List of Publications

This thesis consists of a collection of five papers. Throughout the thesis, the papers are referred to as Paper I, II, III, IV, and V.

Appended Publications

Paper I
W. O. de Morais and N. Wickström. A Serious Computer Game to Assist Tai Chi Training for the Elderly. In Proceedings of the 2011 IEEE 1st International Conference on Serious Games and Applications for Health (SeGAH), pages 1-8, 2011.

Paper II
W. O. de Morais and N. Wickström. A lightweight method for detecting sleep-related activities based on load sensing. In Proceedings of the 2014 IEEE 3rd International Conference on Serious Games and Applications for Health (SeGAH), 2014.

Paper III
W. O. de Morais and N. Wickström. A "Smart Bedroom" as an Active Database System. In Proceedings of the 2013 IEEE 9th International Conference on Intelligent Environments (IE), pages 250-253, 2013.

Paper IV
W. O. de Morais, J. Lundström, and N. Wickström. Active In-Database Processing to Support Ambient Assisted Living Systems. Sensors, 14(8): 14765-14785, 2014.

Paper V
W. O. de Morais and N. Wickström. Evaluation of Extensibility, Portability, and Scalability in a Database-centric System Architecture for Smart Home Environments. Technical Report, Halmstad University, 2015.

Related publications

- J. Lundström, W. O. de Morais, and M. Cooney. A Holistic Smart Home Demonstrator for Anomaly Detection and Response. In Proceedings of the 2015 IEEE 2nd IEEE PerCom Workshop on Smart Environments: Closing the Loop, 2015 (in press).
- W. O. de Morais, M. Mayr, N. Wickström, and R. Philippsen. Ambient Intelligence and Robotics: complementing one another to support Ambient Assisted Living. In Proceedings of Workshop and Tutorials of the 2014 13th Intl. Conf. on Intelligent Autonomous Systems (IAS13) and 2014 1st Intl. Workshop on Intelligent Robot Assistants (IRAS), pages 197-199, 2014.
- W. O. de Morais, J. Lundström, and N. Wickström. A Database-Centric Architecture for Home-Based Health Monitoring. In Ambient Assisted Living and Active Aging, Springer, pages 26-34, 2013.
- W. O. de Morais and N. Wickström. Sleep and night activities of care beneficiaries at the "Trygg om Natten" (Safe at Night) Project. Technical Report. Halmstad University. Diva:24030, 2013.
- W. O. de Morais, A. Sant'Anna, and N. Wickström. A wearable accelerometer based platform to encourage physical activity for the elderly. Gerontechnology, 7(2):181, 2008.

Awards related to this thesis

- **Winner of the Doctoral Colloquium Award**
  9th International Conference on Intelligent Environments (IE) 2013 for the paper "A "Smart Bedroom" as an Active Database System", Athens, Greece, July 2013.

Contents

Chapter 1

Introduction

Smart homes aim at interconnecting heterogeneous home-based digital technologies to offer functionalities that enhance the comfort, entertainment, safety and security of the residents. Ideally, a smart home is an integrated system that monitors the household functioning and learns the habits and preferences of the residents to anticipate their needs or to help them in making informed decisions [Wilson et al., 2014].

During the last decades, there have been an increasing number of academic and industrial research projects towards the development of smart home technologies for healthcare purposes, in particular to assist older and disabled people living alone. Important application areas of smart homes in the healthcare domain include rehabilitation, assisted living, and continuous health and activity monitoring [Kang et al., 2010; Acampora et al., 2013].

Considering the current demographic change, available financial and human resources and future demands for healthcare, smart homes provide a domestic technical infrastructure that has the potential to enable and support active ageing [WHO, 2002], aging in place [Marek and Rantz, 2000] and the recent concept of ambient assisted living (AAL) [van den Broek et al., 2010]. These initiatives focus on strategies that:

- Promote healthy and preventive lifestyles;
- Help older and disabled individuals to live longer, safer and more independently in a residence and community of their choice;
- Support formal and informal caregiving;
- Move healthcare from traditional healthcare environments (*e.g.* hospitals) to the home;
- Reduce costs in healthcare.

Despite the potential benefits, the cost, fitness for purpose, user friendliness and trustworthiness are still not evident for homeowners and are well documented barriers for the adoption of smart home technologies [Balta-Ozkan et al., 2013]. Moreover, the evolving diversity of people's needs and preferences, as well as the heterogeneity and dynamicity of home environments and involved technologies, lead to a number of technical challenges that hinder the development of smart homes and AAL technologies in real life. Several authors remark [Edwards and Grinter, 2001; Nehmer et al., 2006; Eckl and MacWilliams, 2009; Brush et al., 2011; Wilson et al., 2014; Mennicken et al., 2014] the following technical challenges for smart homes:

- **Integratability and Interoperability:** due to the lack of standards;
- **Extensibility and Scalability:** due to the evolving diversity of individual needs, technologies and environments;
- **Security and Privacy:** due to different actors and technologies involved;
- **Dependability:** due to life-threatening consequences;
- **Usability:** due to individual needs, capabilities, and preferences.

Another critical issue associated with the development of complex distributed systems, such as smart environments, is the system architecture [Oussalah, 2014].

Considering the aforementioned aspects and challenges, this thesis concerns the design and development of assistive and monitoring applications for smart environments in healthcare. However, integrating heterogeneous smart home technologies that can interoperate in a reliable and secure way is challenging. Therefore and for the most part, this thesis proposes and investigates the feasibility of a database-centric architecture for smart home environments and AAL. The main hypothesis is that database management systems incorporate features that enable database systems to serve as a platform for smart home and AAL applications.

After this introduction, this chapter presents in Section 1.1 the main research problems investigated in this thesis. In Section 1.2, the research approach is introduced. Section 1.3 presents the main contributions. A summary for each of the appended publications is presented in Section 1.4. The structure of the remainder of this thesis is outlined in Section 1.5.

1.1 Problem and Research Questions

1.1.1 System Architecture for Smart Home Environments

Platforms for smart homes and AAL typically follow different architectural paradigms in a multi-layer logical architecture to support the integration and interoperation of heterogeneous technologies and the development of a variety of monitoring and assistive application scenarios [Becker, 2008; Fagerberg et al., 2010; Brink et al., 2013]. Moreover, storage and processing of short- and long-term measured data are important requirements in these applications. Among existing system architectures, the database management system is the most common architectural component. However, despite the advancements in database technology, modern database management systems are devoted exclusively for data storage and retrieval.

Hence, *it is the hypothesis of this thesis that modern relational database systems can 1) serve as a platform for the implementation, deployment and management of smart homes and AAL applications, and 2) address functional and non-functional requirements of such smart environments*. Therefore, this thesis poses and attempts to answer the following questions:

- *How should a database-centric system architecture be designed to support smart home environments and AAL applications?*
- *How to accommodate the functional and non-functional requirements of smart environments in a database management system?*

1.1.2 Smart Home Technologies in Healthcare

This thesis is also interested in approaches towards the development of smart home technologies for unobtrusive and continuous monitoring of the residents' health as well as assistance for the overall well-being. These are among the main applications of smart homes in healthcare [Demiris and Hensel, 2008]. For example, beds equipped with sensors can provide contactless and semi-constant home-based assessment of sleep patterns, fall risks, and monitoring of other health-related parameters [McGrath and Scanaill, 2013]. Moreover, digital gaming technology is being increasingly integrated into the AAL domain [AAL JP, 2013]. These digital games are commonly referred to as serious games and are games that have, besides the entertainment aspect, real-life purposes (*e.g.*, education, training) [Zyda, 2005].

This thesis implements different smart home technologies to improve comfort, enhance independence, and support continuous care, in particular home-based sleep assessment and monitoring. This thesis also introduces a serious game for home-based fall prevention. Therefore, the following question are investigated:

- *How to incorporate knowledge about normal sleep and load sensing into a method to online detect sleep-related activities and patterns?*
- *How to accommodate the requirements for home-based rehabilitation games (e.g., customization, online feedback, follow-ups, easy setup) in the proposed serious game for home-based fall prevention?*

1.2 Research Approach

To address the questions posed in Section 1.1, literature studies were combined with a pragmatic and exploratory approach concerning the design, implementation and evaluation of proof of concept prototypes for smart home and AAL technologies. Such an approach is a common research methodology in ubiquitous computing [Bardram, 2008] and is based on the construction of working prototypes to ensure functional and non-functional properties in the face of the details of the real world [Weiser, 1993].

Much of the exploratory work originated from the collaboration with the Centre for Health Technology Halland at Halmstad University (HCH)[1]. The collaboration resulted in technology demonstrators, such as the "Smart Bedroom", that are hosted at HCH for permanent exhibition and demonstration[2]. For most of the presented methods and contributions, evaluations with data involving real-life situations have been performed. However, no usability studies involving end-users (*e.g.*, residents, caregivers) and developers have been conducted to evaluate developed applications and the proposed system architecture.

1.3 Contributions

This thesis focuses on and contributes to the research in the Computer Science and Engineering, and with approaches for their application in the Healthcare domain.

In the Computer Science and Engineering domain, the main contributions are:

- Designed, implemented and evaluated a novel database-centric system architecture that employs a database system as a platform for smart home environments and AAL applications.
- Presented a model to abstract and integrate heterogeneous hardware and software technologies into the proposed architecture.
- Implemented and evaluated how characteristics of normal sleep and load sensing are combined into a finite-state machine to detect sleep-related activities.
- Designed and implemented a serious game to measure the similarity between gestures presented by a virtual instructor and the imitated gestures performed by the player.

[1] http://hch.hh.se
[2] http://hch.hh.se/6/259.html

Considering applications of information and communication technologies in the Healthcare domain, the main contributions are:

- Developed a computer game for fall prevention that assists individuals to practice Tai Chi.
- Implemented an unobtrusive measurement system for home-based sleep assessment.
- Developed different smart home technologies to improve comfort, enhance independence, and support continuous care.

1.4 Publications

This thesis consists of a collection of five papers, Paper I, II, III, IV, and V. This section presents a high-level overview of the main contributions of each included paper.

- **Paper I:** introduces a method to develop serious games for home-based computer-assisted fall prevention.

  The objective was to reduce the requirements for complex equipment, processes and settings during the development and use of serious games in healthcare. The approach was demonstrated by the implementation of a serious game for home-based fall prevention: a virtual Tai Chi instructor assists older people to practice Tai Chi at home on their own.

  During the development of the game, a camera and wearable wireless inertial measurement units (WIMUs) are employed to record and measure body movements, for example, of an instructor training Tai Chi. In a subsequent off-line process, collected images and signals are segmented and used to create gesture templates and a virtual instructor.

  During the gameplay, the player is challenged to mimic the virtual instructor. Also in the gameplay, the player's body movements are measured with WIMUs and a flexible distance measure technique, known as longest common subsequence (LCSS), is used to compute online the similarity between the ongoing gestures with a known pre-recorded gesture template of the virtual instructor. The computed similarity is presented to the player as a score, indicating how well the player reproduced the displayed movements.

  The LCSS technique allows matching two sequences by tolerating some elements of these sequences to be unmatched, in time (sequence length), space (sequence amplitude) or both. Such tolerance can be used to overcome small sensor displacement and time lags while measuring gestures

The time and space parameters can be adjusted and this is used to control the game difficulty. The lower the tolerance in time and space, the more difficult the game.

Alternative approaches commonly employ methods for classifying or recognizing Tai Chi gestures, which can require considerable amount of training data. Vision-based motion capture systems and WIMUs are typically combined and require complex equipment and settings that are not convenient in a home environment.

- **Paper II:** introduces a finite-state machine (FSM) that combines known characteristics of normal sleep with signal processing of a strain gauge load cell to detect sleep-related activities and patterns. The purpose was to provide a non-intrusive and home-based sleep-assessment method as an alternative to the labour-intensive clinical-based polysomnogram. Given a bed instrumented with load cells, sleep-related voluntary and involuntary body movements generate distinct disturbances in the load cell signal. These disturbances, combined with a-priori knowledge about normal sleep, are employed to define the conditions for the FSM transitions or state changes. The states indicate whether the person is in bed or not, and if in bed, whether the person is awake or cycling between sleep states. The approach was verified with a dataset collected in real homes of older people receiving night-time home care services.

- **Paper III:** introduces the approach of employing a DBMS as a platform for smart homes and AAL applications. The paper also presented the development of smart environments as active database systems. The aim was to explore database technologies not only for data storage purposes, but to create a database-centric architecture for smart environments. The event-driven architecture, the extensibility capabilities, and the built-in mechanisms for inter-process communication provided by database management systems are employed to support the on-line reactive behaviour of smart environments, as well as to provide a database interface containing a set of methods for data access and manipulation (select, insert, update and delete). The integration of different technologies is achieved with resource adapters, which are simple software applications abstracting hardware and software technologies present in the system. Resource adapters serve as gateways between the environment and the database system. The interoperability among heterogeneous technologies is handled inside of the active database. As a whole, the integration and interoperation of heterogeneous technologies is facilitated and the feasibility of the proposed approach was proved with a real implementation of a "Smart Bedroom" demonstrator.

- **Paper IV:** extends **Paper III** and explores the extensibility capabilities of DBMSs to address inside of the DBMS other requirements of smart environments, such as data processing and analysis, privacy and security, and system maintenance. Active databases can detect and respond to events taking place in the home environment. Modern DBMSs can be extended with user-defined types and functions that operate just as built-in features. These enable the semantics of applications to be integrated and executed within the DBMS. Database extensions can add in-database analytical capabilities to DBMSs. Such active in-database processing avoids transferring sensitive data outside the database. DBMS's mechanisms for authentication and authorization reinforce data security and privacy. Because the domain logic is centralized within the DBMS, code maintenance is facilitated, and as changed are managed on the fly, such an approach avoids system downtime. Three distinct AAL services to enhance nighttime caregiving services were implemented and tested with a dataset collected in real homes.

- **Paper V:** evaluates non-functional properties, such as extensibility, portability and scalability, of the database-centric architecture introduced in **Papers III** and **IV**. The evaluation method encompasses: 1) extending the system with three different test scenarios (data storage, reactive behaviour, and advanced data processing), 2) porting the system architecture and applications to different computing platforms, and 3) evaluating scalability by incrementally adding more processes corresponding to a given test scenario. Evaluation results allowed identifying which components in the database-centric architecture become performance bottlenecks when extending, porting and scaling the system.

1.5 Outline

The remainder of the thesis contains five chapters organized as follows:

Chapter 2
: Presents an overview and the potential of the main features of modern database management systems.

Chapter 3
: Presents an overview of smart home environments as well as the main associated challenges. The different architectural styles employed in existing system architectures, middleware and platforms supporting current smart home environments and AAL are also presented. Given the background and related work, Chapter 3 introduces the database-centric system architecture by describing how different mechanisms provided by

modern database management systems are put together to address functional and non-functional requirements of smart environments. Chapter 3 also presents the how the feasibility of the proposed architecture was evaluated with the development of different smart home and AAL applications.

Chapter 4
Exposes future healthcare challenges related to the ongoing demographic change towards a growing aging population. Given the importance of smart home technologies in health monitoring and assistance, Chapter 4 highlights the purpose, method, results, and the technical contribution associated with the development of home-based applications, such as for sleep assessment and fall prevention.

Chapter 5 *Note: this Chapter is expected to be 2 pages long*
Comments on the general findings of Chapter 3 and Chapter 4, highlighting the main benefits and limitations of the contributions.

Chapter 6 *Note: this Chapter is expected to be 3 pages long*
Covers potential directions for future research and concluding remarks.

Appendix A

Paper I - A Serious Computer Game to Assist Tai Chi Training for the Elderly

A Serious Computer Game to Assist Tai Chi Training for the Elderly

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***Abstract*—This paper describes the development of a computer-based serious game to enable older individuals to practice Tai Chi at home on their own. The player plays the game by imitating Tai Chi movements presented by a virtual instructor on the screen. The proposed system is decomposed into two modules. The first module is the game design, i.e., the process of recording an instructor training Tai Chi. Acquired data are used to create gesture templates and a virtual instructor. The second module is the game play in which the player attempts to mimic the virtual instructor. Gestures are measured in real-time and then compared with the prerecorded Tai Chi gesture template corresponding to the displayed movement. Visual feedback indicates how well the player imitated the instructor. The proposed system is not designed to classify gestures but to evaluate the similarity of a given gesture with a gesture template. The Longest Common Sub-Sequence (LCSS) method is applied to compute such similarity. The proposed approach (1) facilitates the design of assessment tools in which the user has to follow a sequence of predefined movements and (2) applicable to other domains, such as telerehabilitation.**

Keywords- Serious Games; fall prevention;Tai Chi; wearable inertial measurement units; movement analysis; gesture evaluation;

I. INTRODUCTION

The population over 65 years old, in particular the oldest old, is growing, living longer, and is exposed to problems and adverse health conditions common in the late adulthood. Falls, for instance, are a major health issue among older adults and injuries caused by a fall are one of the most widespread public health problems due to associated morbidity, suffering, loss of independence and high costs for the society [1-2]. Not all falls result in injuries, but most hip and wrist fractures are caused by falls [3].

In Sweden, there are more than 18,000 hip fractures per year, most caused by falls, and the cost associated with a hip fracture treatment is about 15,000 EUR per patient during the year following the accident [4].

Fear of falling is also a problem among older adults. Fear of falling commonly hinders seniors in their efforts to carry out daily activities, which might lead them to physical deconditioning, poor balance and social isolation [5].

Preventive approaches generally recommend and encourage a more physically active and healthy lifestyle, but in the case of falls, more effort is devoted to decrease the number and the risk for falls as well as to improve balance.

Tai Chi is one example of such interventions. There is medical evidence that Tai Chi training as well as individualized exercise programs targeting balance and strength training can reduce and prevent falls [6-7]. Randomized studies in fall-prevention found that both nearly twelve-month [8] and a six-month [9] Tai Chi programs are effective in preventing and reducing the number of falls, improving balance and mobility, and in decreasing fear of falling. A Tai Chi program can follow different styles and forms which in turn differ in terms of movements, length, speed and outcomes. Shorter forms, such as the classical 24 forms Yang style, are proposed to reduce fall risks and fear of falling [9-10].

This paper proposes a serious game to enable older people to practice standard or individualized Tai Chi programs at home on their own. Serious games are games that, besides entertainment, motivate and support the player to achieve a major goal, for example a healthier lifestyle [11]. Research suggests that game-based applications targeting seniors might have a positive impact in terms of mental and physical stimulation, self-esteem and attention [12-13]. In this paper, the entertainment aspect of games is exploited to motivate seniors to exercise and maintain their interest in the program.

During game play, a virtual instructor training Tai Chi is displayed and the player is challenged to mimic presented movements. Instead of cameras, wearable sensors are used to measure the player's gestures. Each gesture is compared with a prerecorded Tai Chi gesture template corresponding to the displayed movement. A flexible distance measure technique is applied to calculate the similarity and a visual feedback is presented to the player.

The system presented in this paper is not intended to classify gestures or movements but to evaluate the similarity of a measured gesture with a prerecorded movement template. This approach (1) facilitates the design and implementation of assessment tools in which the user has to follow a sequence of predefined movements, such as in Tai Chi, and (2) makes the system scalable to other application domains, such as telerehabilitation, when the absence of a healthcare professionals, e.g. a physiotherapist, might be compensated for by the system, which assists the patient in executing prescribed rehabilitation exercises.

The remainder of this paper is organized as follows: Section II describes different existing approaches to recognize Tai Chi movements. Section III gives a detailed description of the proposed system. Section IV presents and discusses results and conclusions are presented in Section V.

II. Related Work

An early attempt to recognize Tai Chi movements dates back to the mid-nineties with a virtual reality application to alleviate stress in cancer patients [14]. The proposed system applied a vision-based motion capture system to track the location of the head and hands of the user and Hidden Markov Model to recognize Tai Chi movements. A virtual Tai Chi teacher was used to instruct the player how to improve Tai Chi movements.

Similarly, virtual reality and vision-based motion capture systems have been also explored in [15], allowing the player to learn and practice Tai Chi with a virtual instructor in a 3D virtual world displayed in a wireless head mounted display. The system tracks 41 points on the human body to implement a position-based evaluation system.

Another approach combined visual and body-worn sensors into a motion training system for martial arts [16]. The work introduced the concept of motion chunks and described postures and gestures as static and dynamic motion chunks, respectively. Standard deviation of the raw acceleration data was used to find postures and gestures, Hidden Markov Models to detect motion chunks and Euclidian distance to measure the similarity of two motion chunks. Visual feedback provided to the player displayed the location of the worn sensors and the measured sensor data. Later on, the same authors proposed a framework that applied Hidden Markov Models and Dynamic Time Warping to register, evaluate and recognize 18 different hand movements [17].

As an alternative to video-based motion analysis systems, wearable wired gyroscopes and acceleration sensors, placed on different limbs, have been used to recognize Wing Chum movements and to differentiate experts from amateurs [18].

The same wearable sensor configuration has been used later to recognize Tai Chi movements using a K-Nearest-Neighbor (KNN) classifier [19]. A more recent approach replaced the obtrusive wired body-worn sensors with wearable wireless accelerometers-based platforms [20] worn on each wrist, lower leg and knee as well as on the neck and rear hip. Recognition of Tai Chi movements has been achieved using Hidden Markov Models, and a 3D avatar rendered in real-time provided feedback to the user.

Most of the approaches described in this section applied vision-based motion capture systems to record and measure Tai Chi movements. The main drawback of such an approach is that it requires complex equipment and settings, such as special lightning and background, which might be impractical at the player side.

Hidden Markov Models was the most common technique applied to classify Tai Chi movements. Such a method requires a great deal of time to create the models and large amounts of data to train the system, which results in a better classifier.

This paper differs from previous related work in the following aspects: (1) a camera-based system is used during the game design to record the instructor's performance, but is not used at the game play; (2) gestures are measured by wireless wearable inertial measurement units; (3) the player is expected to reproduce gestures presented by a virtual instructor; (4) gestures produced by the player are not classified but compared with a known gesture template; and (5) a flexible distance measure technique is used for the evaluation of similarity.

III. System Overview

The development of the proposed system is decomposed into two modules named game design and game play. The overall system architecture is presented in Figure 1.

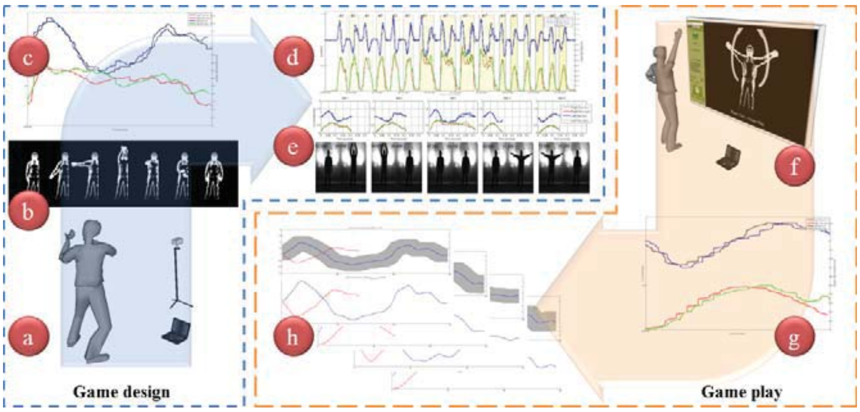


Figure 1. The complete system consists of: (a) the Tai Chi instructor training being recorded using a camera and wearable inertial measurement units; (b) extracted movement silhouettes, which are used to create a virtual instructor; (c) measured kinematic data; (d) image analysis, which is applied to decompose the overall training into smaller segments; (e) a gesture template, which is composed of each segment; (f) the player interacting with the game by reproducing movement instructions; (g) player's gestures being measured; (h) computed similarity between the measured gesture and a stored gesture template.

