTP calls. Since the data that is stored on the server is sensitive, all connections are protected with SSL and each user and home needs a personal certificate to connect to the server.

Data Storage. The data storage provides an API to query and store information about homes in a MongoDB database. This includes the sensor samples that are sent from the homes and other data such as information about primary and secondary users and their access rights. MongoDB is a document database that focuses on scalability. Scalability was deemed an important feature since a useful and commercially viable system needs to be able to support thousands of homes.

Context Recognition. The context recognition system is deployed on the same server as the database in order to remove the overhead of transmitting raw samples over Internet and to facilitate updates. A client sends a query to the CR consisting of a rule document and a time period. The server in turn requests the required data from the DB and infers a corresponding timeline containing the activities that were queried for.

Alarm Checker. This system regularly queries the context recognition module for user-defined alarm conditions. If an alarm condition is detected the system will send a Pushover notification to alert relatives and caregivers.

Connectivity Checker. This systems monitors the connectivity of the test sites and alerts technical support if a given home has not provided any data for a long period of time (due to issues with the Internet connection, the local PC or the sensor system).

End User Devices. The end user, which can be an elderly a relative or a caregiver, can use the Giraff system with a PC or a smart mobile device.

Pushover Client. This software runs on Android and iOS devices and presents short messages to the user. There are different levels of urgency to these messages which controls if the receiver is alerted with a sound during night or not for instance.

Data Visualization. The PC in the home or at the caregivers office runs the data visualization and personalization software “DVPIS”. It enables the user to fetch the elderly’s physiological measurements (e.g. body weight blood pressure etc.) and perform activity queries.

4 The Context Recognition Service

The context recognition is a REST service that runs as a servlet on a central Tomcat server. Queries to this service are done with a lightweight API which is embedded in several services that run on the client computer or on the central server. All computations are done on the central server when querying an activity. This architecture has the advantage of;

- Reducing bandwidth (since it does not need to transfer raw samples across the network).
- Allowing for a more strict access control to sensor data.
- Enabling system updates without requiring changes to client software.

Figure 2 shows the details of the context recognition service. The main point of interest is the inference procedure that is divided into three distinct steps; pre-processing, inference and extraction. The responsibilities of these are as follows.

Preprocessing Module. On the server the client sends a query to the context recognition engine by providing it with an XML-document describing how sensor data and activities correlate. The preprocessing module’s responsibility is to fetch samples from the database and use these samples to build a higher level representation of the events that takes place in the home. This is done by using an appropriate preprocessor for the data. For instance, a timeline that declares

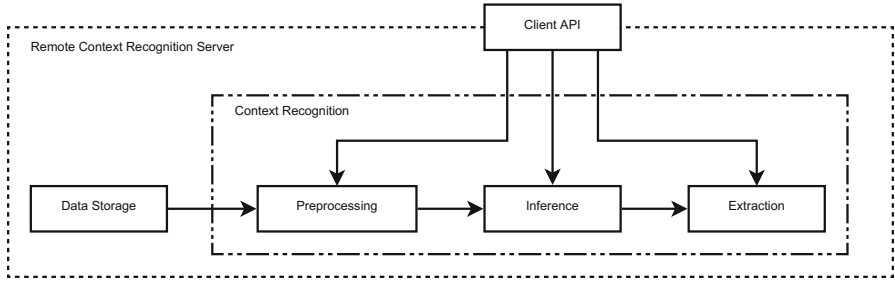


Fig. 2. This figure shows the flow of data within the context recognition module.

if a person is at a location or not, based upon PIR-motion sensors, can be constructed either by looking at individual sensors or by using sensors at other locations as well as terminal conditions. In the former case a temporal threshold parameter needs to be provided to determine the temporal extent to which a person is considered to be in a room, for this to work a continuous sequence of repeated motion readings needs to be generated by the user, and the query is parameterized with a maximum allowed temporal discontinuity between these. In the latter case the person is considered to be at a location until he is sensed somewhere else.

Inference Module. The symbolic models underlying the inference are grounded on a *constraint-based representation*. The key advantage of doing so lies in the widely recognized capability of this paradigm to support search and incremental constraint solving capabilities, and the relative efficiency of the resulting applications. The user-supplied rules used by the inference module define how sensor readings correlate to context that can be inferred. These correlations are expressed as temporal constraints in Allen’s Interval Algebra [1] with metric bounds, however, the overall architecture supports the more expressive INDU algebra [18] which adds constraints on the relative duration of intervals. Activities are inferred by performing temporal constraint propagation on the domains of intervals generated by the preprocessing module and the output is a domain of intervals that are admissible with respect to the rules. The propagation and inference algorithm is described in detail in [24].

Extraction Module. The extraction module’s responsibility is to generate timelines that can be used by other software components (e.g., the visualization software or the alarm system). As the inference and preprocessing module generates large amounts of hypotheses about the activities that have taken place there is the need to provide a system to easily analyze this data. In GiraffPlus this module only supports one type of extraction method, which extracts the maximum duration interval for an activity.

