An Ontology-Driven Elderly People Home Mobilization Approach*

Karagiorgou Sophia[1], Ntalaperas Dimitrios[2], Vafeiadis Georgios[2], Alexandrou Dimitrios[1], Perakis Konstantinos[1], Baltas Dimitrios[2], Amza Claudiu[2], Wanka Anna[3], Freitag Hermine[4], Blok Marije[5], Kampel Martin[6], Veerle de Rond[7], Münzer Thomas[8], and Planinc Rainer[9]

[1] UBITECH LTD
[2] Bluepoint Consulting Srl
[3] Department of Sociology, University of Vienna
[4] Samariterbund Wien
[5] National Foundation for the Elderly
[6] Computer Vision Lab, Vienna University of Technology
[7] SilverFit
[8] Geriatrische Klinik St. Gallen
[9] CogVis Software and Consulting GmbH

Abstract. The use of virtual reality games, known as "exergaming", is gaining more and more interest as a mobilization tool and as a key piece in the delivery of quality health, especially in elderly people. Mobility tracking of elderly people facilitates the extraction of useful spatiotemporal characteristics regarding their activities and behavior at home. Currently, the analysis of human mobility is based on expensive technologies. In this paper, we propose a semantic interoperability agent which exploits mobility tracking and spatiotemporal characteristics to extract human profiling and give incentives for mobilization at home. The agent exploits an extended ontology which facilitates the collation of evidence for the effects of exergaming on the movement control of older adults. In order to provide personalized monitoring services, a number of rules are individually defined to generate incentives. To evaluate the proposed semantic interoperability agent, human mobility data are collected and analyzed based on daily activities, their duration and mobility patterns. We show that the proposed agent is robust enough for activity classification, and that the recommendations for mobilization are accurate. We further demonstrate the agent's potential in useful knowledge inference regarding personalized elderly people home care.

Keywords: sensor and health data integration · ontologies and data models · health semantics · recommendations · knowledge management.

1 Introduction

The increasing trend in the number of elderly people is a major public health challenge. Home support is an important preoccupation for the elderly and their families. It is known that physical activity is important for older adults at any age and health status, i.e. from a 50-year-old up to a 80-year-old.

* This work will be published as part of the book "Emerging Topics in Semantic Technologies. ISWC 2018 Satellite Events. E. Demidova, A.J. Zaveri, E. Simperl (Eds.), ISBN: 978-3-89838-736-1, 2018, AKA Verlag Berlin".

However the home is not a place without risk for the older adults. The means to enhance the health and quality of life by motivating them for physical training in an entertaining way with real-time interventions are very limited. A nowadays popular solution for enhancing the physical activity of older adults is to provide them with computer games which are played via body movement and thus have the inherent effect of unobtrusive physical exercise, i.e. the so-called "exergaming" [21]. These games are based on common sensors that track the user's movement such as the Microsoft Kinect [23] and can therefore easily be played at home. The core idea of exergaming is that they persuade older adults to exercise more simply because they enjoy to play, but there are known barriers to be overcome.

The game must be designed for non-skilled users in order to be accepted by older adults. This includes clear user interfaces, suitable game topics, avoidance of small objects and the encouragement by visual and auditive feedback. Also the social factor and personal preferences, e.g. by providing multi-user games, variety, etc., have to be considered. A very crucial requirement is to mind the mobility of the individual user, as many age-related processes have an impact on the ability to move which may differ from the skills needed to play a game. Common age-related changes are decrements in balance, gait, strength, impacts on visual and hearing senses as well as impairment of memory, attention and vigilance. Additional aspects to be addressed are the longer reaction, the overall movement times and the increased risk of falling. The high importance of this personalization aspect is given by its high correlation with the older adult's motivation to play and hence with the acceptability of exergaming, i.e. if a frail 80-year-old is confronted with games that require unachievable movements, she will feel over strained and soon lose interest. On the other hand, if a healthy 65-year-old is confronted with unchallenging game tasks, she will feel bored and will lose interest as well.

The required personalization can be achieved by manually configuring the exergaming platform based on the supposed mobility of the older adult, but this has many drawbacks, e.g it is hard to assess the mobility beforehand, mobility can change over time, and the individual preferences are not considered. Hence, what is needed is a platform that automatically and continuously adapts to the user's preferences, skills and mobility. Despite the ongoing research and development in the area of exergaming, performed both by industry and the research community, the problem of personalized recommendations are not properly addressed.

The goal of this work is to contribute towards the personalization of elderly people home care [22] by developing an ontology-driven semantic interoperability [26] agent that facilitates diverse human mobility activities to be captured and monitored for motivating further incentives and recommendations. More particularly, the main contributions of our work are as follows:

1. We introduce a semantic interoperability agent that incrementally builds a knowledge base and autonomously learns from the individual playing habits, what kind of games are preferred by the user, as well as her playing skills from the game performance, and utilizes this information to provide personalized and inspiring incentives for future mobilization;

2. We extend a data model described by a standardized ontology which is familiar to domain experts and expose data in a standardized format by supporting interoperability with existing systems and other services;
3. We evaluate the semantic interoperability agent using real-world datasets demonstrating its effectiveness and efficiency. The outcome is a personalized mobility model that is used to provide recommendations and incentives to the end-user.

Figure 1 shows a high-level architecture of the semantic interoperability agent. The remainder of this paper is organized as follows. Section 2 reviews related work on ontology-driven techniques for home health care and positions our approach accordingly. Section 3 presents our motivation and our approach for ontology-driven semantic-aware health care insights and inference. Section 4 validates our proposal using various quantitative and qualitative metrics. Section 5 concludes the paper, also pointing out interesting future research directions.