A. Game Design

The first module encompasses the game design, i.e., the process of recording the gestures of an instructor performing a sequence of Tai Chi movements. Two offline processes are executed to segment acquired data into gesture templates and to produce a virtual instructor.

1) Movement Protocol

A warm-up exercise similar to Tai Chi training has been selected to present the proposed approach. Figure 2 describes the movement protocol.

Figure 2. The Warm-up exercise contains of 5 distinct movements. Movement 1consists of moving and keeping both arms up to and above the head and is followed by Movement 2, moving both arms down to one's side. This process is repeated 3 times. Subsequently, Movement 3 is executed, which consists of moving both arms in a circular manner and is repeated 4 times. Movement 4 consists of moving and keeping both arms slightly above shoulder level. Next, in Movement 5 both arms return to the initial position. Movement 4 and 5 are repeated 3 times.

2) Recording System

To record the instructor training Tai Chi, a Prosilica GC1350 GigE camera (Allied Vision Technologies GmbH, Stadtroda, Germany) is used. Gray-scale images of size 1360x1024 pixels are acquired at a frame rate of 12 images per second.

The SHIMMER [21] wireless sensor platform has been selected as the inertial measurement unit to record gestures and is worn by the instructor in a wristband as demonstrated in Figure 3. The Shimmer is a lightweight platform that integrates processing, storage, communication, sensing, and daughterboard connection capabilities. The baseboard, which contains a 3-axis accelerometer, has been extended with an additional 3-axis gyroscope daughterboard. The firmware running on the platform streams acceleration (±6g) and angular rate data to the host computer at a sampling rate of 50Hz.

Figure 3. The Shimmer is placed inside a wristband. One platform is worn on each wrist by the instructor in the game design and by the player during the game play.

The software system to record data has been developed in the EyesWeb open software platform [22]. The application acquires and stores timestamped visual and kinematic data during the Tai Chi training. Acquired data are processed offline to create gesture templates and a virtual instructor. These two processes are performed in Matlab (MathWorks, Natick, MA).

3) Creating gesture templates

After recording the Tai Chi training, the next step is to decompose acquired data into a sequence of smaller segments. Each segment begins and ends with a posture. The data in between describe the movement dynamics, i.e., the gesture. One approach is to use the standard deviation of the raw acceleration data to segment kinematic data [17].

An alternative is to apply the sum of absolute difference (SAD) between adjacent images as a criterion to detect and discriminate postures and gestures. The SAD of two images gives a numerical value that describes the similarity between these images. The closer the value is to zero, the more similar the images are. As images from the instructor are acquired at a relatively high frame rate, even a short pause or posture will produce a sequence of images that are very similar, i.e., a low SAD. Figure 4 describes the decomposition of a complete training into gesture templates.

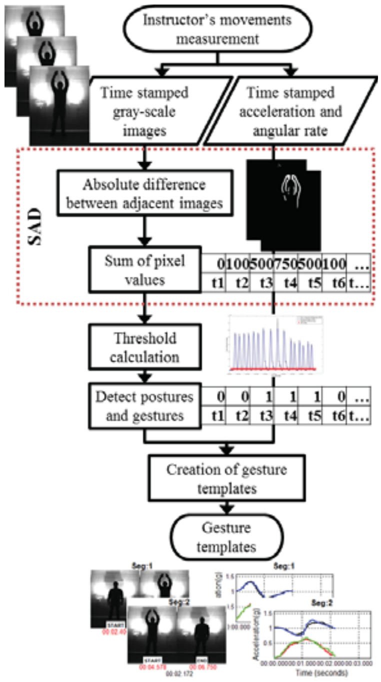


Figure 4. The segmentation of the complete Tai Chi training into gesture templates follows the process described in the flow chart. The process starts with the SAD algorithm. Valley detection is used to select the best threshold value which separates postures (low SAD values) from gestures (high SAD values).

The SAD for all adjacent images produces a $2\times n\text{-}1$ matrix that contains calculated SADs and corresponding timestamps, where n is the number of acquired images.

The next step after calculating the SAD for adjacent images is to compute the threshold value that best differentiate postures and gestures. The threshold value is determined based on the maximum valley value calculated among all valleys detected in the SADs values.

The process produces a set of gesture templates that describe the overall activity or exercise. As collected data are timestamped, a gesture template contains the resultant acceleration and angular rate bounded by the timestamps determined by the beginning and end of each segment. Figure 5 exemplifies the content of a gesture template.

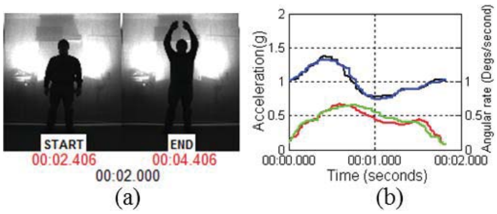


Figure 5. (a) Starting and ending postures of a gesture template. (b) A gesture template contains information about the dynamics of the wrists gestures, such as resultant acceleration, resultant angular rate and associated temporal information.

4) *Creating the Virtual Instructor*

The virtual instructor guides the player during game play by presenting the movements to be reproduced. The virtual instructor is created as a sequence of images frames that are played at the same frame rate used during the recording, i.e. 12 images per second. Figure 6 describes the main operation to produce the virtual instructor.

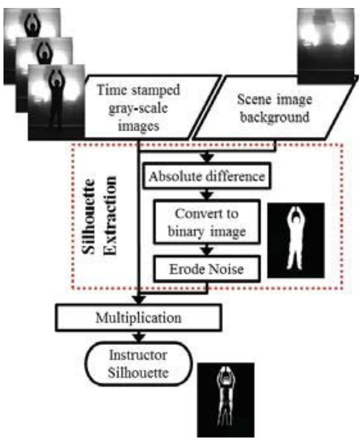


Figure 6. The flowchart describes the process for creation of the virtual instructor. The background is substracted from all acquired images. For each frame, a body silhouette is computed and applied as a mask on the original image to produce the virtual instructor.

Instead of presenting the original recorded images, the silhouette of the instructor's body is extracted and applied as a mask on the original image. Such an approach has the advantage of maintaining information about movements in front of the body, such as hand movements, and preserving the identity of the instructor.

B. *Game Play*

The second module is the game play where the player attempts to mimic the virtual instructor. The game starts with the virtual instructor presenting the exercise to get the player acquainted with the gesture protocol. No gestures are measured at this point. After completing such a demonstration, the game starts the second phase in which virtual instructor repeats the exercise, but the player is challenged to reproduce it.

Instead of using cameras, the same wireless wearable inertial measurement units applied during the game design are used to measure gestures from the player in real-time. The measured gesture is compared with a prerecorded Tai Chi gesture template corresponding to the movement presented by the virtual instructor

The game play application has been developed using the EyesWeb platform and EyesWeb Mobile, an EyesWeb extension to design graphical user interface. Figure 7 details the process in flowchart and presents the GUI for the game.

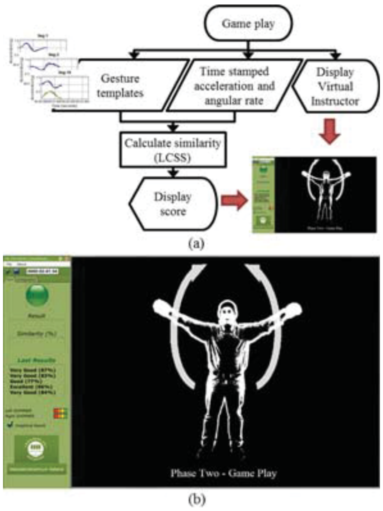


Figure 7. Game play module. (a) The application renders the GUI, measures and evaluates player's gestures, and provides visual feedback. (b) The GUI displays the virtual instructor training. Arrows arround the virtual instructor help the player to remember the movement protocol. Calculated score and last results are displayed on the left.

To calculate the similarity between the measured gesture and a known gesture template the Longest Common Subsequence (LCSS) [23] has been used. This method enables the system to match two sequences by allowing some elements of these sequences to be unmatched, in space (ε), time (δ) or both. Consequently, the method also enables the system to manage with small sensor displacement during the measurement as well as to deal with time lags in gestures. Figure 8 demonstrates the use of the LCCS method in matching acceleration data of two gesture templates representing the same movement. The similarity index returned by the method ranges from 0 (the two sequences do not match at all) to 1 (the two sequences match).

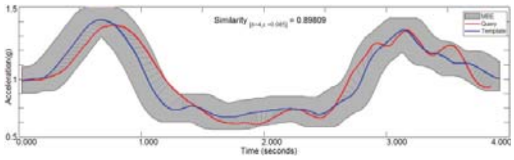


Figure 8. Matching provided by the Longest Common Subsequence distance measure. The Minimum Bounding Envelop (gray area), for a template sequence T and a query sequence Q, demonstrates the tolerance in time (sequence length) and space (sequence amplitude).

The score presented to the player as feedback is determined by calculating the similarity index of each measured property, i.e. the acceleration and angular rate of each arm.

IV. Results and Discussion

A. Gesture templates

As described in the Section II, the game design starts with the recording of the execution of the movement protocol. The exercise duration was approximately 50 seconds and 571 images have been recorded, as well as the kinematic data in that interval. The next step is then to segment recorded data into smaller gesture templates.

The separation is achieved by finding the maximum value among all valley values of the SAD between adjacent images, as presented in Figure 9. SAD values above this threshold value represent gesture segments, otherwise they are posture segments.

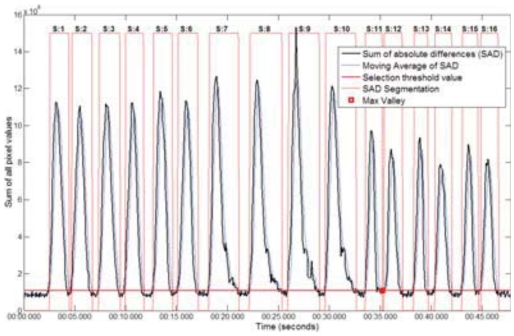
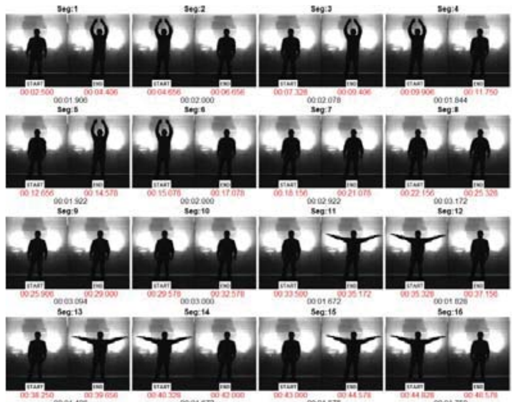
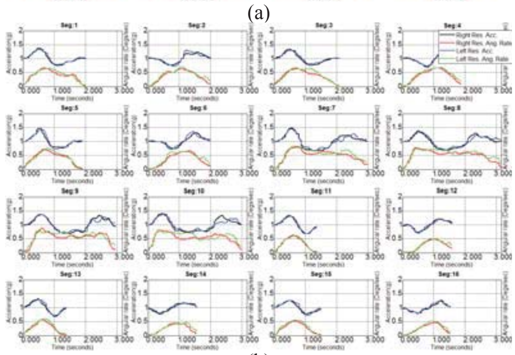


Figure 9. Sum of the absolute difference between adjacent images for the whole set of aquired images in the experiment. The horizontal line slightly above the valleys represents the threshold value, determined by the maximum valley value, distinguishing gestures from postures.

The segmentation process identified all 16 gestures of the movement protocol. Figure 10 presents the results of the segmentation method, and particularly in Figure 10(b), all created gesture templates are presented.



(a)



(b)

Figure 10. Results of the segmentation process. (a) Starting and ending postures as well as the duration of each gesture. (b) Gesture templates containing resultant acceleration and resultant angular rate of both arms.

B. Game play

This subsection presents the main results related to the application and evaluation of the LCSS method to calculate similarity between gestures and known gesture templates.

The first step was to select the best values for the LCSS parameters related to the flexibility in space (ε) and time (δ). The correct selection of ε and δ decreases the computation time and increases the accuracy of the similarity measure [21]. The best values for these parameters have been selected offline by calculating the similarity between a designated gesture template and other templates for different values of space (ε) and time (δ) parameters.

Gesture template number 8 (segment 8 in Figure 10) has been selected as sequence template, and the similarity with other templates has been calculated by ranging the space (ε) parameter values from 0g to 0.18g with a resolution of 0.001g and the time (δ) parameter values from 0 samples to 18 samples with a resolution of 1 sample.

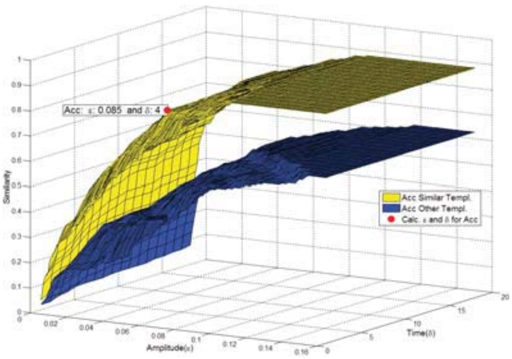


Figure 11. Similarity index (vertical axis) between the sequence template (segment 8 in Figure 10) and other query templates using different values for space (ε) and time (δ) parameters. The upper surface contains similarity values for gesture templates that are very similar to the sequence template. The lower surface contains the similarity values for dissimilar templates.The red dot indicates the best value for ε and δ for maximum separation.

The resultant acceleration data of the left wrist of each template has been selected to demonstrate the process. The calculated similarity values as well as the best values for ε and δ are presented in Figure 11.

The selection has been done by identifying the corresponding ε and δ for the maximum separation between similar and dissimilar gesture templates. The same process has been applied using resultant angular rate data as well for the data recorded from the right wrist.

Once determined, ε and δ can be used to evaluate the similarity of a given gesture with known gesture templates. To demonstrate and evaluate this approach, gestures from the player while playing the game have been recorded and decomposed using the timestamps determined by the gesture templates.

The similarity between each gesture and its corresponding gesture template has been calculated using the LCSS method with 3 different parameters' configuration. In the first configuration, a linear sample-to-sample comparison has been performed by setting δ=0 and ε=0.127, as an analogy to the Euclidian Distance metric. In the second configuration, setting δ=18 and ε=0.0, a non-linear comparison allows the matching of similar sequences that are out of phase. In the third configuration, with δ=4 and ε=0.085, the LCSS method enables the system to match sequences with flexibility in amplitude and time. The results achieved using these 3 parameter configurations are presented in Figure 12.

The first configuration allows distinguishing similar and dissimilar gestures to some extent. However, this approach lacks the ability to evaluate gestures in which the player anticipates or lags behind the instruction presented on the screen.

By controlling the flexibility in space (ε) and time (δ), the LCSS method offers the possibility to configure levels of difficulty for game. A beginner level tolerates, for instance, slower movements (time lag) while an advanced level requires the player to reproduce instructed gestures as similar as (ε=0 and δ=0). The method allows also applying the concept of adaptive difficulty [24] to keep the game interesting and challenging according to the player's progress.

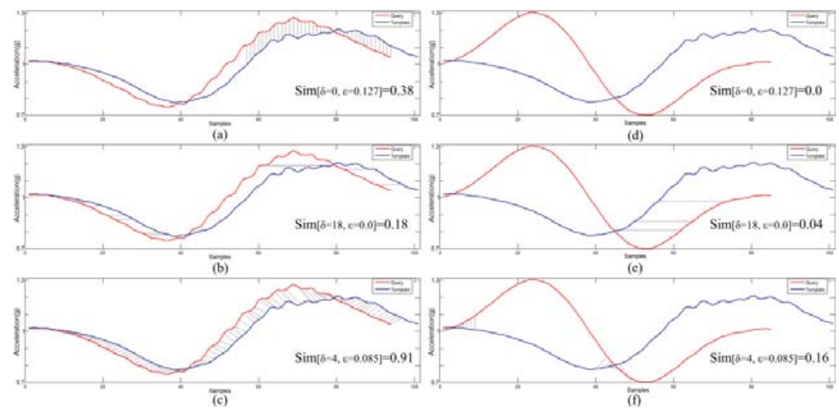


Figure 12. Calculated similarities using different configurations of δ and ε parameters. On the left side, graphs (a), (b) and (c) present the calculated similarity between the player's gesture and the gesture presented by the virtual instructor, i.e. the corresponding gesture template. On the right side, graphs (d), (e) and (f) describe the calculated similarity between a random gesture and the same gesture template used in (a), (b), and (c). The similarity in (a) and (d) has been calculated using a sample-to-sample correspondence, i.e., flexible in amplitude (ε=0.127), but not in time (δ=0). Graphs (b) and (c) present the similarity achieved by trying to match sequences that are out of phase, i.e., flexible only in time(ε=0.0 and δ=18). The similarity presented in graphs (c) and (f) has been determined by the LCSS method. Its flexibility in amplitude and time allows for gestures that match but are performed with some time lag.

Another result is the computed inter-template similarity, i.e. how similar gesture templates are to each other. Figure 11 illustrates the similarity between the gesture template number 8 (segment 8 in Figure 10) with the others. As previously mentioned, the approach presented in this paper does not intend to classify gestures but to evaluate how similar a given gesture is to a known gesture template. The inter-template similarity values enabled the system to cluster similar gesture templates into gesture clusters, as presented in TABLE I. These gesture clusters are the manifestation of the 5 different movements from the movement protocol.

TABLE I. CLASSIFICATION SUMMARY – SEGMENTS ARE CLASSIFIED ACCORDING TO AN INTER-TEMPLATE SIMILARITY ANALYSIS. THE GESTURE TEMPLATES ARE PRESENTED IN FIGURE 10.

	Movements				
	Cluster 1	*Cluster 2*	*Cluster 3*	*Cluster 4*	*Cluster 5*
Gesture Templates	1	2	7	11	12
	3	4	8	13	14
	5	6	9	15	16
			10		

Other aspects of the proposed system that are worth being discussed concern the future work to be done. A planned step is recording the training of a professional Tai Chi instructor. However, as Tai Chi movements are not limited to hand movements, the use of more wearable sensor platforms are needed, for example one on each ankle and one on the chest, at least. Posturographic patterns [25] measured and recorded by a force plate before, during and after the game play could review changes, for example, in stability.

The current graphical user interface lacks a vehicle for providing online feedback to the player regarding the on-going gesture in relation to the virtual instructor. One possible solution is to use the Kinect sensor device (Microsoft Corporation, Redmond, WA) to capture the player motion and provide it as feedback. However, the Kinect sensor cannot detect occluded movements, which are measured by the wearable sensor platforms presented here.

The integration of new devices into the system is facilitated with the use of the EyesWeb software platform, allowing the combination and exploration of different input modalities.

Once these improvements are in place, the next step is to evaluate the game in terms of usability. Two target groups could be included in such an investigation. The first group would include the players, preferably seniors, and the main aspects to be evaluated would be how usable the game is and the players' acceptance of it. The second group would be composed by healthcare professional, such as therapists, who would evaluate and provide feedback about how well the system addresses the desired outcomes.

V. CONCLUSION

This paper presents the development of a computer-based game to assist older individuals in training Tai Chi on their own. A warm-up exercise has been recorded using a camera and wearable sensors. Recorded images have been used to render a virtual instructor during game play. Measured data was decomposed into smaller segments to create a sequence of gesture templates. These templates are used to evaluate the player during the game play, when the player is challenged to reproduce the movements displayed by the virtual instructor.

Results show that the proposed movement segmentation method based on the sum of the absolute difference between adjacent images provided the desired results. Results have demonstrated also that the Longest Common Subsequence method provides flexibility to evaluate the similarity between gestures as well as means to cluster gestures.

In summary, the proposed system enables the design of motion training system, such as computer games, intend to measure or evaluate gestures from the player, who is supposed to follow movement instructions displayed by a virtual instructor on the screen. The user performance is measured by unobtrusive wireless wearable sensors platforms, evaluated by a simple and flexible technique and feedback can be provided in real-time.

This opens up opportunities to apply the method into other domains, such as telerehabilitation. The system could display a virtual physiotherapist who instructs the user about how to perform an individualized physical rehabilitation exercise.

ACKNOWLEDGMENT

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REFERENCES

[1] G. Berleen, A healthier elderly population in Sweden. National Institute of Public Health, Sweden, 2004.

[2] J.A. Stevens, P.S. Corso, E.A. Finkelstein, and T.R. Miller, "The costs of fatal and non-fatal falls among older adults," Injury Prevention, vol. 12, 2006, p. 290.

[3] J.A. Ashton-Miller, "Age-associated changes in the biomechanics of gait and gait-related falls in older adults," in Gait disorders: evaluation and management, J.M. Hausdorff and N.B. Alexander, Eds. Informa HealthCare, 2005. pp. 63–100.

[4] L. Lundin-Olsson and E. Rosendahl, "Att förebygga fallolyckor bland äldre personer," Technical Report, Vårdalinstitutet , Stockholm 2008.

[5] S.L. Tennstedt, "Fear of Falling," in Gait disorders: evaluation and management, J.M. Hausdorff and N.B. Alexander, Eds. Informa HealthCare, 2005. pp. 207–218.

[6] L. D. Gillespie, W. J. Gillespie, M. C. Robertson, S. E. Lamb, R. G. Cumming, B. H. Rowe, "Interventions for preventing falls in elderly people," Cochrane Database of Systematic Reviews 2003, Issue 4. Art. No.: CD000340. doi: 10.1002/14651858.CD000340.

[7] J.T. Chang, S.C. Morton, L.Z. Rubenstein, W.A. Mojica, M. Maglione, M.J. Suttorp, E.A. Roth, and P.G. Shekelle, "Interventions for the prevention of falls in older adults: systematic review and meta-analysis of randomised clinical trials," Bmj, vol. 328, 2004, p. 680.

[8] S.L. Wolf, R.W. Sattin, M. Kutner, M. O'Grady, A.I. Greenspan, and R.J. Gregor, "Intense tai chi exercise training and fall occurrences in

older, transitionally frail adults: a randomized, controlled trial," Journal of the American geriatrics Society, vol. 51, 2003, pp. 1693–1701.

[9] F. Li, P. Harmer, K.J. Fisher, E. McAuley, N. Chaumeton, E. Eckstrom, and N.L. Wilson, "Tai Chi and fall reductions in older adults: a randomized controlled trial," The Journals of Gerontology Series A: Biological Sciences and Medical Sciences, vol. 60, 2005, p. 187.

[10] G. Wu, "Evaluation of the effectiveness of Tai Chi for improving balance and preventing falls in the older population—a review," Journal of the American Geriatrics Society, vol. 50, no. 4, p. 746–754, 2002.

[11] M. Lebram, P. Backlund, H. Engström, and M. Johannesson, "Design and Architecture of Sidh–a Cave Based Firefighter Training Game," in Design and Use of Serious Games, M. Kankaanranta and P. Neittaanmäki, Eds. Springer, 2009, pp. 19–31.

[12] G. R. Whitcomb, "Computer games for the elderly," in ACM SIGCAS Computers and Society, 1990, vol. 20, pp. 112–115.