5 Evaluation in a Swedish Home

Since it is difficult to collect ground truth of performed activities (due to the fact that the elderly can't be asked to annotate what they are doing) an evaluation was done together with a local caregiver with insights into a test subject's daily life and medical history. The goal was to assess how well the system could infer medically meaningful information about the users daily life.

The apartment in this case study is inhabited by an 82 year old man (born 1931) which has been living alone since his wife passed away two years ago. At around the same time the man had a stroke and spends most of his time inside, the exceptions are when he goes outside to do shopping or to visit any of his three sons with his mobility scooter. The man receives help from home care four times a day that ensures that he is feeling well and that he takes his medication. The man's sons live nearby and visits him often, in addition, his grandchildren uses the Giraff telepresence robot to visit him remotely.

An initial working version of all software components of the system is available in the apartment. The apartment is depicted in Fig. 3. Before deploying the system in the home the inhabitant was interviewed. The answers given during the interview was used to determine a good sensor placement that would allow the system to capture as meaningful traces of his daily activities. This resulted in the fact that the laundry room and the study were not instrumented at all

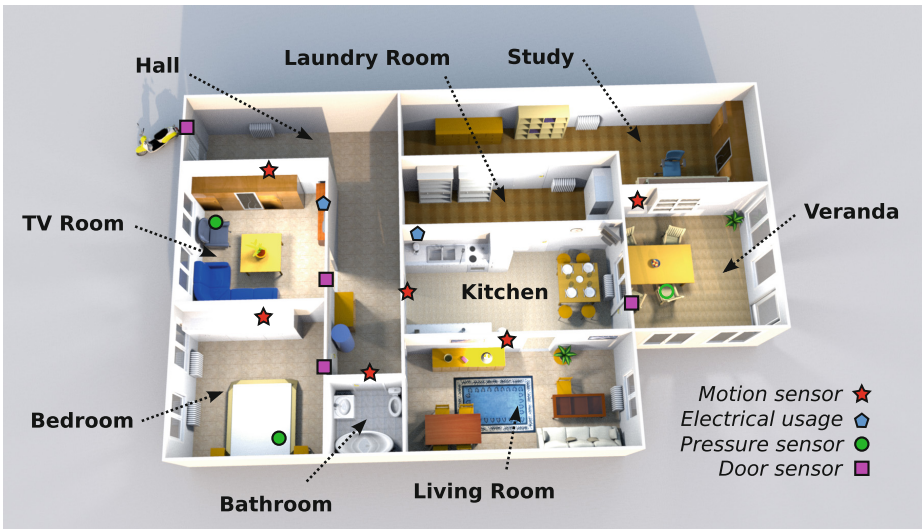


Fig. 3. The layout of the second test site in Sweden. This is not an exact depiction but captures the general layout of the large home.

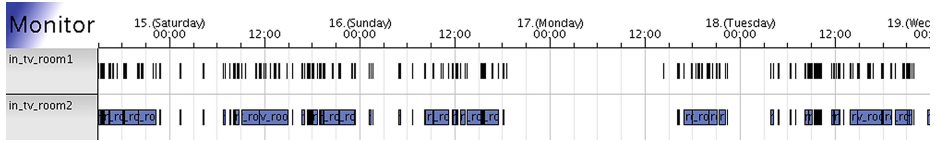


Fig. 4. A pair of timelines showing when the elderly man visits the TV room, constructed using different methods of preprocessing the sensor data.

since the inhabitant almost never used these, and the living room was sparsely instrumented since it was only used when the man had visits. Conversely, the TV-room, the kitchen, the bathroom and the bedroom were considered important and therefore equipped with more sensors.

The session with the caregiver resulted in several queries to the context recognition system using a horizon of two weeks². In the beginning of the session the caregiver claimed that the man had stated that he spends much of his time in front of the TV. The caregiver wanted to know how often and when the person was watching the TV since this behavior can influence his health. Consequently, a query was made to see how much time the user spent in front of the TV using the motion sensor in the TV room³, the output of this query is shown in Fig. 4.

The topmost timeline, `in_tv_room1`, in Fig. 4 shows the result of the first query. Given the fragmented nature of the timeline (containing many short intervals) it appeared as if the person was mostly sitting still in the TV room, or at least not moving enough to trigger the motion sensor frequently enough to generate continuous intervals on the timeline. In order to address this problem, another query was made using data from other motion sensors in the apartment as well, the output of this query is shown bottommost in Fig. 4 as `in_tv_room2`. Here, the data from the additional sensors were used as terminal conditions for ending the activity (the motion sensor placed in the hall adjacent to the TV-room was particularly important). The timeline for `in_tv_room2` is clearly more continuous than `in_tv_room1` but still contains some discontinuity. This is probably due to a bad placement of the motion sensor in the hall, allowing the user to be detected even though he is in the TV-room. At some occasions this can also be due to the fact that he had visitors, e.g. home care or relatives, as they move around the apartment they constantly end the `in_tv_room1` activity.

One responsibility of the context recognition module within GiraffPlus is to provide timelines containing performed activities to a statistics extraction module, the result of the second query forms a much better basis for assessing time spent in front of the TV during the day and can be used over longer horizons

² A more limited timespan was chosen for the graphics used in this paper so that details are visible.

³ The motion sensor was used instead of the electrical usage sensor connected to the TV since the former appeared to be in an always on state. We suspect this happens because the TV consumes enough electricity in standby mode to be considered on.

to detect changes in behavior and anomalies. The rules created to detect when the person is in the TV-room is shown in Listing 1.

```

1  <?xml version="1.0" encoding="UTF-8" ?>
2  <rules home="testsite_se_2">
3
4  <preproc name="TunstallPIRSimple" in="PIR - TV Room"
      out="_in_tv_room1" args=""/>
5  <preproc name="TunstallPIRSimple" in="PIR - TV Room, PIR - Bedroom,
      PIR - Kitchen" out="_in_tv_room2" args=""/>
6
7  <extractor name="max" in="_in_tv_room1" out="in_tv_room1" />
8  <extractor name="max" in="_in_tv_room2" out="in_tv_room2" />
9
10 </rules>

```

Listing 1. A rule that infers when the person has been in the TV room using two different methods.

Even though these queries did not produce optimal visual results, the caregiver had gotten a better understanding of the persons habits, and it can clearly be seen that the person spends many hours a day in front of the TV. Also, the caregiver noted that the man's TV-watching habits were not isolated to daytime. After having inspected the man's TV-watching habits, the caregiver was interested in the evening and night time activities of the man since he could be seen to watch TV late at night at some occasions e.g. on Sunday the 16th. In addition, discussions with the person had revealed that he sometimes went up during the night to read the newspaper in the kitchen.

As the evaluation session continued the caregiver wanted to see when the person went up at night to look at the TV or to read the newspaper so rules were constructed to filter out these events. In addition to processing the sensory data, a rule that filters out events where the person had left the bed and went to either of these locations were constructed using the language of Allen's Interval Algebra. Activity intervals `awake_in_kitchen` and `awake_in_tv_room` were inferred on a timeline so that each filtered interval occurred **AFTER** `in_bed` and **DURING** presence at the respective locations; `in_kitchen` and `in_tv_room`. The output of this query is shown in Fig. 5.

It can be seen that the user typically visits both the TV room and the kitchen when he leaves his bed. Also, this behavior seems to be a part of a habit since it occurs so often. A fraction of the rule document created to detect when the person leaves his bed to visit the TV-room and the kitchen is shown in Listing 2.

To obtain a verification of the inferences produced by the system, the results were discussed by the elderly man. He confirmed the inferences with his own recollection of his activities. During this discussion the man expressed discomfort about the system knowing how often he had been awake during the night. Despite being well informed of the system's capabilities, he expressed that he was less comfortable with an aggregation of long term data about his habits than with alternative technologies such as observing him visually from time to time through a video camera.

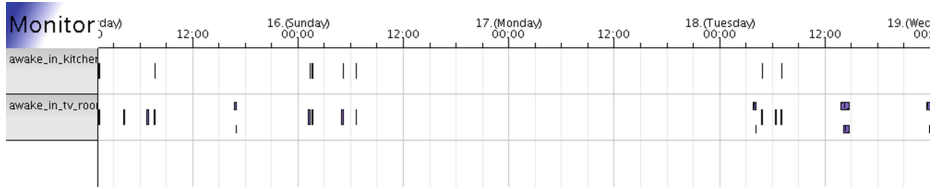


Fig. 5. A pair of timelines showing when the elderly visits the kitchen and the TV-room after having left his bed.

```

1  <?xml version="1.0" encoding="UTF-8" ?>
2  <rules home="testsite_se_2">
3
4  <preproc name="TunstallTrueFalse" in="Bed - Bedroom" out="_in_bed"/>
5  <preproc name="TunstallPIRSimple" in="PIR - Kitchen"
   out="_in_kitchen"/>
6
7  <rule out="_awake_in_kitchen">
8    <constraint from="_awake_in_kitchen" type="during"
   to="_in_kitchen"/>
9    <constraint from="_awake_in_kitchen" type="after" args="[0,1000]"
   to="_in_bed"/>
10 </rule>
11
12 <extractor name="max" in="_awake_in_kitchen"
   out="awake_in_kitchen"/>
13 ...

```

Listing 2. A fraction of a rule that is used to determine which rooms the elderly visits when he leaves his bed.

6 Conclusion

This paper has presented a fully working context recognition system that has been developed for the GiraffPlus project. The system focuses on addressing real world issues such as scarcity of sensors and the need to be able to dynamically adapt the underlying inference model to the needs of the end user and caregivers. Once fully deployed this system will analyze data coming from fifteen test sites in three different countries. In two examples we have shown how queries about the inhabitants' behavior can be customized in cooperation with a medical professional. Future research will focus on expanding the capabilities of the constraint language and evaluating its usability in the different test sites. Furthermore, we will investigate the possibility of making the collected sensor data available to the research community.

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