[13] W. Ijsselsteijn, H. H. Nap, Y. de Kort, and K. Poels, "Digital game design for elderly users," in Proceedings of the 2007 conference on Future Play, 2007, pp. 17–22.

[14] D. Becker and A. Pentland, "Using A Virtual Environment to Teach Cancer Patients T'ai Chi, Relaxation and Self-Imagery," M.I.T. Media Laboratory Perceptual Computing Technical Report No. 390. 1997

[15] P.T. Chua, R. Crivella, B. Daly, N. Hu, R. Schaaf, D. Ventura, T. Camill, J. Hodgins, and R. Pausch, "Training for physical tasks in virtual environments: Tai Chi," Virtual Reality, 2003. Proceedings. IEEE, pp. 87–94.

[16] D.Y. Kwon and M. Gross, "Combining body sensors and visual sensors for motion training," Proceedings of the 2005 ACM SIGCHI International Conference on Advances in computer entertainment technology, 2005, pp. 94–101.

[17] D. Y. Kwon and M. Gross, "A Framework for 3D Spatial Gesture Design and Modeling Using a Wearable Input Device," in Wearable Computers, 2007 11th IEEE International Symposium on, p. 23–26.

[18] E. A. Heinz, K. S. Kunze, M. Gruber, D. Bannach, and P. Lukowicz, "Using wearable sensors for real-time recognition tasks in games of martial arts-an initial experiment," in Computational Intelligence and Games, 2006 IEEE Symposium on, p. 98–102.

[19] K. Kunze, M. Barry, E. A. Heinz, P. Lukowicz, D. Majoe, and J. Gutknecht, "Towards Recognizing Tai Chi–An Initial Experiment Using Wearable Sensors," IFAWC 2006 - 3rd International Forum on Applied Wearable Computing 2006, 2006.

[20] D. Majoe, L. Widmer, and J. Gutknecht, "Enhanced motion interaction for multimedia applications," in Proceedings of the 7th International Conference on Advances in Mobile Computing and Multimedia, 2009, p. 13–19.

[21] A. Burns et al., "SHIMMER™ – A Wireless Sensor Platform for Noninvasive Biomedical Research," Sensors Journal, IEEE, vol. 10, no. 9, pp. 1527-1534, 2010.

[22] A. Camurri, B. Mazzarino, G. Volpe, P. Morasso, F. Priano, and C. Re, "Application of multimedia techniques in the physical rehabilitation of Parkinson's patients," The Journal of Visualization and Computer Animation, vol. 14, 2003, pp. 269–278.

[23] M. Vlachos, M. Hadjieleftheriou, D. Gunopulos, and E. Keogh, "Indexing multi-dimensional time-series with support for multiple distance measures," in Proceedings of the ninth ACM SIGKDD international conference on Knowledge discovery and data mining, 2003, p. 225.

[24] D. McClure. "Adaptive Difficulty, " [Online document], 12 April 2009. Available: http://dmcclure.com/adaptive_difficulty.htm

[25] M. Jacono, M. Casadio, P. G. Morasso, and V. Sanguineti, "The sway-density curve and the underlying postural stabilization process," Motor Control, vol. 8, no. 3, pp. 292–311, 2004.

Appendix B

Paper II - A lightweight method for detecting sleep-related activities based on load sensing

A lightweight method for detecting sleep-related activities based on load sensing

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***Abstract*—Current practices in healthcare rely on expensive and labor-intensive procedures that are not adequate for future healthcare demands. Therefore, alternatives are required to complement or enhance healthcare services, both at clinical and home settings. Hospital and ordinary beds can be equipped with load cells to enable load sensing applications, such as for weight and sleep assessment. Beds with such functionalities represent a tangible alternative to expensive and obtrusive routines for sleep assessment, such as polysomnography. A finite-state machine is proposed as a lightweight on-line method to detect sleep-related activities, such as bed entrances and exits, awakenings, wakefulness, and sleep atonia. The proposed approach is evaluated with a dataset collected in real homes of older people receiving night-time home care services.**

***Keywords*—Healthcare technology, home monitoring, sensor-based monitoring systems, load sensing, sleep assessment, state machines, bed-exit alarms**

I. Introduction

As the elderly population is growing, living longer, and at high risk for age-related health problems and diseases, the demand and, consequently, the cost for healthcare will dramatically increase. Over the last years, there has been an increased interest in using sensor-based monitoring systems to address the future demands for healthcare. These systems provide accurate and reliable data to support better understanding of aging and illnesses, the prevention and management of chronic conditions, and the conservation of healthcare resources [1]. Such systems may represent an alternative to current practices.

The polysomnogram (PSG), for example, is the current gold standard for assessing and evaluating sleep. However, a polysomnographic sleep recording is typically performed at clinical settings by trained personal, and requires the use of electrodes and sensors attached to the body to measure brain, heart, and muscle activity, eye movements, blood oxygen saturation, and respiration [2]. Besides, this method also requires a full night sleep in a laboratory. Non-intrusive alternatives to polysomnography include beds equipped with sensors [3]–[7].

In clinical settings, instrumented beds generate alarms to inform nurses or caregivers when a person is attempting to leave or has left the bed [8]. Falls accidents and injuries related to falls are some the most widespread public health problems among older people, and are associated with morbidity, suffering, loss of independence, and high costs [9]. Most falls happen shortly after getting out of bed, and individuals with cognitive and/or physical impairments are at risk for bed-related falls, either at clinical settings, e.g. nursing homes and hospitals, or at home [10]. In hospitals, patients arousing from a drug-induced coma or unconsciousness are at higher risk [11].

In ordinary homes, beds equipped with sensors can be employed to complement or enhance care delivery and health assessment. In Sweden, county councils and municipalities provide medical, social, and personal care services to people in their own homes. While most home care services are provided during day-time, some individuals require assistance during the night. In a night visit, a night patrol team can help with medication, diapering, toileting, and repositioning in bed [12]. However, supervision visits are more common, i.e., the night patrol team checks if the person is in bed, breathing and doing fine. In Halmstad, Sweden, each night, about 200 homes are visited and 780 km are driven by caregivers delivering night-time home care [13]. Although night-time home care services prevent institutionalization of several individuals [12], not all individuals receiving home care services actually have the need for it because they might have some level of independence. Moreover, some care beneficiaries report about awakenings caused by the night patrol visits [13]. Home-based monitoring systems can, in this scenario, avoid unnecessary night-time visits and sleep disturbances.

This paper focuses on load sensing applications in healthcare and presents a lightweight method to on-line detect sleep-related activities, such as bed entrances and exits, awakenings, wakefulness, and sleep atonia. The proposed method has been implemented as a finite-state machine that operates on features extracted from the weight measured by a load cell placed in a bed. Such an approach is lightweight in the sense it can consume little computational resources and to be integrated into a database-centric architecture for home-based monitoring systems proposed in [14]. In the proposed architecture, authors suggest to implement within the database the logic to monitor and control the home environment. An active database is used in conjunction with sensors and actuators to detect and react to events taking place in the home, such as to detect bed exits and notify caregivers.

The remainder of this paper is organized as follows. An overview of age-related changed in sleep is provided in Section II. Related work is presented in Section III. Section IV describes the proposed method for detecting sleep-related activities. Section V presents and discusses the results of the proposed approach using a dataset collected in different homes of night-time healthcare beneficiaries. Conclusions are covered in Section VI.

II. Sleep and Ageing

Sleep is an active process characterized by changes in brain wave activity, breathing, heart rate, body temperature, muscle tone, and other physiological functions. During normal sleep, nonrapid eye movement (NREM) and rapid eye movement (REM) sleep states alternate cyclically across a sleep episode. NREM sleep is subdivided into 3 stages, in which the last is commonly referred as deep sleep. NREM sleep and REM sleep cycle with a period of approximately 90 minutes. Body movements usually precede REM episodes. NREM sleep is characterized by low muscle activity, while REM sleep by muscle atonia, i.e., absence of muscle activity [15].

As people age, the sleep timing and quality changes, and the incidence of sleep-related problems increases [16]. Sleep complaints are very common among older people. In later adulthood, individuals have more difficulty to fall asleep (long sleep onset, longer than 10 minutes) and to stay asleep at night (reduced sleep time). The sleep becomes more fragmented, the number of arousals and awakenings increases, and the sleep efficiency, i.e., the ratio of time asleep to time in bed, decreases [17], [18]. Ohayon et al. [18] also observed that only sleep efficiency continues to decrease significantly after 60 years of age (3% decrease per decade of age). According to the age-related trend for sleep efficiency proposed by those authors, the sleep efficiency for the individuals over 80 years old ranges from 75% to 85%.

Such background about sleep patterns in late adulthood is used in this work to design the method presented in Section IV.

III. Related Work

During the past few years, there have been many advances in the development of less intrusive alternatives to polysomnography. The actigraph for instance, is a wristwatch-like accelerometer-based device that measures and records movements It has been used in research for many years to study sleep patterns [19]. Non-intrusive alternatives employ beds equipped with load cells.

A load cell is a transducer that converts force into an electrical signal. Strain gauge load cells are typically found in digital kitchen and bathroom weight scales as well as in large industrial scales.

Although not related to sleep assessment, Schmidt et al. [20] equipped several items of furniture and the floor of a laboratory with load cells to capture contextual information about objects, such as weight, position (center of pressure), and interaction with these objects (changes in the load). Their approach is useful to discover where a person is in a bed.

Adami et al. [3] equipped an ordinary bed with load cells underneath each corner support of the bed to continuously monitor, besides weight, sleep characteristics such as bedtime, wake up time, and number and duration of times the person leaves the bed during the night and naps during the day. To detect bed entrances and exits, which in turn enable the computation of the other previously mentioned features, the authors employed a threshold crossing operation on the total weight in bed. Authors selected as threshold value the midpoint value between the averages of the measured weight when the person is in and out of bed. In [4], the k-means algorithm was used to separate the load cell data into two clusters representing in and out of bed. As both methods rely on the total weight in bed, both are subject to false positives, since the bed can be loaded with static weight.

Later on, the same research group at the Oregon Center for Aging and Technology (ORCATECH), Hayes et al. [21] used finite-state machines to derive sleep parameters (bed time, rise time, sleep latency, and nap time) from passive infrared motion sensors installed in the home. Such an approach is compromised by displacements of the motion sensors and by homes with multiple occupants. Austin et al. [22] explored support vector machines (SVM) to classify sleep and wakefulness states using features derived from load cell signals.

The work of Choi et al. [7] presents a bed actigraphy (BACT) system that also employs a bed equipped with load cells to unobtrusively detect sleep and wake stages. However, the lack of the description of some symbolic names prevents the reader to explain and reproduce the approach.

Kortelainen et al. placed an electromechanical film (Emfit Bed Sensor) underneath the mattress to measure heart rate and body movements. Machine learning methods, such as hidden Markov model (HMM), were used for sleep stage classification.

In this work, the proposed approach computes similar sleep-related characteristic on-line using a finite-state machine that operates on the measured weight signal and on the computed standard deviation. Such an approach enables, for example, to differentiate when a bed is occupied by a person or loaded with static weight.

IV. Method

A. *"Trygg om natten" (Safe at Night) dataset*

In 2011, the "Trygg om natten" (Safe at Night) project explored how technology can assist care beneficiaries and caregivers during night supervisions, and also how technology is perceived in terms of integrity and acceptance [13]. The project was conducted in the city of Halmstad, Sweden.

In total, 15 individuals receiving night-time home care (2 men and 13 women), with an average age of 82 years, participated in the project. The home of each these 15 participants was equipped with five types of sensors (see Table I) activated from 10pm until 06am during several nights (approximately 14 nights on average). The study was granted with an ethical approval from the central ethical review board.

The Emfit Bed Sensor was used in the project as the main method to detect bed exits. One strain-gauge load cell was placed at the top-left corner support of the participants bed to serve as a reference to the Emfit Bed Sensor because bed

TABLE I. Sensors used in "Trygg om natten" (Safe at Night) project to collect the dataset [13].

Type	Purpose	Qty.	Output
Passive infrared	Capture human motion	≈ 4	Event
Emfit Bed Sensor	Capture bed exits	1	Event
Magnetic	Capture door openings	1	Event
Inertia sensor	Capture human inactivity (wearable)	1	Event
Load cell	Reference to Emfit Bed Sensor	1	24bit value

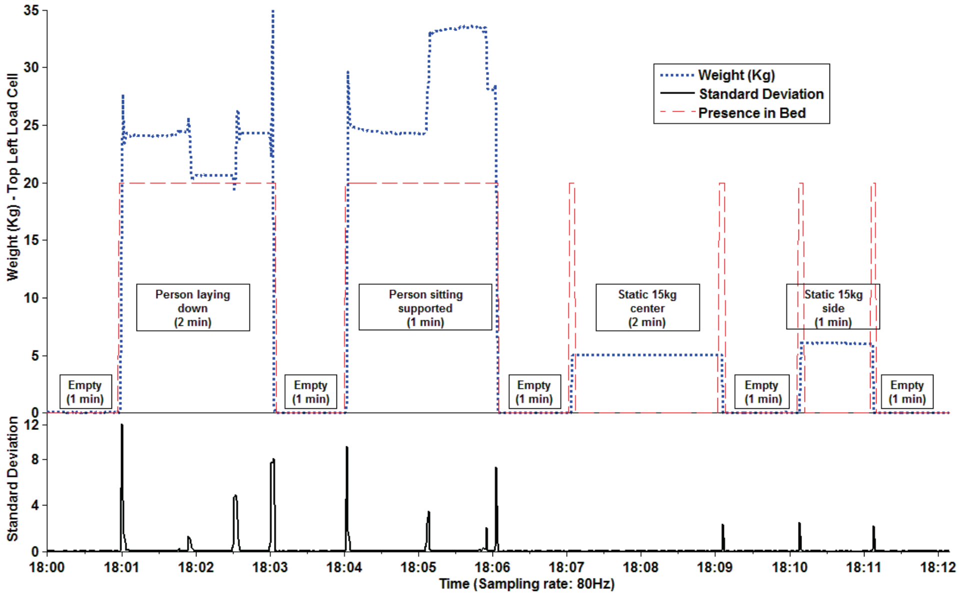

Figure 1. The measured weight (dotted line) and the computed standard deviation (solid line) for different scenarios. Bed entrances and exits (dashed line) are also indicated.

entrances and exits, as well as presence in bed, can be derived by the measured raw weight data.

The load cell was connected to a Texas Instruments 24-bit analog-to-digital converter (ADS1232REF) which connects to a USB port of a low-power, fanless, miniature computer located under the bed. The data collection system running in the host computer measured load cell signals at a sampling rate of 80Hz. Motion sensors were placed in different spots in the house, such as bedroom, living room, bathroom, and kitchen. A magnet sensor installed in the front door captures night-time care visits. All motion and magnet sensors stream their output (events) to the host computer.

The dataset containing the collected data, particularly the load cell data from 7 different homes, is used in this work to design and evaluate the proposed approach to assess sleep. The dataset for the remaining 8 participants was not available during the method design.

B. A finite-state machine to detect sleep-related activities in bed

Given a bed instrumented with load cells, when the bed is occupied by a person, voluntary and involuntary body movements generate disturbances in the load cell signal that are not present when the bed is unoccupied or loaded with static weight.

Figure 1 presents the calibrated weight data, measured from the top left load cell installed in an ordinary bed, at four distinct scenarios: when a person is laying down or sitting on the bed, and when the bed is loaded with 15 kilos of static weight placed on the center of the bed and on the left side. All these four scenarios are separated by a one minute interval when the bed is unoccupied. Figure 1 also illustrates the standard deviation of the presented weight data. The standard deviation is higher in periods of high muscle activity (e.g., while entering or leaving the bed, and while turning the body) than in periods of low or no muscle activity.

Figure 2 depicts two distinct intervals of the computed standard deviation. The first (blue line on the left), presents the values for the standard deviation when a person is on the bed. The second (green line on the right), presents the standard deviation values when the bed is unoccupied. A threshold can be computed to separate the signal into two clusters.

A method for finding a threshold in a signal is the Otsu algorithm [23], which maximizes the between cluster distance when dividing the distribution values into two clusters, for example, in-bed and out-of-bed clusters, or low and high activity clusters.

By analyzing the weight signal and the computed standard deviation of, a finite-state machine can continuously detect bed entrances and exits, as well as periods of high and low muscle activity, i.e., wakefulness and sleepiness periods, respectively. Moreover, such an approach enables to differentiate when a bed is occupied by a person or loaded with static weight.

The transition between states is therefore determined by a threshold crossing mechanism that takes into account the standard deviation or/and the mean value of the measured weight. Both the standard deviation and the mean value are calculated with a moving window with size being 40 samples, which corresponds to half of the signal sampling rate (80

Hz). A moving window smaller than 40 samples creates too much granularity, while a bigger window delays the detection. Figure 3 illustrates the proposed finite-state machine used to detect sleep-related activities. The state machine contains four finite states described as follows:

- **Bed Out state.** In this state the bed is unoccupied. The weight on the bed and the standard deviation of the weight signal are lower than estimated threshold values for these two features.
- **Awake state.** In this state the bed is occupied and the bed occupant is awake. The standard deviation of the weight signal is high and is associated with high muscle activity.
- **Atonia state.** In this state the bed is occupied and muscle activity is low or absent. The bed occupant might be in a state of sleep.
- **Awakening state.** In this state the bed is occupied and muscle activity has started to increase.

The transitions between the previously described states depend on the inputs and on the internal state of state machine, for example, to be at the *Awake* state the person must first be in bed. The state machine operates on the following inputs:

1) The standard deviation (σ_w) of the last 40 weight samples;
2) The estimated threshold for the standard deviation ($t\sigma_{inout}$) indicating presence or absence in bed, and high muscle activity;
3) The mean (m_w) value of the last 40 weight samples.
4) The estimated threshold for the mean value (tm_{inout}) indicating presence or absence in bed;
5) The estimated threshold for the standard deviation ($t\sigma_{atonia}$) indicating presence in bed, and low or absent muscle activity;
6) The time duration ($time$) in seconds that state machine remains on a specific state, such as *Awakening* state.
7) The sleep latency time (T) in minutes. The sleep latency is higher if the person left the bed than after short awakenings.

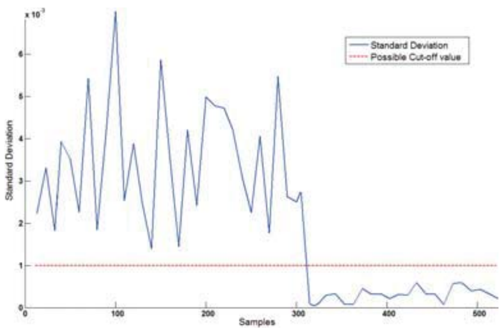

Figure 2. The cut-off value separates two intervals for the standard deviation into two clusters, bed occupied and unoccupied, respectively. The same approach, but with a different cut-off value, can differentiate periods of high muscle activity from periods of low or no muscle activity.

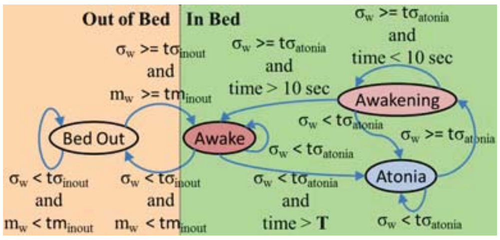

Figure 3. The proposed finite-state machine to detect sleep-related activities. Bed entrances and exits can be captured by the method. Awake, awakening, and sleep (lack of muscle activity) states are estimated.

C. State machine implementation

For each of the 7 collected datasets, a corresponding database was created to store the measured data from the load cell and environment sensors. A resource adapter [14] has been implemented to read the dataset files and stream the collected data to the database.

The thresholds for the standard deviation ($t\sigma_{inout}$) and the median value (tm_{inout}) were estimated using the Otsu method [23]. As the estimated ($t\sigma_{inout}$) and (tm_{inout}) thresholds were quite similar among all the datasets, the minimum values of ($t\sigma_{inout}$) and (tm_{inout}) were selected. The threshold for the awakening time duration ($time$) was set to 10 seconds and the expected sleep latency time (T) was set to 1) 10 minutes if the individual was not in bed before the first occurrence of a sleep atonia state, or 2) 3 minutes, if the individual remained in bed after an awakening longer than the awakening time duration ($time$). These sleep-relating timings have been investigated in [17], [18].

The proposed state machine is implemented as an user-defined function (UDF) for a PostgreSQL database [25], and integrated into the database-centric architecture proposed in [14]. An active rule periodically triggers execution of the UDF implementation of the state machine. The estimated thresholds for the standard deviation ($t\sigma_{inout}$) and mean weight (m_w) are declared as variables in the declarations section of the UDF. The UDF computes the standard deviation (σ_w) and the mean weight (m_w) of the last 40 stored samples, and later processes the states transitions. The computed states are stored into a table.

V. Results and Discussion

To illustrate the results achieved, two individuals participating in the project (Person1 and Person2) where selected to demonstrate the proposed method.

Although the method still needs to be validated against the polysomnography and results are preliminary, some of them worth to be discussed.

Figure 4 depicts common sleep-related activities and sensor events for one of the selected datasets. Areas in the figure in which the weight signal varies a lot, due to body movements, identify periods in which the person is awake. Areas in which

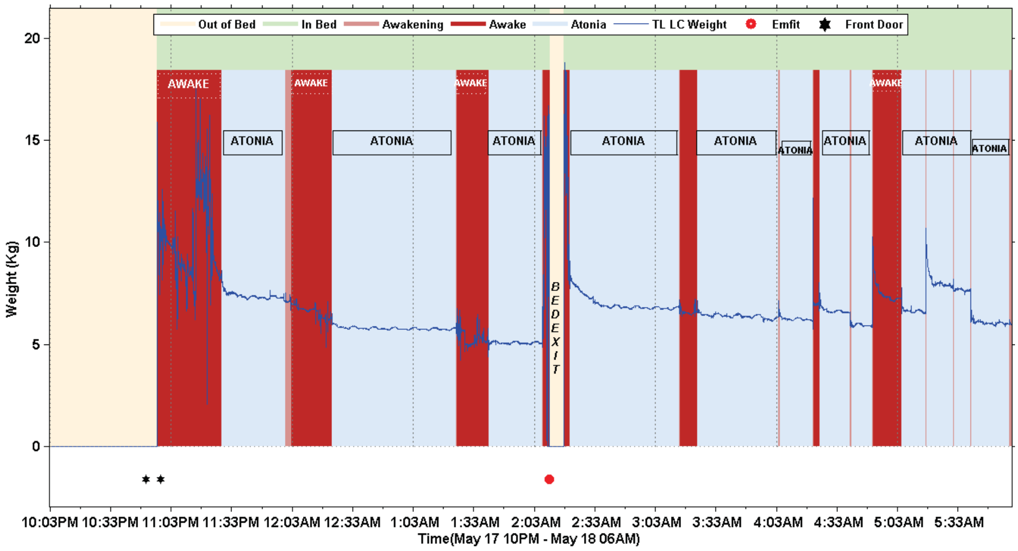

Figure 4. Detected sleep activities for the selected user (Person1) are highlighted according to the legend. In the lower area in the graph, black stars represent night-time home care visits, while entering and leaving the home. Red circles indicate bed exits detected by the Emfit Bed Sensor. Adapted from [24].

the weight signal is, somewhat, stable identify periods of low or no muscle activity (muscle atonia). Short areas between awake and atonia areas or states identify awakenings. Areas in the figure in which the weight signal is equal or very close to zero, identify: 1) periods in which the person is not in bed; 2) bed exits. In the same figure, the bed exit detect by the proposed state machine corresponds to the bed exit event measured by the Emfit Bed Sensor.

Tables II and III present the detect activities and the estimated sleep parameters, as well as events measured by other sensors installed in the home of the selected individuals, (Person1 and Person2), who had the measurement system installed at home during 19 and 25 days, respectively.

According to the age-related trend for sleep efficiency proposed in [18], the sleep efficiency for the individuals participating in the "Trygg om natten"project [13] must range from 75% to 85%. The estimated average sleep efficiency presented in Tables II and III are in accordance with the trend presented in [18].

Another observation is the inconsistency between the number of bed exits detected by the proposed approach (**BEx** in Table III) and the number of bed exits detected by the Emfit Bed Sensor (**BedSensor** in Table III, used as bed-exit alarm).

For the one individual (Person2, Table III), the Emfit Bed Sensor missed 17 bed exits (about 20%) and generated 6 inexistent bed exits. Besides, the Emfit Bed Sensor was not capturing bed entrances and when they occur. For the other individual (Person1, Table II), the Emfit Bed Sensor missed 12 bed exist or approximately 60% of all bed exists.

Figure 5 illustrates such scenario in which the proposed approach detected a bed exit that was missed by the Emfit Bed Sensor.

TABLE II. A SUMMARY OF DETECTED ACTIVITIES AND SENSOR EVENTS FOR PERSON1. **BEX** (NUMBER OF BED EXITS), **BIN** (BED ENTRANCES), **BT** (BED TIME), **SL** (SLEEP LATENCY), **TIB** (TIME IN BED), **TIA** (TIME IN ATONIA), **SE** (SLEEP EFFICIENCY, WHICH IS THE RATIO OF THE ESTIMATED **TIA** TO THE ESTIMATED **TIB**). ADAPTED FROM [24].

Date	BEx	BIn	Awake	Atonia	Awanening	Bed Sensor	Visits	BT	SL	TiB	TiA	SE
May 10-May 11	2	3	16	15	15	0	0	22:32:44	00:28:36	06:58:23	04:36:52	66%
May 11-May 12	2	3	15	20	19	2	3	22:32:17	00:37:08	07:03:52	04:43:39	67%
May 12-May 13	2	3	10	10	10	1	2	23:02:50	00:03:12	06:48:33	04:42:59	69%
May 13-May 14	1	2	6	7	6	1	2	22:44:26	00:41:11	06:14:00	04:52:46	78%
May 14-May 15	2	2	6	5	5	2	7	00:53:46	00:02:22	04:13:17	03:25:47	81%
May 15-May 16	2	3	6	3	3	0	5	22:39:20	00:03:25	07:03:19	06:06:20	87%
May 16-May 17	0	1	9	9	9	0	1	22:48:46	00:35:58	07:09:47	05:37:16	78%
May 17-May 18	1	2	12	12	12	1	2	22:56:18	00:31:35	06:55:24	05:09:01	74%
May 19-May 20	4	5	7	6	5	1	2	22:41:58	00:17:44	05:07:37	03:38:12	71%
May 20-May 21	2	3	12	11	10	1	4	22:58:30	02:04:30	06:28:00	03:36:23	56%
May 21-May 22	1	2	7	5	5	0	4	23:00:01	00:37:05	04:45:06	02:59:27	63%
May 22-May 23	0	1	10	12	12	0	2	22:54:58	00:11:09	07:02:39	05:38:00	80%
May 23-May 24	0	1	13	15	14	0	2	22:43:10	00:05:12	07:14:01	05:33:32	77%
May 24-May 25	2	3	14	12	12	0	2	23:18:25	00:40:27	06:28:44	04:08:10	64%

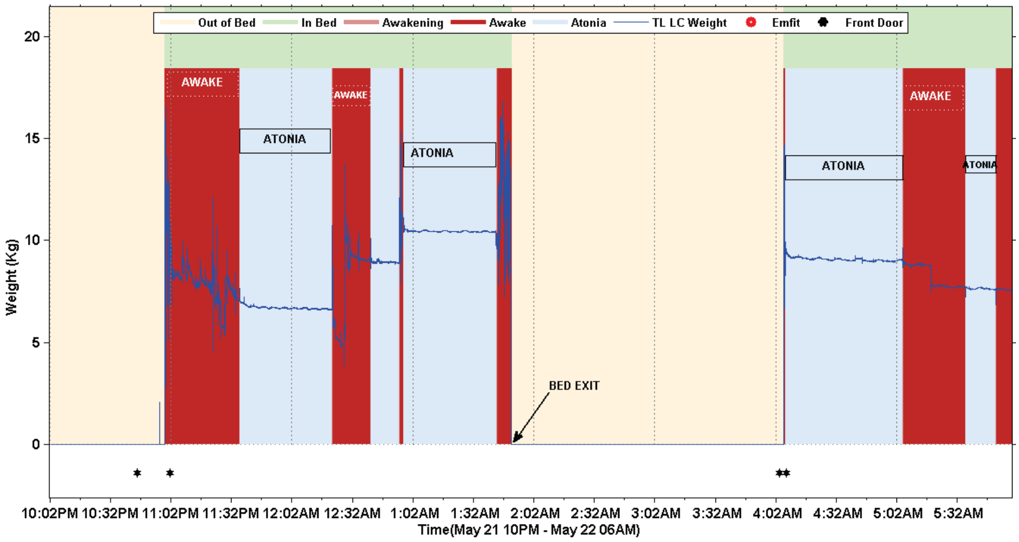

Figure 5. The proposed approach detected a bed exit that was missed by the Emfit Bed Sensor. Adapted from [24].

Table IV presents a comparison for all individuals of bed exits detected by the proposed state machine and the Emfit Bed Sensor. A possible reason for such inconsistency could be the fact that some individuals leave and return to the bed for a short instant of time or the Emfit Bed Sensor was not working properly.

In hospitals, the proposed approach might enhance interventions targeting fall and pressure sores prevention, by detecting when individuals are leaving the led, agitated in bed or at the same rest position for a long-period of time.

At home settings, it can enable remote monitoring of individuals that require night-time supervision. In the current practice, a night patrol team visits the home of the care beneficiary to check if the person is in bed and doing fine. Remote monitoring can avoid unnecessary visits, which in turn might reduce sleep disturbance complaints and conserve healthcare resources. Those requiring night patrol visits can benefit from such type of home-monitoring system because the system can provide reliable information about sleep patterns, allowing visits to be schedule when the care beneficiary is more likely to be awake.

TABLE III. A SUMMARY OF DETECTED ACTIVITIES AND SENSOR EVENTS FOR PERSON2. **BEX** (NUMBER OF BED EXITS), **BIN** (BED ENTRANCES), **BT** (BED TIME), **SL** (SLEEP LATENCY), **TIB** (TIME IN BED), **TIA** (TIME IN ATONIA), **SE** (SLEEP EFFICIENCY, WHICH IS THE RATIO OF THE ESTIMATED **TIA** TO THE ESTIMATED **TIB**). ADAPTED FROM [24].

Date	BEx	BIn	Awake	Atonia	Awanening	Bed Sensor	Visits	BT	SL	TiB	TiA	SE
Oct 28-Oct 29	4	5	13	16	16	0	0	22:24:48	00:29:49	07:13:54	04:13:21	58%
Oct 29-Oct 30	5	6	12	12	12	0	0	22:17:54	00:04:48	08:15:50	08:02:23	97%
Oct 30-Oct 31	3	4	7	15	14	0	0	22:23:30	00:05:23	07:21:59	07:18:02	99%
Oct 31-Nov 01	3	4	7	8	7	2	1	22:32:05	00:06:29	07:14:36	06:58:11	96%
Nov 01-Nov 02	3	4	9	7	6	4	3	22:07:26	00:02:21	07:37:28	07:30:28	98%
Nov 02-Nov 03	5	6	9	5	4	5	4	22:08:07	00:07:19	07:34:50	07:17:54	96%
Nov 03-Nov 04	3	5	12	14	13	4	4	¡ 10PM	NA	07:38:02	07:18:27	96%
Nov 04-Nov 05	4	5	8	7	6	5	3	22:22:23	00:02:42	07:16:01	07:07:38	98%
Nov 05-Nov 06	6	7	12	9	9	4	3	22:20:04	00:35:46	07:22:14	06:36:59	90%
Nov 06-Nov 07	4	5	7	5	5	4	5	22:22:25	01:21:07	07:23:03	05:55:37	80%
Nov 07-Nov 08	4	5	8	4	3	4	3	22:23:45	00:11:42	07:13:24	07:07:20	99%
Nov 08-Nov 09	4	5	7	5	4	4	3	22:28:16	00:25:02	07:17:07	06:36:13	91%
Nov 09-Nov 10	4	5	12	13	12	4	3	22:34:37	00:05:33	07:08:42	06:35:18	92%
Nov 10-Nov 11	2	3	9	11	10	2	1	22:26:27	00:02:28	07:20:06	07:06:22	97%
Nov 11-Nov 12	4	5	10	10	9	5	2	22:36:43	00:36:20	07:02:45	06:20:20	90%
Nov 12-Nov 13	4	6	13	16	16	4	2	¡ 10PM	NA	07:41:12	07:10:55	93%
Nov 13-Nov 14	5	6	18	20	19	5	1	22:20:58	00:05:40	07:17:06	06:14:32	86%
Nov 14-Nov 15	6	6	12	13	13	5	3	22:29:19	00:30:54	07:07:20	06:11:41	87%
Nov 15-Nov 16	2	4	10	11	11	3	2	¡ 10PM	NA	07:48:42	06:59:11	89%
Nov 16-Nov 17	5	6	12	9	9	5	1	22:37:22	00:28:16	07:06:35	05:45:40	81%
Nov 17-Nov 18	2	4	11	14	13	3	1	¡ 10PM	NA	07:46:08	06:26:54	83%
Nov 18-Nov 19	4	5	15	14	14	3	2	22:20:43	00:40:05	07:26:55	05:48:14	78%
Nov 19-Nov 20	3	4	12	12	11	3	1	22:14:52	00:18:38	07:36:14	05:33:51	73%
Nov 20-Nov 21	5	6	18	19	19	5	1	22:18:49	00:05:04	07:19:32	04:56:24	67%

TABLE IV. INCONSISTENCY BETWEEN THE NUMBERS OF BED EXITS DETECTED BY THE PROPOSED APPROACH AND BY THE EMFIT BED SENSOR FOR ALL DATASETS. INEXISTENT BED EXITS INDICATED BY THE EMFIT BED SENSOR ARE ALSO INCLUDED.

	P1	P2	P3	P4	P5	P6	P7
Total BEx	21	94	22	93	0	16	119
Total BedSensor	9	83*	1*	NA	11	40*	92*
False BedSensor	0	6	1	NA	11	27	6
Difference	57%	18%	100%	NA	100%	19%	28%
Px: Personx. * including inexistent bed exists. NA: Not Available							

VI. CONCLUSION

The ongoing work presented in this paper proposed a finite-state machine as a lightweight on-line method for detecting sleep-related activities, such as bed entrances and exits, awakenings, wakefulness, and sleep atonia. The method employs a load cell placed in the top left corner of a bed and analyzes the measured weight and the computed standard deviation.

The proposed approach was evaluated with a dataset collected at real homes of night-time care beneficiaries. Although results show that the proposed method is able the accurately detect, if compared to the Emfit Bed Sensor, bed entrances and exits, the method still needs to be validated using polysomnographic sleep recordings so more conclusions can be draw about the accuracy to detect sleep awakenings, awake and sleep states. The availability of just one load cell installed in the beds limited the amount of features that could be used by the method. One of these features is the center of pressure or center of mass, which can indicate the position and displacement of the person in the bed.

Beds equipped with load cells enable load sensing applications to measure, besides weight, bed entrances and exits, and whether the occupant is awake or asleep. Such unobtrusive measurement system might represent an alternative to current methods used to assess sleep disorders, both in clinical and home settings. The method proposed in this work has the potential to serve as a tool for remote night-time sleep monitoring, avoiding unnecessary home care visits.

ACKNOWLEDGMENT

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REFERENCES

[1] A. G. Ekeland, A. Bowes, and S. Flottorp, "Effectiveness of telemedicine: a systematic review of reviews," *International journal of medical informatics*, vol. 79, no. 11, pp. 736–771, 2010.

[2] C. A. Kushida, M. R. Littner, T. Morgenthaler, C. A. Alessi, D. Bailey, J. Coleman Jr, L. Friedman, M. Hirshkowitz, S. Kapen, M. Kramer *et al.*, "Practice parameters for the indications for polysomnography and related procedures: an update for 2005," *Sleep*, vol. 28, no. 4, pp. 499–521, 2005.

[3] A. Adami, T. Hayes, and M. Pavel, "Unobtrusive monitoring of sleep patterns," in *Engineering in Medicine and Biology Society, 2003. Proceedings of the 25th Annual International Conference of the IEEE*, vol. 2, 2003, pp. 1360–1363.

[4] A. Adami, A. Adami, G. Schwarz, Z. Beattie, and T. Hayes, "A subject state detection approach to determine rest-activity patterns using load cells," in *Engineering in Medicine and Biology Society (EMBC), 2010 Annual International Conference of the IEEE*, 2010, pp. 204–207.

[5] A. Adami, T. Hayes, M. Pavel, and C. Singer, "Detection and classification of movements in bed using load cells," in *Engineering in Medicine and Biology Society, 2005. IEEE-EMBS 2005. 27th Annual International Conference of the*, 2005, pp. 589–592.

[6] A. Adami, A. Adami, C. Singer, T. Hayes, and M. Pavel, "A system for unobtrusive monitoring of mobility in bed," in *Computational Science and Engineering Workshops, 2008. CSEWORKSHOPS '08. 11th IEEE International Conference on*, 2008, pp. 13–18.

[7] B. H. Choi, J. W. Seo, J. M. Choi, H. B. Shin, J. Y. Lee, K. S. Park *et al.*, "Non-constraining sleep/wake monitoring system using bed actigraphy," *Medical & biological engineering & computing*, vol. 45, no. 1, pp. 107–114, 2007.

[8] E. Capezuti, B. L. Brush, S. Lane, H. U. Rabinowitz, and M. Secic, "Bed-exit alarm effectiveness," *Archives of gerontology and geriatrics*, vol. 49, no. 1, p. 2731, 2009.

[9] G. Berleen and G. Watson, *A healthier elderly population in Sweden!* National Institute of Public Health, Sweden, Statens Folkhälsoinstitut, 2004.

[10] J. Hilbe, E. Schulc, B. Linder, and C. Them, "Development and alarm threshold evaluation of a side rail integrated sensor technology for the prevention of falls," *International Journal of Medical Informatics*, vol. 79, no. 3, pp. 173–180, 2010.

[11] A. Hendrich, "Predicting patient falls," *AJN The American Journal of Nursing*, vol. 107, no. 11, pp. 50–58, 2007.

[12] B. Malmberg, M. Ernsth, B. Larsson, and S. H. Zarit, "Angels of the night: Evening and night patrols for homebound elders in sweden," *The Gerontologist*, vol. 43, no. 5, pp. 761–765, 2003.

[13] R. Thörner, M. Persson, H. Eriksson, A. Isaksson, and J. Lundström, "Trygg om natten," Centre for Health Technology in Halland, Halmstad University, Halmstad, Sweden, Tech. Rep., 2011.

[14] W. O. de Morais and N. Wickstrom, "A" smart bedroom" as an active database system," in *Intelligent Environments (IE), 2013 9th International Conference on*. IEEE, 2013, pp. 250–253.

[15] M. A. Carskadon, W. C. Dement *et al.*, "Normal human sleep: an overview," *Principles and practice of sleep medicine*, vol. 4, pp. 13–23, 1994.

[16] A. B. Neikrug and S. Ancoli-Israel, "Sleep disorders in the older adult–a mini-review," *Gerontology*, vol. 56, no. 2, pp. 181–189, 2009.

[17] S. H. Feinsilver, "Sleep in the elderly: What is normal?" *Clinics in geriatric medicine*, vol. 19, no. 1, pp. 177–188, 2003.

[18] M. M. Ohayon, M. A. Carskadon, C. Guilleminault, and M. V. Vitiello, "Meta-analysis of quantitative sleep parameters from childhood to old age in healthy individuals: developing normative sleep values across the human lifespan," *Sleep*, vol. 27, pp. 1255–1274, 2004.

[19] S. Ancoli-Israel, R. Cole, C. Alessi, M. Chambers, W. Moorcroft, and C. Pollak, "The role of actigraphy in the study of sleep and circadian rhythms. american academy of sleep medicine review paper," *Sleep*, vol. 26, no. 3, pp. 342–392, 2003.

[20] A. Schmidt, M. Strohbach, K. Laerhoven, A. Friday, and H.-W. Gellersen, "Context acquisition based on load sensing," in *UbiComp 2002: Ubiquitous Computing*, ser. Lecture Notes in Computer Science, G. Borriello and L. Holmquist, Eds., 2002, vol. 2498, pp. 333–350.

[21] T. L. Hayes, T. Riley, M. Pavel, and J. A. Kaye, "Estimation of rest-activity patterns using motion sensors," in *Engineering in Medicine and Biology Society (EMBC), 2010 Annual International Conference of the IEEE*. IEEE, 2010, pp. 2147–2150.

[22] D. Austin, Z. T. Beattie, T. Riley, A. M. Adami, C. C. Hagen, and T. L. Hayes, "Unobtrusive classification of sleep and wakefulness using load cells under the bed," in *Engineering in Medicine and Biology Society (EMBC), 2012 Annual International Conference of the IEEE*. IEEE, 2012, pp. 5254–5257.

[23] N. Otsu, "A threshold selection method from gray-level histograms," *IEEE Transactions on Systems, Man and Cybernetics*, vol. 9, no. 1, pp. 62–66, 1979.

[24] W. O. de Morais and N. Wickström, "Sleep and night activities of care beneficiaries at the "trygg om natten" (safe at night) project," Halmstad University, Tech. Rep. hh:diva-24030, 2013.

[25] The PostgreSQL Global Development Group, "Postgresql 9.2 documentation," 2013.

Appendix C

Paper III - A “Smart Bedroom” as an Active Database System

A "Smart Bedroom" as an Active Database System

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***Abstract*—Home-based healthcare technologies aim to enable older people to age in place as well as to support those delivering care. Although a number of smart homes exist, there is no established method to architect these systems. This work proposes the development of a smart environment as an active database system. Active rules in the database, in conjunction with sensors and actuators, monitor and respond to events taking place in the home environment. Resource adapters integrate heterogeneous hardware and software technologies into the system. A "Smart Bedroom" has been developed as a demonstrator. The proposed approach represents a flexible and robust architecture for smart homes and ambient assisted living systems.**

Keywords- Smart environments, DBMS, active databases, AAL, healthcare, system architecture

I. Introduction

Smart homes (SH) integrate distinct network-enabled devices to provide advanced functionalities to occupants, such as improved comfort and safety as well as management of energy use [1]. Lately, there has been an increased interest in using the pervasive infrastructure of SH to offer services supporting healthy behaviors, early disease detection, treatment compliance, caregiving support, and aging in place [2].

Several SH and ambient assisted living (AAL) projects have been developed with the main goal of enabling older or disabled people to live longer and more independently in the own homes [3]. Most of these projects deliver solutions for functional, safety, and physiological monitoring as well as for cognitive and sensory support [4]. Moreover, SH and AAL systems can provide a supportive work environment for caregivers, reducing the burden of care [5]. The integration of medical devices into SH and AAL systems enables healthcare professionals to remotely monitor and assist individuals with disabilities, chronic conditions, or special needs [6].

Although some architectural aspects are common among existing implementations of SH and AAL projects, there is still no established method for designing and implementing such systems neither a common standard for intercommunicating and integrating devices and applications inside of SH [7].

Recently, research efforts to create a common platform to serve as a foundation for AAL application resulted in several initiatives, such as the Soprano [8], Persona [9] and UniversALL [10] projects. These platforms are based on the Open Services Gateway initiative (OSGi) framework [11] and aim to facilitate the integration, provision, and usage of devices and services in the system.

This work has its focus on the architecture for smart environment applications and proposes an architecture that exploits capabilities provided by database management systems (DBMSs) other than data management.

Modern DBMSs, such as PostgreSQL [12], are mature technologies supporting several mechanisms that can be exploited to address important requirements of smart environment applications, such as authentication, availability, security, privacy, reliability, extensibility, and scalability. DBMSs enable, for example, developers to extend the database with user-defined functions (UDFs), meaning that the semantics of an application can be encapsulated within the DBMS itself. For instance, UDFs enable the integration of statistical models and machine learning techniques into the database, which in turn enables recognition and prediction of health-related events [13]. In-database processing reduces the amount of code at the application level and avoids data transfers, because UDFs have direct access to data, which can lead to better performance. Together with database views, UDFs enable the creation of database APIs, hiding the underlying database model. Moreover, DBMSs support mechanisms, known as active rules, which can be used to detect and react to events such as data manipulation operations (table inserts and updates). Databases exploiting active rules are called active databases [14]. Database views, UDFs, and active rules can be added or modified "on the fly" without affecting client applications connected to the database (given that their signature remains the same). The flexibility and robustness provided by these mechanisms are particularly important in the context of healthcare-related smart environment applications, where users' needs and preferences evolve over time and the system's acceptance is directly linked to how these issues are addressed [15].

Existing SH and AAL platforms use DBMSs exclusively for data storage and retrieval. The use of other functionalities supported by DBMSs, such as authentication, availability, security, privacy, reliability, extensibility, and scalability, can facilitate the development of these platforms. Thus, the main difference between the approach presented in this work and related projects is that the active database in the proposed architecture contains the model and the logic for describing and controlling a smart environment. Although active databases, combined with temporal reasoning, have been suggested previously to support independent living in a SH [16], the authors have focused their studies on the formation and validation of active rules.

Therefore, this work presents the way active databases support the development of smart environment systems by moving the reactive behavior from the application or middleware layer into the DBMS. In such a context, an active database is used together with sensors and actuators to monitor and respond to events taking place in the environment. Resource adapters mediate the communication between the active database and the hardware or software technologies in the environment. Resource adapters stream the data measured by sensors or entered by the user to the database. Resource adapters also control actuators or provide feedback information to the user in response to messages sent by the database.

To illustrate the proposed approach, a "Smart Bedroom" demonstrator has been developed and is presented in this work. The Smart Bedroom includes a set of sensors and actuators in a bedroom environment and has as its main component an ordinary adjustable bed, named "Smart Bed". Functionalities to improve comfort, enhance independence, and support medical care are demonstrated.

The remainder of this paper is organized as follows: Section II presents the proposed architecture and describes the method for developing a smart environment as an active database. Section III presents the main functionalities development in the Smart Bedroom according to the proposed approach. Section IV summarizes and presents future directions of this research work.

II. Method

The proposed system architecture exploits active databases in conjunction with sensors and actuators, among other hardware and software technologies, to monitor and respond to events happening in the home environment. Sensors and actuators provide the means for perceiving and controlling the environment. Such devices are integrated into the system using resource adapters. Resource adapters communicate with the database through a database API defined within the database itself. The reactive behavior is achieved using active rules. The main system's components are illustrated in Fig. 1 and are further explained in later subsections.

A. *Resource Adapters*

Resource adapters are software components that facilitate the integration and interoperation of heterogeneous hardware and software technologies into the system (e.g., sensors, actuators, user interfaces, script engines, etc.). Most importantly, resource adapters serve as a gateway between the environment and the database. Resource adapters stream the data collected by sensors or entered by the user to the database and control actuators or user interfaces in response to commands received from the database. Resource adapters communicate with the database through a database API while the database communicates back with resource adapters using a messaging mechanism.

In the class diagram in Fig. 2, the Storage class encapsulates methods for accessing, manipulating, and querying data providers, such as PostgreSQL. The UserInterface class leverages user interface components that enable users to input or receive feedback. The InterProcessComm class abstracts interprocess communication mechanisms used by the database to control or notify resource adapters about data changes.

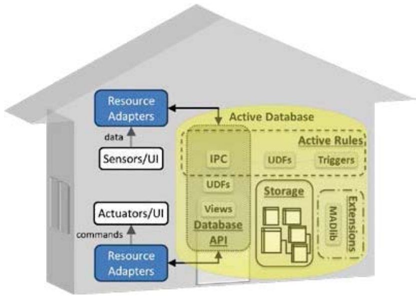

Figure 1. The proposed architecture includes Resource Adapters and an Active Database. Resource adapters integrate hardware and software technologies into the system. Adapters communicate with the database through the Database API. The database API is defined using UDFs and Views. Active rules, implemented using Triggers and UDFs deliver reactive functionalities. Messaging mechanisms (IPC) notify Resource Adapters with commands. Besides, data mining capabilities can be achieved with database extensions.

The Communication class encapsulates the underlying implementation of communication protocols, such as serial communication, used to communicate with sensors and actuators. The Adapter class is associated with the previous classes and handles the configuration of its subclasses by retrieving such information from the database. Classes derived from the Adapter class, such as the PIR class, abstract resource-specific data formats, operations, and recovery from faults, such as communication disconnections.

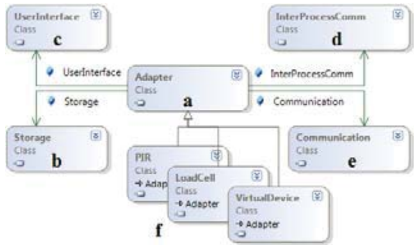

Figure 2. Classes associated with the Adapter class (a): Storage (b), User Interface (c), Interprocess Communication (d) and Communication Protocols (e). Derived classes (f) deal with resource-specific functionalities.

B. *Active Database*

The active database (see Fig. 1) contains four related features provided by the system: Storage, Database API, Active Rules, and Extensions. In a database, data is stored into tables. The Storage aspect of the system includes tables that are used to store data being collected and streamed to the database by resource adapters. Storage also includes tables storing information that are used to configure resource adapters.

Developers implementing resource adapters do not have knowledge about the internal Storage model. They are provided instead with a Database API, which exposes data access and manipulation (select, insert, update) using Views and UDFs. The database notifies adapters about data changes or events using external or built-in mechanisms for interprocess communication, which prevents adapters from querying (pooling) the database periodically. PostgreSQL provides the NOTIFY and LISTEN commands for interprocess communication.

As mentioned previously, an active database can monitor and react in a timely manner to specific circumstances of relevance to an application [14]. The reactive behavior in an active database system is provided by Event-Condition-Action structures, commonly referred to as active rules, meaning that when an event happens, the condition is evaluated, and if it holds, an action is executed. In PostgreSQL, for example, active rules are implemented using triggers and UDFs.

III. Results

To demonstrate the feasibility of the proposed architecture, a Smart Bedroom demonstrator has been implemented. The Smart Bedroom has as its main component an ordinary adjustable single bed. The four bed supports have been fitted with one load cell each to measure weight on the bed. The electric motor actuator in the bed and the load cells have been connected to digital output and analog input modules, respectively. These modules are connected to an Ethernet-based programmable fieldbus controller unit fixed in the bed frame. An Emfit Bed Sensor placed under the mattress measures presence, vital signs, and movements on the bed. The programmable controller and the Emfit sensor are connected via standard Ethernet ports to a wireless router located under the bed. A custom Bluetooth-enabled accelerometer-based platform in the upper section of the bed frame measures the inclination angle of the back/shoulder section. The ceiling and table lamps are attached to wall-plug socket receivers and controlled (switch on/off, dim) wirelessly using a Telldus TellStick Duo connected to the host computer. Motion sensors detect presence in the bedroom. A sound level dose meter measures the sound level in the room and transmits its data to the host computer via Bluetooth.

An HP Touch Smart has been used as the host computer and connects wirelessly to other devices through either Wi-Fi or Bluetooth. Resource adapters have been developed in C# programming language. The PostgreSQL database has been selected as the DBMS. The Database API and the active rules have been implemented in PostgreSQL using the procedural language PL/pgSQL. The overall system configuration and the implemented bed are presented in Fig. 3.

A. *A Smart Environment as an Active Database*

For all the aforementioned sensor and actuator devices, a corresponding resource adapter has been implemented. Resource adapter abstracting sensors stream measured data to the database. Active rules monitor the incoming data for features or patterns that will cause the system to react to events taking place in the room. Resource adapter abstracting actuators subscribe to specific notifications in the database.

1) *Presence in Bed detection using Active Rules*

Load cell sensors in the bed enable the system to detect presence or absence in bed, because voluntary and involuntary body movements create different forces than when the bed is unoccupied. A method for distinguishing from (i.e., finding a threshold) the characteristics of the two signals is the Otsu algorithm [17]. This algorithm computes the threshold that maximizes the separation between cluster distances when dividing the distribution values into two clusters.

An active rule (trigger) monitors the table in which load cell signal values are stored to detect when a person enters or leaves the bed. Equation (1) describes the active rule condition for detecting presence in bed, combining the binary signals computed from the class separation thresholds O_{σ} and O_M, calculated using the Otsu method [17].

$$\text{Presence} = \left((\sigma > O_{\sigma})\ AND\ (M < O_M)\right), \tag{1}$$

where M is the median and σ the standard deviation of a dataset containing 5 seconds of load cell samples (12Hz x 5sec = 60 samples).

The overall set of functionalities provided by the Smart Bedroom is listed in TABLE I. Rows in TABLE I present functionalities implemented in the Smart Bedroom demonstrator, classified as services to improve comfort, enhance independence, and support medical care. Although the medical care category includes mostly services for physiological monitoring, a resource adapter could interface the Smart Bedroom with emergency alarm systems. Columns identify devices utilized in the implementation of such functionalities. White (□) and black (■) squares indicate sensors and actuators, respectively. Load cell data, for example, are reused or adapted to enable services such as automatic light control, bed-exit alarms, and movement-on-the-bed assessment. Functionalities, such as bed-exit alarms, have increased availability in the system because redundant data are provided by distinct sensors, that is, the bed-exit alarm is enabled by active rules monitoring the Emfit Bed sensor, load cells data, and motion sensors (PIR).

TABLE I. The complete set of services provided by the "Smart Bedroom" demonstrator.

		Adjust. bed	Accelerom.	Tell Stick	Load cells	Emfit	Sound meter	GUI	PIR
Comfort	Automatic lighting			■	□	□			□
	Light control			■				□	
	Bed adjustment	■	□					□	
	Wakeup light			■					
Independence	Night light			■	□	□			□
	Transfer support	■	□					□	
	Weight assessment				□			■	
	Time in bed				□	□		■	
	Wakeup time				□	□		■	
	Bed time				□	□		■	
	Noise assessment						□	■	
Medical Care	Heart rate					□		■	
	Breathing					□		■	
	Movement in bed				□	□		■	
	Bed-exit alarm				□	□		■	□
	Center-of-pressure				□			■	

Reuse

Redundancy

IV. Conclusion

Database management systems support several mechanisms besides data management that can be exploited to facilitate the development of smart environment applications. This work presented the design and development of a Smart Bedroom as an active database system by encapsulating the semantics of the Smart Bedroom application into an active database. Resource adapters with single responsibilities facilitated the integration and interoperation of heterogeneous technologies. Although the presented work is ongoing, the overall approach leveraged a robust and flexible system that facilitates reuse, adaptation, and maintenance of functionalities without affecting other artifacts connected to the database. Exploring other DBMS capabilities, such as authentication mechanisms, balance loading, and roles, encompasses future work, which also includes investigating the integration of statistical models and machine learning techniques into the database to find patterns or unknown relationships in stored health-related data. For example, MADlib [18] adds in-database analytic capabilities to PostgreSQL. Usability, responsiveness, and scalability also require further evaluation.

Acknowledgment

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References

[1] M. C. Mozer, “The neural network house: An environment hat adapts to its inhabitants,” in Proc. AAAI Spring Symp. Intelligent Environments, 1998, pp. 110–114.

[2] E. Dishman, “Inventing wellness systems for aging in place,” Computer, vol. 37, no. 5, pp. 34–41, May 2004.

[3] M. Chan, D. Estève, C. Escriba, and E. Campo, “A review of smart homes - Present state and future challenges,” Computer Methods and Programs in Biomedicine, vol. 91, no. 1, pp. 55–81, Jul. 2008.

[4] G. Demiris and B. K. Hensel, “Technologies for an aging society: a systematic review of ‘smart home’ applications,” Yearb Med Inform, pp. 33–40, 2008.

[5] H. G. Kang, D. F. Mahoney, H. Hoenig, V. A. Hirth, P. Bonato, I. Hajjar, and L. A. Lipsitz, “In Situ Monitoring of Health in Older Adults: Technologies and Issues,” Journal of the American Geriatrics Society, vol. 58, no. 8, pp. 1579–1586, 2010.

[6] V. Rialle, F. Duchene, N. Noury, L. Bajolle, and J. Demongeot, “Health ‘Smart’ Home: Information Technology for Patients at Home,” Telemedicine Journal and e-Health, vol. 8, no. 4, pp. 395–409, Dec. 2002.

[7] J. E. Kim, G. Boulos, J. Yackovich, T. Barth, C. Beckel, and D. Mosse, “Seamless Integration of Heterogeneous Devices and Access Control in Smart Homes,” in Intelligent Environments (IE), 2012 8th International Conference on, pp. 206–213, 2012.

[8] P. Wolf, A. Schmidt, and M. Klein, “SOPRANO-An extensible, open AAL platform for elderly people based on semantical contracts,” in 3rd Workshop on Artificial Intelligence Techniques for Ambient Intelligence (AITAmI’08), 18th European Conference on Artificial Intelligence (ECAI 08), Patras, Greece, 2008.

[9] M.-R. Tazari, F. Furfari, J.-P. L. Ramos, and E. Ferro, “The PERSONA service platform for AAL spaces,” Handbook of Ambient Intelligence and Smart Environments, pp. 1171–1199, 2010.

[10] M.-R. Tazari, F. Furfari, Á. F. VALERO, S. Hanke, O. Höftberger, D. Kehagias, M. Mosmondor, R. Wichert, and P. WOLF, “The universAAL Reference Model for AAL,” Handbook on Ambient Assisted Living-Technology for Healthcare, Rehabilitation and Well-being. AISE Book Series, vol. 11, 2012.

[11] Open Services Gateway initiative. OSGi Alliance. Available at: http://www.osgi.org.

[12] The PostgreSQL Global Development Group. PostgreSQL 9.2.3 Documentation, 2013. Availatle at: http://www.postgresql.org/docs/9.2

[13] D. J. Cook, J. C. Augusto, and V. R. Jakkula, “Ambient intelligence: Technologies, applications, and opportunities,” Pervasive and Mobile Computing, vol. 5, no. 4, pp. 277–298, 2009.

[14] N. W. Paton and O. Díaz, “Active database systems,” ACM Computing Surveys (CSUR), vol. 31, no. 1, pp. 63–103, 1999.

[15] G. Demiris, H. J. Thompson, B. Reeder, K. Wilamowska, and O. Zaslavsky, “Using informatics to capture older adults’ wellness,” International journal of medical informatics, 2011.

[16] J. C. Augusto and C. D. Nugent, “A new architecture for smart homes based on ADB and temporal reasoning,” in Proceedings of 2nd International Conference On Smart homes and health Telematic, ICOST2004, Assistive Technology Research Series, pp. 106–113, 2005.

[17] N. Otsu, "A threshold selection method from gray level histograms," IEEE Tram. Syst., Man, Cybern., vol. SMC-9, pp. 62-66, 1979.

[18] J. M. Hellerstein, C. Ré, F. Schoppmann, D. Z. Wang, E. Fratkin, A. Gorajek, K. S. Ng, C. Welton, X. Feng, and K. Li, “The MADlib analytics library: or MAD skills, the SQL,” Proceedings of the VLDB Endowment, vol. 5, no. 12, pp. 1700–1711, 2012.

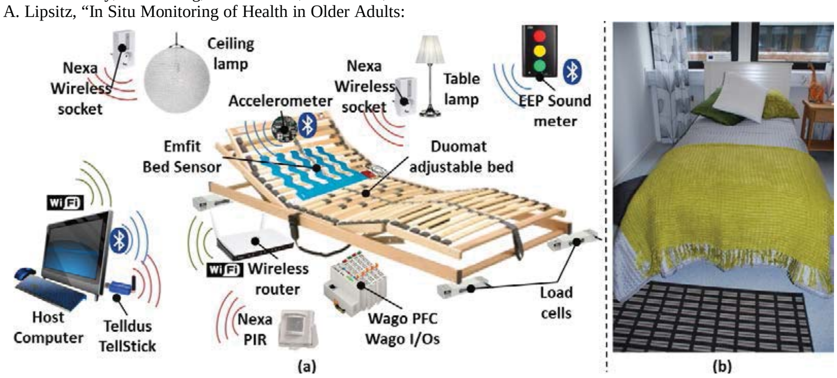

Figure 3. The main hardware components in the system are illustrated in (a). Hardware and software technologies in the are abstracted by resource adatpters. An active database server implemented in PostgreSQL, runs in the Host computer. Active rules monitor and react to events happening in the bedroom. On the right, (b) presents the “Smart Bedroom” demonstrator at the Centre for Health Technology in Halland at Halmstad University.

Appendix D

Paper IV - Active In-Database Processing to Support Ambient Assisted Living Systems

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Article

Active In-Database Processing to Support Ambient Assisted Living Systems

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Abstract: As an alternative to the existing software architectures that underpin the development of smart homes and ambient assisted living (AAL) systems, this work presents a database-centric architecture that takes advantage of active databases and in-database processing. Current platforms supporting AAL systems use database management systems (DBMSs) exclusively for data storage. Active databases employ database triggers to detect and react to events taking place inside or outside of the database. DBMSs can be extended with stored procedures and functions that enable in-database processing. This means that the data processing is integrated and performed within the DBMS. The feasibility and flexibility of the proposed approach were demonstrated with the implementation of three distinct AAL services. The active database was used to detect bed-exits and to discover common room transitions and deviations during the night. In-database machine learning methods were used to model early night behaviors. Consequently, active in-database processing avoids transferring sensitive data outside the database, and this improves performance, security and privacy. Furthermore, centralizing the computation into the DBMS facilitates code reuse, adaptation and maintenance. These are important system properties that take into account the evolving heterogeneity of users, their needs and the devices that are characteristic of smart homes and AAL systems. Therefore, DBMSs can provide capabilities to address requirements for scalability, security, privacy, dependability and personalization in applications of smart environments in healthcare.

Keywords: healthcare technology; smart homes; ambient assisted living; database management systems; active databases; in-database processing; data mining

1. Introduction

Storage is an important and required functionality in continuous, long-term, home-based monitoring systems, and the database management system (DBMS) is the most common, but not fully exploited, component among software architectures underpinning smart environments, such as smart homes, and ambient assisted living (AAL) systems.

As an extension [1] and an alternative to existing platforms supporting the development of smart homes and AAL systems, this work proposes a database-centric architecture that explores the capabilities of DBMSs beyond those of data management.

1.1. Background

Home care has been suggested to be a sustainable alternative to traditional care, because it has the potential to prevent unnecessary acute or long-term institutionalization and to enable individuals to stay in their homes and communities for as long as possible [2]. Similar to other countries in Europe, in Sweden, county councils and municipalities provide medical, social and personal care services for care beneficiaries in their own homes. Most people receiving home care services are old or disabled individuals living alone.

Home care visits are normally planned, but when social alarm devices are offered to care beneficiaries, unplanned emergency response visits also occur. A social alarm is a portable device and includes a push-button to alert a care unit. Social alarms can include also a movement sensor that automatically triggers an alarm upon inactivity. The device is commonly worn as a wrist-watch or as a pendant necklace.

Although most home care services are provided during the daytime, some individuals require assistance during the night. In a nighttime visit, a night patrol team can help with medication, diapering, toileting and repositioning in bed [3]. However, supervision visits are more common, *i.e.*, the night patrol team, without waking up the resident, checks if the person is in bed, breathing and doing fine. In Halmstad, Sweden, about 200 homes are visited and around 780 km are driven each night by caregivers providing nighttime home care [4].

Even though home care services prevent the institutionalization of many individuals [3], there are a number of issues that will likely limit their efficiency and effectiveness in the near future. By the year 2050, about 27% of the European population is expected to be of the age 65 years and above, and in Sweden, older adults will account for 23% of the Swedish population [5]. While many individuals will remain healthy and independent into late adulthood, others will be highly dependent on informal or professional care [6]. Consequently, the demand for home care services will drastically increase, and as it currently stands, the healthcare system is not prepared to address these demands, mostly due to the shortage of professionals specializing in geriatric care [7] and nighttime caregiving [3,8].

When it comes to nighttime home care, not all individuals receiving such services are actually in need of it, because they are still relatively independent and can use the social alarm device to request assistance if it is ever needed [4]. Furthermore, some care beneficiaries report being awakened by the night patrol supervision visit, and these individuals often trigger their alarm within minutes after a supervision visit [4].

Smart home technologies can enhance or complement home health care and have been shown to be integral parts of a cost-effective healthcare system [9,10]. A smart home provides a home-based infrastructure that integrates network-enabled devices with different capabilities to offer advanced functionalities to the residents. Traditionally, smart homes have included solutions to enhance the comfort and safety of residents, as well as systems to manage and conserve energy [11,12]. However, over the past several years, there has been an increased interest in using the pervasive infrastructure of smart homes to support aging in place and AAL.

Systems targeting aging in place and AAL aim to support older or disabled individuals with services that: (1) promote healthier lifestyle and enhanced quality of life; (2) enable early disease detection and treatment compliance; (3) support informal and professional caregiving; and (4) enable individuals to live independently for a longer time in their own homes [13,14].

The current practice of assessing the nature of chronic diseases is limited to clinic-based assessments scheduled at discrete points in time, and the management of illnesses is limited to a few medical visits and to self-reports [15]. The collection and analysis of functional, safety, security and physiological parameters, as well as cognitive and social support are the most common smart home applications in healthcare [16].

In-home health monitoring provides accurate and reliable long-term data to support better decision making, better understanding of aging and illnesses, the prevention and management of chronic diseases, healthier attitudes and behaviors and the conservation of healthcare resources [15,17]. Moreover, the long-term storage of health-related information enables the use of data mining methods that can reveal unknown patterns or relationships that can indicate the onset of a health-related problem [18].

Smart homes and AAL systems are complex to build, use and maintain [19]. One factor contributing to such complexity is the inherent diversity that is characteristic of smart homes and that leads to technical issues related to personalization, integration, interoperation, extensibility and dependability. Individuals have needs, preferences, habits and adverse health conditions that differ and evolve over time. Home environments also differ, and heterogeneous technologies, such as sensors and actuators, are employed in these systems. These distinct devices are provided by different manufacturers, and they operate and communicate with different standards and protocols. Thus, there is no universal arrangement of devices to fit every home environment.

The acceptance of smart homes and AAL systems is also an issue and is directly linked with the system's ability to address an individual's evolving needs, as well as their concerns for privacy, security and dependability [20]. Regarding privacy, not all individuals will accept technologies that monitor all aspects of their lives. Cameras, for example, are perceived as invasive technologies. Moreover, collected data from such systems are very sensitive. In the same way that data analysis of stored data can predict the onset of a health-related problem, data analysis could also predict the predisposition of a person to commit a crime [21]. As a consequence, there are different issues related to data security, such as who is going to use or have access to the data and how and where the data is going to be processed, stored and used. Concerns related to dependability are associated with trust, e.g., can users rely on the system and what if the system stops working altogether.

1.2. Related Work

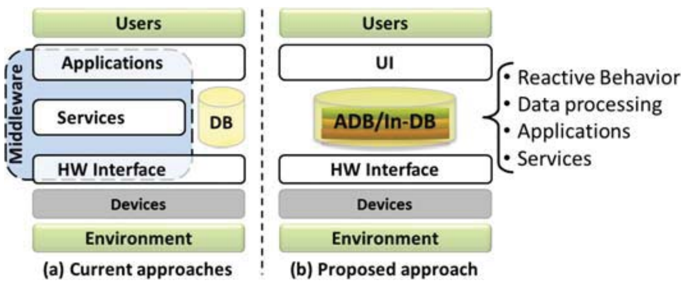
A number of smart homes and AAL projects have been developed over the past several years (reviewed in [22,23]) along with the technical infrastructures that serve as foundations for AAL applications [24]. Although some architectural aspects are common among existing smart environments and AAL platforms, there is still no widely adopted method for developing these systems [25]. Different software architectures have been proposed for the smart environment and AAL domains, including service-oriented architecture (SOA), service-oriented device architecture (SODA), peer-to-peer architecture (P2P), event-driven architecture (EDA), component and connector (C2), multi-agent system (M.A.S) and blackboard. However, as discussed in [26], none of them can perfectly fit the requirements for AAL systems, specifically the requirement for integration [26].

Sensors and actuators provide the means for perceiving and controlling the environment. These devices, among others, are provided by different manufacturers and operate and communicate through different standards and protocols. The open-service gateway initiative (OSGi) framework is commonly used to abstract and integrate devices, such as sensors and actuators, as well as to create service-oriented applications.

Several projects have adopted platforms or middlewares based on SOA and built on top of the OSGi service framework. The Gator Tech Smart House [27], PERSONA (PERceptive Spaces prOmoting iNdependent Aging) [28], SOPRANO (Service Oriented PRogrammable smArt enviroNments for Older Europeans) [29] and universAAL (UNIVERsal open platform and reference Specification for Ambient Assisted Living) [30] are examples of smart homes and AAL projects based on SOA and OSGi.

Current infrastructures supporting smart environments and AAL solutions typically implement the domain logic along with methods for data analysis, data mining and machine learning, as well as the mechanisms for security and privacy at the application, service or middleware layers (Figure 1a).

Figure 1. (**a**) Existing infrastructures supporting smart environments and AAL systems perform data processing at different layers; (**b**) in the proposed database-centric architecture, the reactive behavior and data processing are integrated and performed within the database management system (DBMS). Notation: ADB, active database; DB, database; In-DB, in-database processing, HW, hardware; UI, user interface.



Modern DBMSs—such as PostgreSQL [31]—provide mechanisms that can be utilized to address important requirements for data processing and analysis, security, privacy, dependability, extensibility and scalability in smart home and AAL systems. Such mechanisms have not been explored by current smart environments and AAL infrastructures that employ DBMSs exclusively for data storage and retrieval.

1.3. Approach and Contribution

In response to the challenges previously described and as an alternative to current approaches, this work presents a database-centric system architecture that exploits mechanisms provided by DBMSs to support the development of AAL applications. The aim is to push the reactive behavior and the data processing, which are commonly implemented at different software layers within existing architectures, into the DBMS (Figure 1b).

This work exploits active databases to detect and respond to events taking place in the home environment, such as bed-exits. The extensibility capabilities of DBMSs, which are mostly provided by user-defined functions, are also explored in this work to perform in-database processing. This means that the domain logic (e.g., for detecting and responding to emergencies) is integrated into the DBMS itself. Three distinct AAL services—bed-exit detection, discovery of common room transitions and behavior modeling—are implemented using the proposed database-centric architecture and are evaluated with a dataset collected in real homes from older individuals living alone.

Active databases and in-database processing avoid transferring sensitive data outside the database. Moreover, the domain logic is centralized into the DBMS and managed on the fly.

The remainder of this paper is organized as follows. An overview of the capabilities of DBMSs, other than data management, is presented in Section 2. Section 3 describes a motivating scenario for AAL applications. The proposed database-centric architecture and its main components are presented in Section 4 and are evaluated with the development of three home-based healthcare services in Section 5. Conclusions are presented in Section 6.

2. Capabilities of Database Management Systems

Traditionally, DBMSs are passive components in architectures supporting smart environments and AAL solutions and are employed exclusively to store and manage data for later retrieval. The SQL (Structured Query Language) language is used solely for specifying the database schema and for accessing or manipulating data. However, DBMSs can do much more than data management.

DBMSs incorporate active rule processing mechanisms in the form of database triggers. These provide an event-driven architecture that enables the DBMS to monitor and react to events taking place inside or outside of the database, for example, to enforce referential integrity or to react to sensor data being inserted into the database, respectively.

Moreover, DBMSs enable developers to implement new procedures, functions and data types that are stored within the DBMS. DBMSs also promote mechanisms for controlling security and privacy. DBMSs are very dependable systems, mostly due to high-availability, robustness and reliability, and they enable changes in the domain logic, reactive behavior and security policies to be managed on the fly. This facilitates the system's scalability, maintainability and personalization, because changes in software applications connected to the DBMS are not required [32].

Although the aforementioned capabilities are present in the most widely-used commercial (e.g., Oracle, Microsoft SQL Server and IBM DB2) and open-source (e.g., PostgreSQL and MySQL) DBMSs, the database-centric architecture presented in this work focuses only on the capabilities provided by PostgreSQL [31].

2.1. Active Databases

The SQL language enables the creation of database triggers that provide an in-database event-driven architecture to detect and respond to events, such as data manipulation operations, such as table insertions and updates. Database triggers are event-condition-action (ECA) structures—commonly referred to as active rules—meaning that when an event occurs, the condition is evaluated, and if it holds, an action is executed. The action can be executed before or after a data manipulation operation, for example, after a table insertion and/or update.

DBMSs exploiting active rules are called active databases [33]. An active database can monitor and respond to specific circumstances of relevance to an application in a timely manner [33]. For example, active rules can react to incoming sensor data to control smart environments [34]. Active databases can also prevent client applications from periodically querying (polling) the database for data changes. Periodic polling mechanisms can be inefficient (too many queries due to a short polling interval) and inaccurate (delayed response due to a long polling interval). To notify client applications about the occurrence of a certain event, such as a data change, active database systems can make use of external or built-in inter-process communication mechanisms. Such an approach requires the client application to be always connected to the DBMS and to subscribe to notifications published by the DBMS.

PostgreSQL, for example, provides a built-in asynchronous publish-subscribe mechanism for inter-process communication using the NOTIFY (publish), LISTEN (subscribe) and UNLISTEN (unsubscribe) commands.

2.2. SQL Extensions

DBMSs enable the SQL language to be extended with user-defined types (UDTs), user-defined aggregates (UDAs), user-defined functions (UDFs) and stored procedures (SPs). UDTs, UDAs, UDFs and SPs can subsequently be included in SQL statements and queries. Moreover, the actions invoked by database triggers are commonly implemented as UDFs or SPs. UDFs and SPs enable in-database processing and analytics—*i.e.*, the semantics of applications, statistical models and machine learning techniques—to be integrated and performed within the DBMS. SQL extensions, including database triggers, are implemented in SQL language or using database vendor-specific procedural languages, such as PL/pgSQL (procedural language for PostgreSQL), Python variants [31] and C language.

PostGIS [35], for example, is a free and open source database extension that adds spatial and geographic objects for PostgreSQL. Advanced algorithms, such as methods for statistical analysis and machine learning, can also be integrated into modern DBMSs. For example, MADlib [36] is an open-source library that adds in-database analytical capabilities for PostgreSQL. The MADlib library supports established methods for supervised learning (linear and logistic regression, decision trees and support vector machines), unsupervised learning (k-means clustering and association rules) and descriptive statistics, and it comes with support modules that provide array operators and probability functions among many other methods [36].

Database extensions are stored into the DBMS and are managed on the fly without requiring system restarts. In-database processing facilitates code reuse and maintainability, avoids data movement and improves performance and security. Performing data processing inside the DBMS is more efficient than with external data mining programs [37,38]. The in-database implementation of different statistical models and machine learning techniques, along with their advantages, can be found and are discussed in [37–42].

2.3. Security and Privacy

In addition to active databases and in-database processing, which avoid transferring sensitive data from the database to external applications, DBMSs provide other mechanisms to enforce data security and privacy, such as authentication and authorization.

DBMSs support authentication mechanisms that are used to check and confirm the identity of a user, device or software application trying to access database resources. Besides password-based authentication, DBMSs, such as PostgreSQL, enable authentication methods and protocols, such as Lightweight Directory Access Protocol (LDAP) authentication, the Kerberos network authentication protocol, and Secure Sockets Layer (SSL) certificates, among others.

DBMs also support authorization mechanisms that are used to manage and control users' access permissions to database resources. PostgreSQL manages database access permissions using the concept of roles that can be attributed to a DBMS user or to a group of DBMS users [31].

3. Motivating Scenario: The "Trygg om natten" (Safe at Night) Project

The "Trygg om natten" (Safe at night in Swedish) project was conducted in Halmstad, Sweden and explored how technology could assist care beneficiaries and caregivers during nighttime supervisions [4]. The study also focused on how technology was perceived by the participants in terms of integrity and acceptance.

The criteria for selecting participants for the project were that individuals had to be beneficiaries of nighttime supervisions, live alone in their own house or apartment without pets and sustain some level of independence, such as for showering, dressing, eating, functional mobility and personal and toilet hygiene. In addition, an approval of the night patrol team was also required. Individuals diagnosed with some type of dementia or not able to give informed consent were excluded.

In total, 15 out of 30 nighttime supervisions beneficiaries (2 men and 13 women) with an average age of 82 years participated in the project. Ten participants lived in apartments and five in houses.

The home of each participant was equipped with five types of sensors (Table 1) that were active from 10 p.m. until 6 a.m. every night for approximately 14 days.

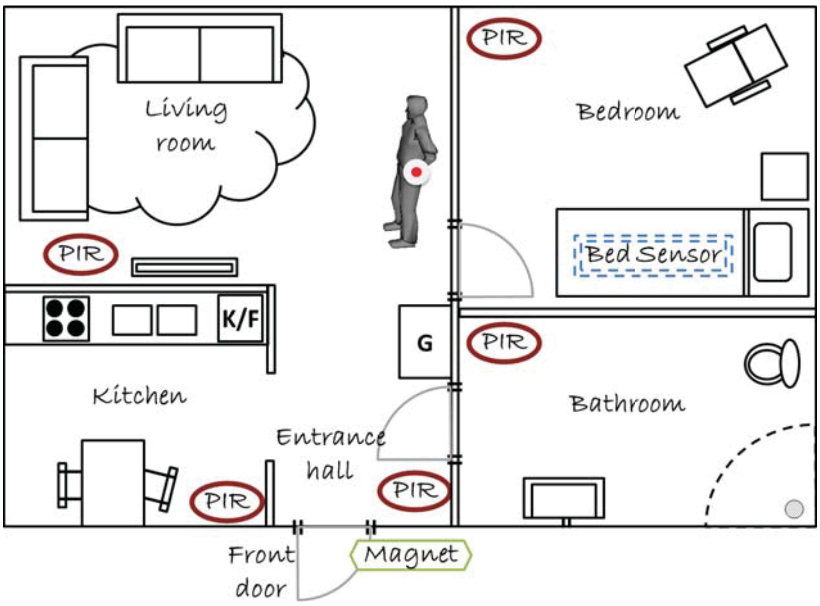
Table 1. Sensors used in the "Trygg om natten" (Safe at night) project [4].

Type	Purpose	Quantity	Output
Passive infrared (PIR)	Capture human motion	3–5	Binary
Quasi-electric film (Emfit)	Capture bed exits	1	Binary
Magnetic	Capture door openings	1	Binary
Inertial sensor	Capture human activity (wearable)	1	Binary
Load cell	Reference for the Emfit sensor	1	24-bit value

Two data collections were discontinued during the project, one due to the illness of the participant and another because the participant no longer had the need for nighttime supervision.

Figure 2 illustrates possible placements of different types of sensors within the home environment. The Emfit Bed Sensor was used in the project as the main method to detect bed exits. One strain-gauge load cell was placed at the top-left corner support of the participant's bed to serve as a reference for the Emfit Bed Sensor. Bed entrances and exits, as well as presence in bed, were derived from the measured weight data. Motion sensors in different locations in the home captured human movement in the bedroom, living room, bathroom and kitchen. A magnet sensor installed in the front door monitored whether the front door was opened or closed. The intent with the magnet sensor in the front door was to capture nighttime supervision visits. Except for the load cell, all of the other sensors transmitted the measured data wirelessly to a low-power, fanless, miniature host computer located under the bed.

Figure 2. Example of a sensor setup for a given home environment. PIR denotes passive infrared motion sensors; the magnet to capture door openings; the bed sensor to detect bed exits; the resident wears a social alarm. A load cell to measure weight is placed on the top-left leg support of the bed.



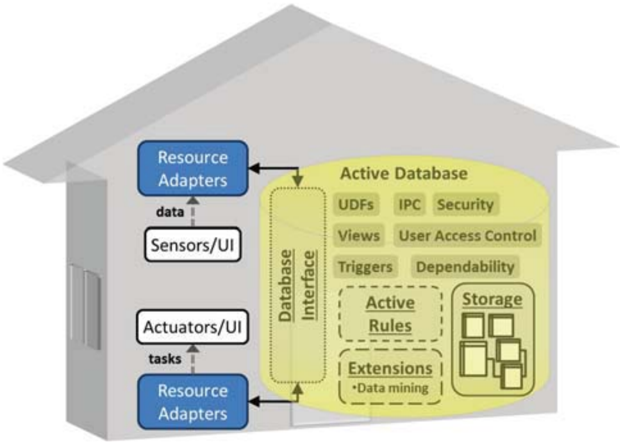
The load cell was connected to an analog-to-digital converter that was connected to a USB port of the host computer. The study was granted ethical approval from the central ethical review board. One of the outcomes of the study was a set of requirements and specifications for AAL services, particularly those related to nighttime caregiving. The dataset collected during the "Trygg om natten" project was used in this work to evaluate the proposed services.

4. Database-Centric Architecture to Support Ambient Assisted Living Systems

This section presents how different DBMSs capabilities fit together in the proposed database-centric system architecture to support smart homes and AAL systems.

Figure 3 summarizes the framework in which the proposed system operates and its main components, described in the next subsections.

Figure 3. The proposed system architecture, including resource adapters and the active database. Notation: UI, user interface; UDFs, user-defined functions; IPC, inter-process communication.



4.1. Resource Adapters

As there is still no adopted standard for communicating with and integrating devices and applications inside smart homes [43], resource adapters have been designed to abstract heterogeneous hardware technologies (sensors and actuators) and software technologies (user interfaces and files) in order to facilitate their integration and interoperation into the system. Resource adapters resemble context widgets and context services [44], but with fewer responsibilities (no data aggregation or peer-to-peer communication). Resource adapters encapsulate the underlying implementation of different communication protocols and abstract resource-specific data formats. Recovery from faults, such as communication disconnections, can also be provided. Resource adapters serve as a gateway between the environment and the DBMS and are implementable in different programming languages, such as C# and Python. Resource adapters stream data acquired by sensors or entered by the user into the database.

They also control actuators and user interfaces in response to commands received from the database. Resource adapters communicate with the database through the database interface (Figure 3), and the DBMS employs inter-process communication mechanisms to communicate with resource adapters. Therefore, resource adapters keep an open connection with the DBMS and subscribe to specific event channels.

4.2. Active Database

The active database (Figure 3) includes several modules that are used as follows.

4.2.1. Storage

The storage module includes the tables for storing sensor data, processed information and meta-data (location, capabilities and configuration) of the hardware and software resources that are present in the environment. Developers implementing resource adapters do not have access to the internal storage model. They are provided instead with a database interface.

4.2.2. Database Interface

The internal database model is protected from direct access by the database interface module that exposes data access (selections) and manipulation (insertions, updates and deletions) using views and UDFs. Listing 1 shows an example of such an approach.

Listing 1. UDF written in PL/pgSQL for inserting converted weight samples into table $weight$.

```
1. CREATE FUNCTION weight_insert( adc_out integer, ts timestamp )
2. RETURNS boolean AS $$
3. DECLARE
4.     voltage_weight_ratio numeric := −41943.0;
5.     weight_sample numeric;
6. BEGIN
7.     weight_sample := adc_out / voltage_weight_ratio;
8.     INSERT INTO weight VALUES ( weight_sample, ts );
9.     RETURN true;
10. END;
11. $$ LANGUAGE PLPGSQL
```

The UDF named $weight\_insert$ abstracts the insertion into table $weight$ and is also used to process the input parameters. The UDF $weight\_insert$ receives two parameters, the output of the analog-to-digital converter (adc_out) and timestamp (ts). In Listing 1, Line 7, the voltage-to-weight ratio ($voltage\_weight\_ratio$) variable is used to convert the readout value (adc_out) to weight ($weight\_sample$), which is later inserted into table $weight$. Such an approach facilitates changes in the logic, such as in the voltage to weight conversion, because it is performed on the fly and does not require modifications or recompilations of resource adapters.

To notify resource adapters about data changes or events, the active database makes use of built-in mechanisms in PostgreSQL for inter-process communication (NOTIFY and LISTEN commands), and this prevents resource adapters from periodically querying (polling) the database.

4.2.3. Active Rules

The reactive behavior in the system is supported by the active rules module. In conjunction with sensors and actuators, active rules implemented as database triggers (Listing 2) can monitor and react to events happening in the environment.

Listing 2. A database trigger monitors when a sequential sample identifier ($sample\_id$) of a first in, first out (FIFO)-type of table ($weight\_fifo$) wraps around to execute an action ($check\_presence\_absence$).

```
1. CREATE TRIGGER weight_fifo_after_insert
2.         AFTER INSERT
3.         ON weight_fifo
4.         FOR EACH ROW
5.         WHEN( NEW.sample_id == 40 )
6.         EXECUTE PROCEDURE check_presence_absence();
```

In Listing 2, the ECA rule represented by the trigger $weight\_fifo\_after\_insert$ is associated with the table $weight\_fifo$ and fires after table insertion events. If the condition specified by the Boolean expression in Listing 2 Line 5 is satisfied, the action—$check\_presence\_absence$—is executed. Because the analog-to-digital samples the load cell at 80 Hz, the trigger fires every half second or every 40th insertion and is intended to detect bed entrances and exits.

4.2.4. Database Extensions

Active rules invoke actions that can be functions added by database extensions, such as MADlib [36], or can be user defined. These functions implement both short-term and long-term types of services. Short-term services are those that respond to simple events, such as generating an alarm indicating a bed exit. Long-term services are defined as services requiring datasets collected over a longer period of time and the analysis of patterns in such data, for example, to gain knowledge about preferences or to detect abnormal behaviors [45]. Because sensitive data are involved in the data processing, implementing the methods for such analysis into the DBMS itself avoids data movement and leads to better performance and security.

4.2.5. Security

Table 2 presents possible access privileges according to different roles in the system (similarly to [46]). The owner can grant or revoke the access privileges of other system users. Software developers creating resource adapters are granted execute permission on specific UDFs within the database interface.

Table 2. Access privileges according to different roles.

Role	**Access Level**			
	View	**Add**	**Modify**	**Administer**
Owner	X	X	X	X
Family	X	X	X	X
Healthcare	X	X	X	
Other users				
Devices		X		

5. Experimental Results: In-Database Services Supporting AAL Systems

Three distinct AAL services for home-based health monitoring, inspired by the "Trygg om natten" project (Section 3), are presented and implemented following the proposed architecture.

To accommodate the proposed architecture, a database server was configured in a computer running CentOS 6.4 with PostgreSQL (version 9.2.3) and the MADlib [36] library extension. To implement the proposed services, additional tables were created to store temporary and derived data, such as descriptive statistics and transition matrices. A separate computer running MS Windows 7 hosted resource adapters (implemented in C#) that read the measurements from the "Trygg om natten" dataset files to the corresponding database. The dataset from a single care beneficiary, who was an active man, living alone in his own apartment and receiving daytime home care services and nighttime supervision, was selected to present the implementation results.

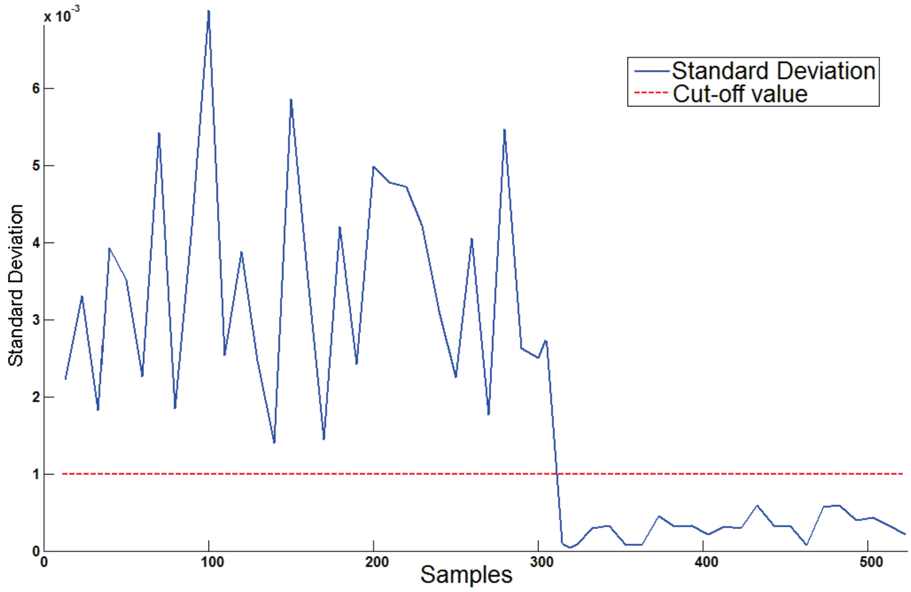
5.1. Detection of Bed Presence and Absence

A service to detect presence in bed can enable the night patrol team to remotely check if individuals are in bed, so as not to disturb their sleep. Voluntary and involuntary body movements create disturbances in the load cell signal that are not present when the bed is unoccupied or is loaded with static weight. Figure 4 presents the standard deviation of a weight signal measured by a load-cell sensor in the moments before the person left the bed. By analyzing the measured weight and its standard deviation, a method to detect the presence or absence of a person in bed can be implemented as an active rule (trigger) that monitors the table in which the measured weight is stored.

The active rule triggers every half second and invokes a UDF that checks for bed exits and entrances. The condition (Equation (1)) for the detection consists of checking intervals in which the median (m_w) and the standard deviation (σ_w) of the weight signal are greater than the respective estimated thresholds for the mean value (O_{m_w}) and standard deviation (O_{σ_w}).

$$Presence = ((\sigma_w \geq O_{\sigma_w}) AND (m_w \geq O_{m_w})) \tag{1}$$

Figure 4. A cut-off value can separate the standard deviation of the measured weight signal into in-bed signals and out-of-bed signals.



The mean value and standard deviation of the weight signal are calculated with a moving window with the last 40 inserted weight samples (approximately half a second or half of the signal sampling rate, which was 80 Hz). Smaller window sizes can lead to high granularity that makes it difficult to find the separating threshold, and larger window sizes can delay the detection of bed entrances and exits.

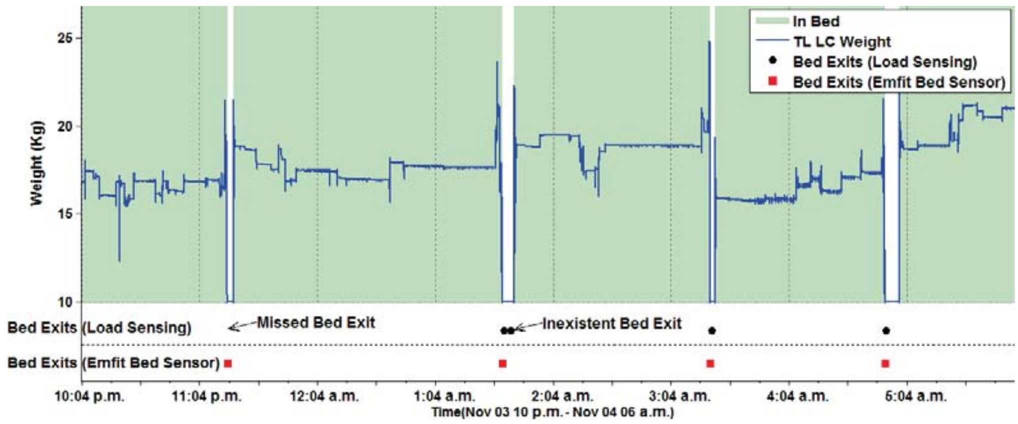
A method for finding a threshold in a signal (*i.e.*, binarizing) is the Otsu algorithm [47], which maximizes the between-cluster distance when dividing the distribution of values into two clusters, for example, the presence and absence clusters. For each individual, corresponding thresholds have been calculated.

For the selected individual, 27 bed presences and 16 bed absences were detected by the active rule based on measured weight. To identify true and false positives, the dataset containing load cell signals was manually labeled and served as a baseline for comparison.

All bed presence and absence detections were validated as true positives. Bed absence detections outnumbered bed presence detections, because on many occasions, the individual left the bed after the sensors became inactive at 6 a.m.

The proposed approach to detect bed exits and entrances also detected more bed-exit events than the bed-exit detection provided by the Emfit Bed Sensor. Figure 5 presents one missed and one nonexistent bed exit using the Emfit Bed Sensor. For the same individual, the Emfit Bed Sensor missed approximately 60% of all bed exits. Such a mismatch might be caused by the antidecubitus mattress that the individual was using to prevent and treat pressure sores.

Figure 5. Bed entrances and exits are accurately detected by the active rule, while the bed-exit detection provided by the Emfit Bed Sensor misses bed exits or generates nonexistent bed exits. Because the sensors were active from 10 p.m. until 6 a.m., it was not possible to detect when the individual went to bed or when he left. TL LC denotes top-left load cell.



The overall approach avoids raw load cell data, which exposes private and sensitive information, from being transferred and processed outside of the DBMS. In this system, several resource adapters can subscribe to the service and are notified when bed entrances and exits are detected.

5.2. Common Event Transitions during the Night

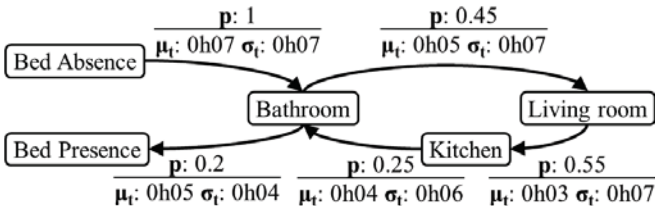
The purpose of this service is to enable the detection of anomalies by discovering simple associations between presence detections in the bathroom, living room, kitchen, entrance hall and bed. Strong associations indicate common room transitions and room activity, and deviations from such associations can enable the detection of anomalies.

A method for finding such expected patterns in sequences of events (*i.e.*, sequential data mining [48]) is by estimating the probability $p(e_y|e_x)$ of one event e_x being followed by another type of event e_y (similar to [49]). By considering only the previous detected event, a transition matrix can be computed online for each individual using an active rule. Each element in the transition matrix P contains the probability of event e_i being followed by event e_j, and this is denoted as $P_{ij}(e_j|e_i)$, which is also referred to as the confidence in association rules [50]. The transition matrix can be visualized as a graph by plotting associations over a certain confidence threshold.

An active rule monitors incoming events from all sensors (Table 1 in Section 3) and updates the transition matrix table, which describes the transition probability of events happening during the night. The computation of statistics, such as the mean and standard deviation of the transition time between two events, is also triggered by the rule. Bed-exit events generated by the previously proposed active rule were used due to the higher accuracy than bed-exit events detected by the Emfit Bed Sensor (Figure 5 in Section 5.1).

Figure 6 presents likely transitions of events in the home environment of the selected subject. An observation from the figure is that when the observed individual leaves the bed, the most likely event is a visit to the bathroom. Such a transition takes an average of 7 min with a standard deviation of 7 min.

Figure 6. Transition probabilities (p) of events for a confidence threshold of 0.2. Mean (μ_t) and standard deviation (σ_t) of the transition time (normally distributed).



The knowledge provided by the transition matrix can be used to detect anomalies during future nights. Anomaly detection mechanisms can also be implemented with active rules. Because health-related conditions evolve over time and because health changes might not be evident in the short-term, the amount of stored data to be processed increases by a large amount every day. Therefore, in-database sequential data mining avoids transferring stored long-term data to external data analysis tools to update transition probabilities.

5.3. Modeling of Early Night Behavior Using Decision Trees

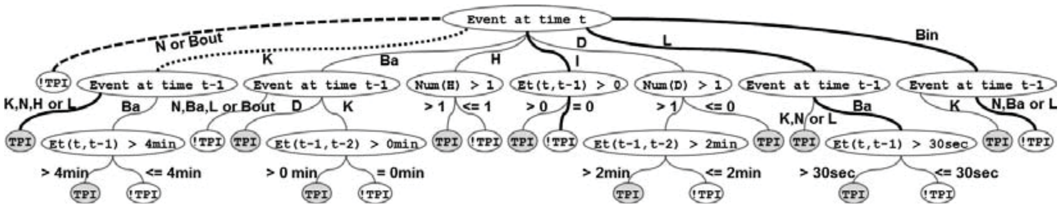
Another way to model transitions is with a service that models typical sensor triggering transitions over a certain time span during the night. Such a service could help to discover changing trends in the level of independence of the individual being monitored.

For this service, a decision tree using the C4.5 implementation in MADlib was trained with data from a single individual to discriminate between the time period from 10 p.m. to midnight (TPI denotes Time Period I) and the period from midnight to 6 a.m. (!TPI denotes not Time Period I). The training data consisted of 15 features that were computed for each observation by processing a sliding window with a width of 20 min over the 14 days of collected data. No feature selection has been applied due to the rather low number of features used. This process resulted in training data with approximately 300 observations.

The events in the collected data are denoted as bathroom (Ba), kitchen (K), hallway (H), and living room (L), and each event represents activity in a certain room. Other events include inactivity registered from the wearable inertial sensor (I), door openings (D) and bed entrances and exits (Bin and Bout, respectively), which are computed using the proposed active rule for detecting bed entrances and exits. The features used in the calculations are the type of sensors that fired in the last four events and are denoted as $event\ at\ time\ t$. The transition time between the four last events for the window is computed as $Et(t, t-k)$, where k is the number of previous events. The number of each type of event and the lack of events (denoted by N) in a window are also computed.

The generated decision tree for the same individual is shown in Figure 7. Thick edges represent where the majority of data points were concentrated. The tree hierarchy reflects variable importance. Figure 7 illustrates (by hierarchy and bold edges) that the last occurring event is important. An example of this is the lack of events (N) in a window, and the presence or absence in bed were the most informative, while discriminating between TPI and !TPI.

Figure 7. A decision tree distinguishes different time periods during the night. Notation: Ba, bathroom; K, kitchen; H, hallway; L, living room; I, inactivity; D, door openings; Bin, bed entrances; Bout, bed exit; N, lack of events. TPI, Time Period I; !TPI, not Time Period I.



One interpretation of the model is illustrated by the dashed edge from the root node. This link revealed that the individual was more likely to be active during the modeled time period TPI than the rest of the night (!TPI). Moreover, the dotted edge shows that the individual was active in the kitchen, hallway and living room during TPI. In order to validate the decision tree model, a 10-fold cross-validation was performed, and a mean accuracy of 81% was achieved. The accuracy shows that, despite the complexity of human behavior, the model is able to explain key features of the early night that could be used when analyzing deviations in long-term trends.

Similar to updating transition probabilities, in-database retraining of decision trees avoids data movement, and this promotes privacy. The processing time to create or update a probability matrix and to train a decision tree can be negligible for a small dataset, but quite significant for a dataset containing months of stored data.

6. Conclusions

This work has shown how different capabilities of DBMSs (e.g., triggers, user-defined functions and existing database extensions for in-database analytics) fit together in a database-centric architecture intended to support the development of home-based healthcare applications. The proposed software architecture represents an alternative to existing platforms supporting the development of smart homes and AAL systems.

DBMSs are mature and dependable technologies and provide mechanisms that can address the processing, security, privacy and personalization requirements of smart homes and AAL systems. These mechanisms, however, are not fully exploited in current smart home and AAL infrastructures.

In the system design presented here, database triggers are used to detect and respond to events taking place in the home environment. The event-driven architecture provided by active databases makes it possible to implement an in-database service to monitor an individual's presence or absence in bed, as well as to discover common room transitions and deviations during the night.

User-defined functions are exploited to perform in-database processing, *i.e.*, the domain logic is integrated into the DBMS itself. A database interface created with user-defined functions and views protects the internal database model against direct access. Existing DBMS extensions for data mining, such as MADlib, enable the development of services to model early night behaviors. Database roles can promote security by controlling user access to database resources, such as tables that contain private data.

The proposed and implemented AAL services, which have been validated with a dataset collected in real homes, reside within the database and avoid exporting sensitive data to external data analysis tools.

Therefore, active in-database processing avoids data movement from the DBMS to external applications. Such an approach can lead to improved performance, security and privacy while still benefiting from the on the fly management capabilities of DBMSs. Centralizing the domain logic into the DBMSs reduces code duplication, promotes code reuse and facilitates system maintenance and adaptability as the environment and individual needs evolve.

Although these are important system properties supported by the presented database-centric platform, the proposed approach requires developers to have knowledge of relational DBMSs, their features, such as for security, and procedural programming languages, such as PL/pgSQL and PL/Python [31], that extend the SQL standard.

Even though resource adapters keep an open connection with the DBMS to subscribe to notifications from the database, this is not a limitation, because resource adapters, for example running on battery powered devices, can connect and disconnect to the DBMS when necessary.

Up to now, besides the results reported in this work and in [1], the presented database-centric architecture has been used to develop a smart bedroom [34] and to integrate an autonomous mobile robot to such a smart environment [51]. Future work encompasses developing, deploying and evaluating smart environments that encompass a whole home environment and that provide actuation services to improve comfort, independence and medical care using the presented database-centric platform. To facilitate interoperation, semantic description for the environment, devices and user activities will also be investigated.

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Author Contributions

Wagner O. de Morais proposed, designed and implemented the database-centric platform to support smart environments and AAL systems. All authors participated in the design of the AAL services used to evaluate the proposed architecture. Wagner O. de Morais wrote the main paper, whereas, Jens Lundström assembled the dataset used in the experiments and wrote about the selected data mining methods. Nicholas Wickström provided revisions and critical feedback. All authors contributed extensively in the discussion of the proposed approach. All of the authors read and approved the final manuscript.

Conflicts of Interest

The authors declare no conflicts of interest.

References

1. De Morais, W.O.; Lundström, J.; Wickström, N. A Database-Centric Architecture for Home-Based Health Monitoring. In *Ambient Assisted Living and Active Aging*; Springer: Berlin, Germany, 2013; pp. 26–34.
2. Tarricone, R.; Tsouros, A.D. *Home Care in Europe: The Solid Facts*; WHO Regional Office: Copenhagen, Denmark, 2008.
3. Malmberg, B.; Ernsth, M.; Larsson, B.; Zarit, S.H. Angels of the night: Evening and night patrols for homebound elders in Sweden. *Gerontologist* **2003**, *43*, 761–765.
4. Thörner, R.; Persson, M.; Eriksson, H.; Isaksson, A.; Lundström, J. Trygg om natten. In *Technical Report, Centre for Health Technology in Halland*; Halmstad University: Halmstad, Sweden, 2011. (In Swedish)
5. United Nations, Department of Economic and Social Affairs, Population Division. World Population Prospects: The 2012 Revision, Key Findings and Advance Tables (Working Paper No. ESA/P/WP.227). Available online: http://esa.un.org/wpp/index.htm (accessed on 16 December 2013).
6. Berleen, G.; Watson, G. *A Healthier Elderly Population in Sweden!*; Swedish National Institute of Public Health: Östersund, Sweden, 2004.
7. Kovner, C.T.; Mezey, M.; Harrington, C. Who cares for older adults? Workforce implications of an aging society. *Health Affairs* **2002**, *21*, 78–89.
8. Arber, S.; Venn, S. Caregiving at night: Understanding the impact on carers. *J. Aging Stud.* **2011**, *25*, 155–165.
9. Society, R. *Digital Healthcare: The Impact of Information and Communication Technologies on Health and Healthcare*; Technical Report; Royal Society: London, UK, 2006.
10. Kubitschke, L.; Cullen, K. *ICT & Aging-European Study on Users, Markets and Technologies*; Technical Report; Empirica and WRC on Behalf of the European Commission, Directorate General for Information Society and Media: Bonn, Germany, 2010.
11. Mozer, M.C. The neural network house: An environment hat adapts to its inhabitants. In Proceedings of the AAAI Spring Symposium Intelligent Environments, Menlo Park, CA, USA, 23–25 March 1998; pp. 110–114.
12. Das, S.K.; Cook, D.J.; Battacharya, A.; Heierman, E.O., III; Lin, T.Y. The role of prediction algorithms in the MavHome smart home architecture. *IEEE Wirel. Commun.* **2002**, *9*, 77–84.
13. Dishman, E. Inventing wellness systems for aging in place. *Computer* **2004**, *37*, 34–41.
14. Van den Broek, G.; Cavallo, F.; Wehrmann, C. *AALIANCE Ambient Assisted Living Roadmap*; IOS Press: Berlin, Germany, 2010; Volume 6.
15. Kang, H.G.; Mahoney, D.F.; Hoenig, H.; Hirth, V.A.; Bonato, P.; Hajjar, I.; Lipsitz, L.A. *In Situ* Monitoring of Health in Older Adults: Technologies and Issues. *J. Am. Geriatr. Soc.* **2010**, *58*, 1579–1586.
16. Demiris, G.; Hensel, B.K. Technologies for an aging society: A systematic review of "smart home" applications. *Yearb. Med. Inform.* **2008**, *3*, 33–40.

17. Paré, G.; Jaana, M.; Sicotte, C. Systematic review of home telemonitoring for chronic diseases: The evidence base. *J. Am. Med. Inform. Assoc.* **2007**, *14*, 269–277.
18. Rashidi, P.; Cook, D.J. Mining and monitoring patterns of daily routines for assisted living in real world settings. In Proceedings of the 1st ACM International Health Informatics Symposium, Arlington, VA, USA, 11–12 November 2010; pp. 336–345.
19. Eckl, R.; MacWilliams, A. Smart Home Challenges and Approaches to Solve Them: A Practical Industrial Perspective. In *Intelligent Interactive Assistance and Mobile Multimedia Computing*; Springer: Berlin, Germany, 2009; pp. 119–130.
20. Demiris, G.; Thompson, H.J.; Reeder, B.; Wilamowska, K.; Zaslavsky, O. Using informatics to capture older adults' wellness. *Int. J. Med. Inform.* **2011**, *82*, e232–e241.
21. The Economist. In *New Rules for Big Data*; The Economist Newspaper Limited: London, UK, 2010; Available online: http://www.economist.com/node/15557487 (accessed on 10 December 2013).
22. Chan, M.; Estève, D.; Escriba, C.; Campo, E. A review of smart homes—Present state and future challenges. *Comput. Methods Programs Biomed.* **2008**, *91*, 55–81.
23. Rashidi, P.; Mihailidis, A. A Survey on Ambient-Assisted Living Tools for Older Adults. *IEEE J. Biomed. Health Inform.* **2013**, *17*, 579–590.
24. Fagerberg, G.; Kung, A.; Wichert, R.; Tazari, M.R.; Jean-Bart, B.; Bauer, G.; Zimmermann, G.; Furfari, F.; Potort, F.; Chessa, S.; *et al*. Platforms for AAL Applications. In *Smart Sensing and Context*; Springer: Berlin, Germany, 2010; pp. 177–201.
25. Augusto, J.C.; Callaghan, V.; Cook, D.; Kameas, A.; Satoh, I.; Saba, T.; Chorianopoulos, K.; Howard, N.; Cambria, E.; Gupta, V. Intelligent Environments: A manifesto. *Hum. Centr. Comput. Inf. Sci.* **2013**, *3*, 1–18.
26. Becker, M. Assisted Living Systems-Models, Architectures and Engineering Approaches. In *Software Architecture Trends and Promising Technology for Ambient Assisted Living Systems*; Karshmer, A.I., Nehmer, J., Raffler, H., Tröster, G., Eds.; Schloss Dagstuhl–Leibniz-Zentrum fuer Informatik, Germany: Dagstuhl, Germany, 2008.
27. Helal, S.; Mann, W.; El-Zabadani, H.; King, J.; Kaddoura, Y.; Jansen, E. The gator tech smart house: A programmable pervasive space. *Computer* **2005**, *38*, 50–60.
28. Fides-Valero, Á.; Freddi, M.; Furfari, F.; Tazari, M.R. The PERSONA Framework for Supporting Context-Awareness in Open Distributed Systems. In *Ambient Intelligence*; Springer: Berlin, Germany, 2008; pp. 91–108.
29. Klein, M.; Schmidt, A.; Lauer, R. Ontology-centred design of an ambient middleware for assisted living: The case of soprano. Towards Ambient Intelligence: Methods for Cooperating Ensembles in Ubiquitous Environments (AIM-CU). In Proceedings of the 30th Annual German Conference on Artificial Intelligence (KI 2007), Osnabrück, Germany, 10–13 September 2007.
30. Tazari, M.R.; Furfari, F.; Valero, Á.F.; Hanke, S.; Höftberger, O.; Kehagias, D.; Mosmondor, M.; Wichert, R.; Wolf, P. The universAAL Reference Model for AAL. In *Handbook on Ambient Assisted Living: Technology for Healthcare, Rehabilitation and Well-Being*; IOS Press: Amsterdam, The Netherlands, 2012; Volume 11, pp. 610–625.

31. The PostgreSQL Global Development Group, PostgreSQL 9.3.3 Documentation. Available online: http://www.postgresql.org/docs/9.3/static/index.html (accessed on 6 January 2014).
32. Silberschatz, A.; Korth, H.F.; Sudarshan, S. *Database System Concepts*; McGraw-Hill: New York, NY, USA, 2011; Volume 6.
33. Paton, N.W.; Díaz, O. Active database systems. *ACM Comput. Surv. (CSUR)* **1999**, *31*, 63–103.
34. De Morais, W.O.; Wickström, N. A "Smart Bedroom" as an Active Database System. In Proceedings of the IEEE 9th International Conference on Intelligent Environments (IE), Athens, Greece, 18–19 July 2013; pp. 250–253.
35. The PostGIS Development Group, PostGIS 2.1.2dev Manual. Available online: http://postgis.net/docs/manual-2.1/ (accessed on 6 January 2014).
36. Hellerstein, J.M.; Ré, C.; Schoppmann, F.; Wang, D.Z.; Fratkin, E.; Gorajek, A.; Ng, K.S.; Welton, C.; Feng, X.; Li, K.; *et al.* The MADlib analytics library: Or MAD skills, the SQL. *Proc. VLDB Endow.* **2012**, *5*, 1700–1711.
37. Cohen, J.; Dolan, B.; Dunlap, M.; Hellerstein, J.M.; Welton, C. MAD skills: New analysis practices for big data. *Proc. VLDB Endow.* **2009**, *2*, 1481–1492.
38. Ordonez, C. Data set preprocessing and transformation in a database system. *Intell. Data Anal.* **2011**, *15*, 613—631.
39. Sarawagi, S.; Thomas, S.; Agrawal, R. Integrating association rule mining with relational database systems: Alternatives and implications. *Data Min. Knowl. Discov.* **2000**, *4*, 89–125.
40. Ordonez, C. Integrating K-means clustering with a relational DBMS using SQL. *IEEE Trans. Knowl. Data Eng.* **2006**, *18*, 188–201.
41. Ordonez, C. Building statistical models and scoring with UDFs. In Proceedings of the 2007 ACM SIGMOD International Conference on Management of Data, Beijing, China, 12–14 June 2007; pp. 1005–1016.
42. Ordonez, C. Statistical model computation with UDFs. *IEEE Trans. Knowl. Data Eng.* **2010**, *22*, 1752–1765.
43. Kim, J.E.; Boulos, G.; Yackovich, J.; Barth, T.; Beckel, C.; Mosse, D. Seamless Integration of Heterogeneous Devices and Access Control in Smart Homes. In Proceedings of the 8th International Conference on Intelligent Environments (IE), Guanajuato, Mexico, 26–29 June 2012; pp. 206–213.
44. Dey, A.K.; Abowd, G.D.; Salber, D. A conceptual framework and a toolkit for supporting the rapid prototyping of context-aware applications. *Hum. Comput. Interact.* **2001**, *16*, 97–166.
45. Aztiria, A.; Augusto, J.C.; Basagoiti, R.; Izaguirre, A. Accurate Temporal Relationships in Sequences of User Behaviours in Intelligent Environments. In *Ambient Intelligence and Future Trends-International Symposium on Ambient Intelligence (ISAmI 2010)*; Augusto, J., Corchado, J., Novais, P., Analide, C., Eds.; Springer-Berlin: Heidelberg, Germany, 2010; Volume 72, pp. 19–27.
46. Señor, I.C.; Alemán, J.L.F.; Toval, A. Personal Health Records: New Means to Safely Handle Health Data? *Computer* **2012**, *45*, 27–33.
47. Otsu, N. A Threshold Selection Method from Gray-Level Histograms. *IEEE Trans. Syst. Man Cybernet.* **1979**, *9*, 62–66.

48. Agrawal, R.; Srikant, R. Mining sequential patterns. In Proceedings of the Eleventh International Conference on Data Engineering, Taipei, Taiwan, 6–10 March 1995; pp. 3–14.
49. Guralnik, V.; Haigh, K.Z. Learning Models of Human Behaviour with Sequential Patterns. In Proceedings of the AAAI-02 Workshop "Automation as Caregiver", Edmonton, Canada, 29 July 2002; pp. 24–30.
50. Agrawal, R.; Imielinski, T.; Swami, A. Mining association rules between sets of items in large databases. *ACM SIGMOD Record* **1993**, *22*, 207–216.
51. De Morais, W.O.; Mayr, M.; Wickström, N.; Philippsen, R. Ambient Intelligence and Robotics: Complementing one another to support Ambient Assisted Living. Intelligent Robot Assistants IRAS 2014. In Proceedings of the Workshop and Tutorials IAS-13, 13th International Conference on Intelligent Autonomous Systems, Padova, Italy, 15–19 July 2014.

Appendix E

Paper V - Evaluation of Cross-Platform Scalability of a Database-centric Architecture for Smart Home Environments

Evaluation of Extensibility, Portability, and Scalability in a Database-centric System Architecture for Smart Home Environments

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Abstract. Advances in database technology allow modern database systems to serve as a platform for the development, deployment and management of smart home environments and ambient assisted living systems. This work investigates non-functional issues of a database-centric system architecture for smart home environments when: (1) extending the system with new functionalities other than data storage, such as online reactive behaviors and advanced processing of longitudinal information, (2) porting the whole system to different operating systems on distinct hardware platforms, and (3) scaling the system by incrementally adding new instances of a given functionality. The outcome of the evaluation is demonstrated, and analyzed, for three test functionalities on three heterogeneous computing platforms. As a contribution, this work can help developers in identifying which architectural components in the database-centric system architecture may become performance bottlenecks when extending, porting and scaling the system.

Keywords. database-centric architecture, smart environments, ambient assisted living, quality attributes, scalability

1. Introduction

The inherent and evolving diversity (e.g. users, needs and technologies) of smart environments still challenges the development of smart homes and ambient assisted living (AAL) systems. People have unique needs and preferences that change over time and these can lead to *extensibility* and *scalability* issues when modifying systems. To address peoples needs, heterogeneous technologies are employed. These technologies are provided by different vendors, and operate and communicate using different standards and protocols. *Integratability* and *interoperability* issues come as a result of these, as well as data heterogeneity. Homes also differ and people are very concerned about technologies that can monitor or take control of several aspects of their lives. These raise *privacy* and *security* issues. Some individuals might rely on different technologies to cope with different kinds of impairments and limitations, and thus technology's *dependability* is

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Figure 1. The model captures the evolving diversity of needs across the life-span. Over time, different technologies are employed to cater to the need of primary users (the individual) and secondary users (relatives, caregivers, and healthcare professionals). Such diversity is in the nature of smart homes and AAL.

imperative. Over time, technology can also assist and benefit other users, such as formal and informal carers, and healthcare professionals. Figure 1 attempts to illustrate such evolving diversity.

Because of the aforementioned reasons, and because no universal selection and arrangement of devices or system configuration will fit every home settings, smart environments must be *extensible* to respond to evolving requirements with *scalable* solutions tailored according to individual needs and settings.

In general, one of the critical issues in the design and development of complex systems, such as smart environments, is its architecture [1]. Successful system architectures organize the elements that constitute the system not only to support functional properties, i.e. the system behavior, but also non-functional critical properties (also known as quality attributes), which affect both system design and run-time behavior [2]. Moreover, an important principle in the development of system architectures for smart environments is to *build to change instead of building to last* [2].

Previously in [3], a database-centric architecture for smart environments is proposed. According to the authors, features of modern database management systems (DBMS) allow a database system to serve as a platform for the development, deployment, and management of smart homes and AAL applications. The practical implication of the proposed approach was investigated with the integration and interoperation of heterogeneous technologies in a "smart bedroom" demonstrator. Later in [4], active in-database processing using machine learning methods was employed not only to support "smart" reactive behavior of smart environments, but also to accommodate privacy and security requirements.

This work concerns the evaluation of non-functional issues in a database-centric architecture when:

1. Extending the system with new features, *i.e.* extensibility;
2. Porting the architecture to different computing platforms, *i.e.* portability;
3. Increasing the load in the system by adding new running instances of a functionality, *i.e.* horizontal scalability.

As contribution, this work provides a method to:

1. Understand how the system and implemented applications behave when ported across different operating systems on different computing hardware;
2. Identify which architectural components are mostly affected when extending, porting and scaling the system.

The remainder of this paper is structured as follows. Related work is presented in Section 2. An overview of the database-centric system architecture for smart environments is given in Section 3. Section 4 describes the methodology for evaluation. Section 5 concerns the experimental system setup and data, while the evaluation results are presented in Section 6. Discussions and conclusions are covered in Section 7.

2. Related Work

Although the development of system architectures, middleware paradigms and platforms for smart homes and AAL systems has been the main topic of a number of research projects [5,6], there is still no broadly adopted method for developing smart environments [7] or accepted metrics for evaluating them [8]. Moreover, given the evolving diversity of smart environment discussed Section 1, it is very unlikely that one single system architecture will perfectly fit the all requirements and environments [9]. As a consequence, comparing and selecting a suitable architecture or platform for smart environments is difficult. Memon *et al.* recently identified that AAL research has not focused and addressed sufficiently non-functional properties, such as interoperability, usability, reliability, data accuracy, security, and privacy [6].

Design principles, such as economy of mechanisms, client simplicity, and levels of indirection, have been employed to address portability, extensibility and robustness requirements in a middleware for interactive workspaces called iROS [10]. The authors concluded that a centralized design and implementation facilitated extensibility, portability, maintainability, scalability and robustness. Although the authors reported that the resulting scalability was acceptable for that class of smart environments, no information is provided if the scalability tests included different operating systems or if extensibility created any scalability issues.

An evaluation of six well-known AAL platforms, such as universAAL [11], according to different quality attributes (reliability, security, maintainability, efficiency and safety) is reported in [12]. To evaluate the different platforms, the authors conducted a survey using semi-structured interviews. The number of interviewees was not mentioned. The authors observed that there are considerable differences among AAL platforms and several of the above quality attributes are only partially addressed or not addressed at all.

To what concerns AAL applications, the organizers of the “Evaluating AAL Systems through Competitive Benchmarking” (EvALL) competition selected five metrics split into two categories, named hard and soft metrics [13]. Hard metrics, which can be objective measured or quantified, include accuracy and availability. Soft metrics include installation complexity, user acceptance and integrability.

3. Database-centric System Architecture for Smart Environments-An Overview

Modern database systems can serve as a platform for smart home environments and AAL [3]. In the proposed database-centric architecture, the domain logic is contained within the DBMS, which becomes the most important architectural element in the system. Associated benefits of such an integrated and centralized approach are improved performance, security, data management, and ease of implementation [3,4]. The programming model of the aforementioned architecture is a collection of independent software components, called resource adapters, which communicate with a central entity, *i.e.*, the DBMS, referred in the architecture as active database. An overview of such integrated architecture is presented in Figure 2. The main architectural components are described in the following subsections.

3.1. Active Database

In the active database, database triggers, user-defined functions (UDFs) and mechanisms for interprocess communication (IPC) are employed to detect and respond to events taking place in the environment. UDFs, IPC mechanisms and database views are used to create a database interface, which offers a clean interface with a set of methods for data access and manipulation (select, insert, update and delete), as well as to notify client applications connected to the active database. Besides of interoperability at the data level, such an approach facilitates the portability of client application across distinct computing platforms because most of functional logic is implemented in the active database. The authors also take advantage of UDFs to perform in-database processing, *i.e.*, the DBMS is extended with the logic to process stored data. This logic may correspond to the semantics of an application or of a method for machine learning. Data security is an outcome of this, because no sensitive information is maintained outside the active database.

3.2. Resource Adapters

The concept of resource adapter was proposed by the authors to abstract and integrate heterogeneous technologies (*e.g.*, sensors, actuators, user interfaces, software libraries) into the system [3]. The main functional aspects of a resource adapter are: 1) stream data acquired by sensors or entered by the user to the active database, or 2) control actua-

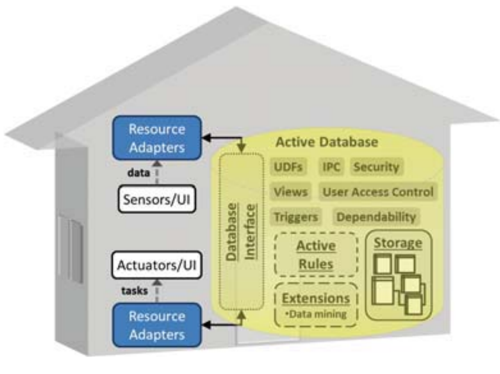

Figure 2. A database-centric architecture has been suggested as a platform for the development of smart environments [3]. Resource adapters and the active database are the two main components in the architecture.

tors or user interfaces in response to commands received from the active database. Resource adapters do not interact directly with the tables in the active database, but using methods provided by the database interface. Such an approach is aligned with the principles of "economy of mechanisms" (*i.e.*, less mechanism to port) and "client simplicity" (*i.e.*, move the complexity to the server) [10], which are strategies for facilitating portability. Resource adapters are responsible for initiating the communication session with the active database and use a hybrid communication model. For streaming or querying data from the active database, resource adapters employ a client-server computing model and intermittent connections with the active database are more common. However, it has been observed that maintaining a continuous connection improves the throughput of resource adapters abstracting sensors that generate data at higher sampling rates (more than 10Hz). A publish-subscribe pattern enables resource adapters to receive notifications from the active database, such as control commands and actions to be executed, and this avoids database polling. A continuous connection with the active database is required to enable this messaging pattern. Each resource adapter has a universally unique identifier (UUID), which also identifies a unique channel used by the active database to publish notifications specific to a resource adapter. The active database also has its own UUID and corresponds to a global channel that all resource adapters are listening to, so the active database can notify all resource adapters more efficiently.

4. Methodology

Figure 3 illustrates the process for evaluating scalability when extending a system with new functionalities. The complete scenario encompasses three related test functionalities exemplifying applications that are typically implemented in smart homes and AAL systems. Functional, physiological and safety monitoring and assistance are the main ap-

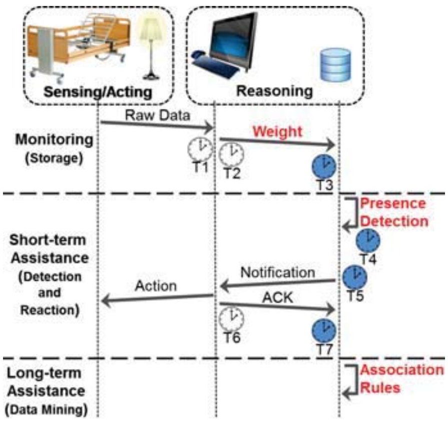

Figure 3. Weight monitoring, bed-exit detection and common event transitions are the selected test functionalities for monitoring, short- and long-term assistance, respectively. The white clocks are timestamps attributed by resource adapters. Blue clocks are timestamps attributed by the active database.

plications of smart homes in healthcare [14]. Storage of long-term health-related data is one of the most important features in these systems. Therefore, monitoring is the first test functionality. As an extension of the first functionality, the other two test functionalities include short- and long-term forms of assistance. Short-term types of assistance include solutions that on-line detect and respond to events. Long-term types of assistance encompasses solutions that require datasets collected over a longer period of time and employ advanced methods for data analysis. The rationale behind the proposed scenario is that:

- Extensibility implies that all three functionalities must be incorporated into the system;
- Portability encompasses the cross-platform capability of the underlying software architecture and the three functionalities, *i.e.*, to run on different computing platforms; and
- Scalability requires an objective evaluation on the overall effect of loading the system with more instances of running functionalities, such as monitoring.

To objectively evaluate scalability, the interaction between different components must be measured for each test functionality on different computing platforms. Ideally, given the test functionality and the system configuration, by gradually adding new instances of the selected functionality, the workload in the system will increase and consequently lead to increased delays in data streaming and processing as well as latencies in responding to events. These are issues that can compromise the reliability of a system. Therefore, to isolate the system components that are affected by the computational workload, the following measures are computed:

Pre-processing Delay ($T2-T1$)**:** time to pre-process the raw sensor reading and make it available for storage.

Storage Delay ($T3-T2$)**:** time required to transmit and store data.

Detection Delay ($T4-T3$)**:** time to process an event of interest.

Detection Latency ($T4-T1$)**:** total time to detect an event of interest.

Notification Delay ($T5-T4$)**:** time to generate a notification for a detect event.

Notification Latency ($T6-T5$)**:** time taken for the notification to reach its destination.

Detection/Notification Latency ($T6-T4$)**:** time from the detection of an event to the reception of the notification for that event.

Reaction Latency ($T6-T1$)**:** is the total reaction time or system response time.

ACK Delay ($T7-T6$)**:** time to acknowledge a notification.

Notification/ACK Latency ($T7-T5$)**:** time taken from the generation of a notification until it is acknowledged.

As a result, the proposed approach can help in identifying which and how many functionalities are supported by a given computing platform configuration, and which architectural components are mostly affected when extending, porting and scaling the system.

Table 1. The selected computing platforms. The high-end computer (Dell Optiplex) is at least two times more powerful than the others.

	Dell Optiplex 7010	**Dell Latitude E7240**	**Raspberry Pi B Rev 2**
CPU	Intel(R) i7-3770	Intel(R) i5-4300U	ARM11
Speed	3.40GHz	1.90GHz	1000 MHz (overclocked)
Cores / Threads	4 / 8	2 / 4	1 / 1
RAM	16 GiB	8 GiB	512 MiB
Storage	500 GiB SSD	125 GiB SSD	4 GiB SDHC Class 10
OS	CentOS Linux 7	MS Windows 7	Raspbian wheezy GNU/Linux 7

5. Experimental System Setup and Data

Three distinct hardware platforms running different operating systems were selected for the evaluation. The configuration of each computer is presented in Table 1.

In [3], a smart bedroom demonstrator has been implemented according to the database-centric architecture. The demonstrator features a smart bed that, among other functionalities, provides weight monitoring. Later in [4], the authors propose an in-database method that on-line detects bed entrances and exits. Another in-database method reported by the authors employs association rules to detect common room transitions and anomalies during the night. Therefore, weight monitoring, bed-exit detection and common event transitions have been selected as the three test functionalities composing the experiment (Figure 3).

Using the smart bed, a dataset containing 75 seconds of weight data was collected and is used in this experiment to implement the three test functionalities described in Section 4. A subject participating in the data collection was instructed to lie-down in bed 15 seconds after the measurement started, and to leave the bed after 45 seconds. A resource adapter was created to simulate a weight measurement system installed in the smart bed. The resource adapter reads samples from the dataset file and streams the data to the active database at the same sampling rate of the real system, *i.e.*, 80Hz. This constitutes the weight monitoring functionality. For the reactive short-term form of assistance, a threshold-crossing mechanism was used to detect bed entrances and exits. Association rules to detect common event transitions were used to implement a long-term type of assistance. Particular details of these two methods are found in [4]. An overview of the amount of computation of each functionality is given as follows:

Weight monitoring: generates 80 inserts in the active database per second.

Bed-exit detection: includes the workload of the weight monitoring and generates 2 trigger firing every half second. The triggers UDF computes the mean value and the standard deviation of the last 80 inserted samples to detect bed exits and entrances. Detected events are inserted into a separate table. Each new event generates an IPC notification to resource adapters interested in that type of event.

Common event transitions: includes the workload of the weight monitoring and bed-exit detection functionalities. A trigger fires on every bed entrance or exits and updates the tables for computing the association rules, such as transition matrix, support metric, confidence metric tables.

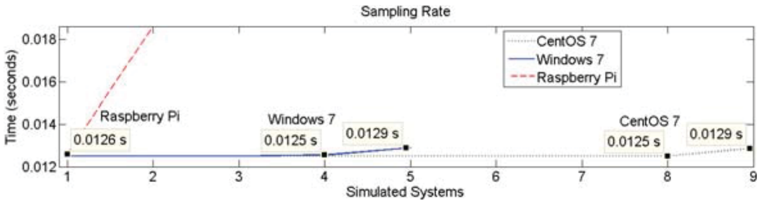

Figure 4. Data tips in the graph show the sampling rate for one or more simulated systems in different computing systems. System should maintain a constant sampling rate. Hence, the graph helps in identifying the maximum number of simulated systems executing in parallel in each computing platform.

6. Evaluation Results

Each selected computing platform configuration was tested for each test functionality, and hosted both the simulated systems and the active database. For each test functionality (described in subsection 5 and illustrated in Figure 3), a corresponding in-database method was implemented in PostgreSQL [15] using PL/pgSQL. PostgreSQL is well known by its extensibility features, which enable new added functions and data types to perform as they were native objects. Moreover, extensions are added and modified "on the fly", which is a required capability for smart environments.

Because PostgreSQL [15] is a cross-platform DBMS, portability was not an issue. PostgreSQL's binary installation packages are available for CentOS and MS Windows 7. For the Raspberry Pi, it was necessary to build and install PostgreSQL using its source code distribution. In each system setup, PostgreSQL was configured for security communication and improved performance. The resource adapter was implemented in Python, and as a result, the same code runs on the selected operating systems. Because the domain logic resides in the active database and data manipulation is provided by the database interface, these facilitated the portability of the resource adapter and the test functionalities.

To evaluate the scalability of each test functionality in the different computation platforms, the simulation started with the execution of one instance of the simulated system. After this first execution, two instances where executed at the same time. The execution of multiple simulated systems was gradually increased until the system workload affected the execution (resource starvation) of involved components. A process manager was implemented to synchronize the execution of the simulated systems. In order to achieve more accurate results, the process was repeated 20 times, and the average values of the measures are used.

A system will not scale if not able to maintain the average sampling rate of 80Hz (one sample every 0.125 seconds). This time different will accumulate over time and will result into delays and latencies in different system modules. Figure 4 illustrates the effect of increased system workload on the simulated sampling rate. The Raspberry Pi is able to host only one simulated weight monitoring system. The Raspberry Pi might be suitable for scenarios in which sensors generate data at very low sampling rate (less than 1Hz), for example, motion sensors. Windows can support up to four simulated systems executing simultaneously with the active database. CentOS supports up to eight systems.

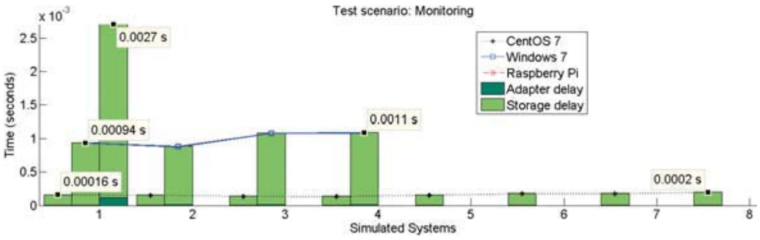

Figure 5. Lines in the graph indicate the total storage latency (pre-processing delay plus the storage delay).

Figure 5 illustrates the evaluation results for the monitoring test functionality. A common observed effect was an increase in storage delay, especially in the Raspberry Pi system. Compared with the high-end computer running CentOS, the storage delay in the Raspberry Pi is 16 times bigger, and in Windows 7 is twice as big.

An increased storage delay is also present in the Windows-based system as well as in the short-term reaction test functionality. In that functionality, the Windows-based system also presented an increased notification delay as more systems were executed concurrently (Figure 6). For the CentOS-based machine, the total reaction time plus notification acknowledgement is less than a millisecond. Hence, the overhead of monitoring and reacting through the active database and using the DBMS as interprocess communication mechanism is even less than that.

Figure 7 presents the evaluation results for all test functionalities for the computer with highest computing capabilities. All measures are mostly constant for the different experiments, except for the notification latency when the advances data processing functionality is simulated. This means that the communication between the active database and the resource adapters can be affected by the created workload for this particular case.

The experimental results are summarized in in Table 2. An overall observation is that architectural components abstracting hardware and software technologies are the most affected by increased system computational workload. Interestingly, the number of supported systems in a given computing platform, at least for the monitoring functionality, is

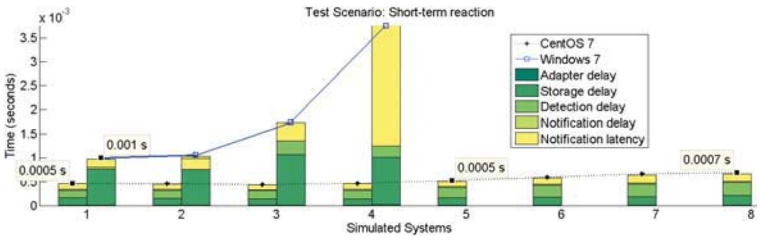

Figure 6. Effect of the reactive behavior for the computers running Windows 7 and CentOS. Lines indicate the total reaction storage latency (the sum of all delays since the sensor reading until a response is provided). The high-end computer running CentOS can maintain the same average performance up to 5 simultaneous systems. Data tips indicate the total reaction time plus notification acknowledgement.

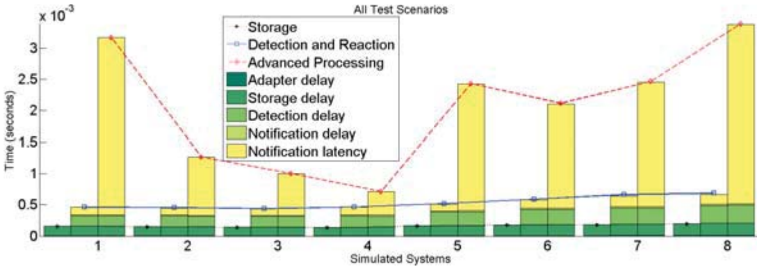

Figure 7. The evaluation of all test functionalities for the high-end computer. Lines indicate the response time or reaction latency (the sum of all delays since the sensor reading until a response is provided). The notification latency is clearly affected by the advanced data processing associated with the association rules method.

equal to the number of logical cores in the CPU of the platform. It worth mentioning the time resolution issues in Windows 7 [16], which affect the measured values both from the resource adapters and the database system. This prevents comparing the architecture accurately on different operating systems (Windows 7 and CentOS) on top of the same hardware platform. It prevents also generating accurate timestamps and timer functions. To cope with this issue, a busy-waiting method was implemented and is also used to simulate the real sampling rate. More experiments are necessary to evaluate the proposed test functionalities and system configurations on a distributed scenario, *i.e.*, the resource adapters and the active database running on separate machines. However, such an approach could lead to even higher delays and latencies due to the network communication.

7. Conclusion

Embracing extendable, portable and scalable system architectures, which can respond to evolving needs, is the most reasonable strategy to realize successful smart environments. However, the most important aspect is actually to provide evidence that a given system architecture supports these non-functional requirements.

This work investigated extensibility, portability and scalability of a database-centric system architectures for smart environments. To isolate system components that may become performance bottlenecks, different measures were employed to examine the interaction and behavior of different components in the system. Three test functionalities

Table 2. Summary. Meas. Not supported means that the storage or the reaction latency was higher than the sampling rate.

	Dell Optiplex 7010	**Dell Latitude E7240**	**Raspberry Pi B Rev 2**
Extensibity	All functionalities	All functionalities	All functionalities
Portability	All functionalities	All functionalities	All functionalities
Scalability (Monitoring)	8 Simulated Systems	4 Simulated Systems	1 Simulated System
Scalability (Short-term)	8 Simulated Systems	4 Simulated Systems	Not supported
Scalability (Long-term)	8 Simulated Systems	Not supported	Not supported

(data storage, online reactive behavior and advanced data processing) on three heterogeneous computing platforms were implemented and evaluated.

Results demonstrated the flexibility of the database-centric architecture for being extended and ported across different operating systems and computer hardware. PostgreSQL plays an important role in this because of its extensible and cross-platform design. Results also revealed which functionalities and how many instances of a given functionality are supported in three different computing platforms. Resource starvation added delay in the input data streaming and processing, as well as latency in event processing and response. Components abstracting hardware and software technologies are the most affected when increasing the computational workload in the system. As a conclusion, this work can help developers in identifying which architectural components become performance bottlenecks when extending, porting and scaling a database-centric system architectures for smart home environments.

References

[1] M. C. Oussalah, editor. *Software Architecture 1*. Wiley-ISTE, Hoboken, NJ, June 2014.

[2] Microsoft P. & P. Team. *Microsoft® Application Architecture Guide*. Microsoft Press, Redmond, washington, 2nd edition, October 2009.

[3] W. O. de Morais and N. Wickström. A "smart bedroom" as an active database system. In *Proceedings of the 2013 IEEE 9th International Conference on Intelligent Environments (IE)*, pages 250–253. IEEE Computer Society, 2013.

[4] W. O. de Morais, J. Lundström, and N. Wickström. Active in-database processing to support ambient assisted living systems. *Sensors*, 14(8):14765–14785, 2014.

[5] G. Fagerberg, A. Kung, R. Wichert, M-R. Tazari, et al. Platforms for AAL applications. In *Smart Sensing and Context*, pages 177–201. Springer, 2010.

[6] M. Memon, S. R. Wagner, C. F. Pedersen, F. H. A. Beevi, and F. O. Hansen. Ambient assisted living healthcare frameworks, platforms, standards, and quality attributes. *Sensors*, 14(3):4312–4341, 2014.

[7] J. C. Augusto, V. Callaghan, , D. Cook, A. Kameas, and I. Satoh. Intelligent environments: a manifesto. *Human-centric Computing and Information Sciences*, 3(1):1–18, 2013.

[8] A. Santos, , H. Rodrigues, and R. José. Evaluating a crowdsourced system development model for ambient intelligence. In J. Bravo et al., editors, *Ubiquitous Computing and Ambient Intelligence*, pages 145–152. Springer, 2012.

[9] M. Becker. Software Architecture Trends and Promising Technology for Ambient Assisted Living Systems. In A. I. Karshmer et al., editors, *Dagstuhl Seminar Proceedings*, 2008.

[10] S. R. Ponnekanti, B. Johanson, E. Kiciman, and A. Fox. Portability, extensibility and robustness in iROS. In *Proceedings of the 2003 IEEE 1st International Conference on Pervasive Computing and Communications (PerCom 2003)*, pages 11–19. IEEE, 2003.

[11] M-R. Tazari, F. Furfari, A. F. Valero, S. Hanke, et al. The universAAL Reference Model for AAL. *Handbook on Ambient Assisted Living-Technology for Healthcare, Rehabilitation and Well-being. AISE Book Series*, 11:610–625, 2012.

[12] P. O. Antonino, D. Schneider, C. Hofmann, and E. Nakagawa. Evaluation of AAL Platforms According to Architecture-Based Quality Attributes. In D. V. Keyson et al., editors, *Ambient Intelligence*, volume 7040, pages 264–274. Springer Berlin Heidelberg, 2011.

[13] P. Barsocchi, S. Chessa, F. Furfari, and F. Potorti. Evaluating Ambient Assisted Living Solutions: The Localization Competition. *Pervasive Computing, IEEE*, 12(4):72–79, October 2013.

[14] G. Demiris and B. K. Hensel. Technologies for an aging society: a systematic review of "smart home" applications. *Yearbook of medical informatics*, pages 33–40, 2008.

[15] The PostgreSQL Global Development Group. *PostgreSQL 9.4.1 Documentation*. 2015. `http://www.postgresql.org/docs/9.4/static/index.html`.

[16] Microsoft® MSDN. Acquiring high-resolution time stamps, 2015. `https://msdn.microsoft.com/en-us/library/windows/desktop/dn553408.aspx`.