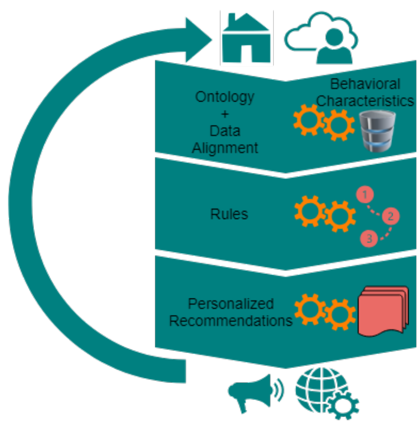

Fig. 1. High-Level Architecture.

2 Related Work

Various approaches have been proposed for using mobility tracking data to facilitate semantic-aware health care services. In the following, we present a review of the literature by using a categorization of the methods according to their applied use and the type of the devised techniques.

Several works present *literature reviews* of data-driven health care systems. Zenunia et al. [8] explore several repositories for ontology and semantic data management for health services, conduct a survey on most representative applications in semantic health care and analyze the data mining and data analytics approaches currently used to find useful patterns and extract knowledge in these repositories. Chao et al. [7] present a literature review which summarizes and synthesizes the impact of using the Nintendo Wii exergaming [24] in older adults by concluding that it is not a very promising intervention means to improve physical function, cognition and psychosocial outcomes but it is instead a safe and feasible tool to engage them in exercise. Sarafianos et al. [13] review the recent advances in 3D human pose estimation from image sequences. A taxonomy of the current approaches is proposed based on the input and their key characteristics.

Other approaches consider *spatiotemporal data analysis*, information and images collected from wearables and other monitoring devices. Temporal aspects to model behavior are considered by Floeck et al. [1], where activity data are obtained from different sensors within a flat by learning an inactivity profile from sensorial data in order to model the temporal behavior, but does not consider spatial aspects. Another approach introduced by Felzenszwalb et al. [2] focuses either on temporal or spatial aspects of the scene. Hence, the combination of both spatial and temporal knowledge was recently introduced by Planinc et al. [9] and resulted in a solid foundation for a behavior model. Their spatiotemporal behavior model analyses the scene in order to provide spatial knowledge about regions of interest as well as functional areas within a room (i.e. walking and sitting areas). The behavior over time is modeled within each area separately by Planinc et al. [6], by using activity histograms or inactivity profiles and modeling activity throughout the day.

Another category, to which the present work most closely relates, involves *ontology-driven* approaches for health care services. A HealthIoT ontology is proposed by Rhayem et al. [14] to overcome the problem of both medical connected objects and their data to achieve efficient semantic representation to facilitate patient monitoring, diagnosis and decision making. A hybrid framework which supports knowledge-driven and probabilistic-driven methods for event recognition is presented by Crispim-Junior et al. [10]. The framework separates semantic modeling from raw sensor data by using an intermediate level of semantic representation, introduces an algorithm for sensor alignment that uses concept similarity to address the inaccurate temporal information and proposes a combined use of an ontology language, to overcome the issues arising at the model definition. Lasierra et al. [5] developed an ontology-driven solution that enables a wide range of remote chronic patients to be monitored at home. Riaño et al. [4] introduce an ontology for the care of chronically ill patients and implement personalization processes which facilitate the support of a decision making tool targeted at health care professionals.

Several methods address health care services from an applied perspective based on *gamification and applications*. An application for mobile devices, developed for the Android platform in the JAVA programming language and XML markup to identify the frailty phenotype among the elderly was proposed by Silva dos Santos et al. [15] which allows the monitoring of the clinical status and prognosis of the patient. Harris et al. [11] studied the effects of exergaming on the balance and postural control of older adults and people with idiopathic Parkinson's disease. Their findings suggest that exergaming can be an appropriate therapeutic tool for improving balance and postural control. Dubois and Charpillet [16] proposed a low-cost ambient system for helping elderly to stay at home. The system recognizes the activity of the person based on Hidden Markov Models and measures gait parameters from the analysis of simple features extracted from depth images. Vernon et al. [12] examined the reliability of using the Microsoft Kinect *Timed Up and Go* component and whether it helps to improve patient's performance and physical conditions following a stroke.

From the point of *sociology view*, Wanka and Gallistl [17] suggest that the study of aging and technologies can profit from a comprehensive integration of theories from the sociology of aging, critical gerontology and science-and-technology offerings to facilitate active living.

Although the current approaches of data-driven health care systems use monitoring devices, ambiguous semantics and data curation from diverse sources, each individual work merely focuses on a single one of them. Compared to the aforementioned approaches, the proposed method differs in that it exploits user-driven behavioral characteristics using spatiotemporal information to provide concrete and targeted recommendations. It also infers useful personalized knowledge which is built incrementally from individual users movements and behavior at home and is delivered back to the end-user in the form of recommendations and incentives for exercise. This work introduces a *semantic interoperability agent* which promotes easy data exchange with existing and other systems and efficiently blends data-driven and semantic-aware health services to fuel personalized interventions which improve the self-esteem and the quality of elderly people life. A fringe benefit of the agent is that in this way, it supports several frameworks as it is based on *standardized data format* and provides the flexibility to be built on top existing and future systems.

3 Semantic Interoperability Agent

The semantic interoperability agent proposed in this paper consists of 4 components: the *Ontology*, the *Data Alignment*, the *Personalized Recommendations* and the *Interfaces*. The framework is realized by means of a knowledge base which is built incrementally from user-driven behavioral characteristics and is used to store information that corresponds to the movement sequences, along with interfaces that provide mechanisms for accessing and updating this information.

The *Ontology* contains the entities and relations describing the movement sequences and the type of movements. The *Data Alignment* consists of a set of classes which model the Ontology and specify the conditions which trigger recommendations. The *Personalized Recommendations* consist of a set of methods which provide a rule based mechanism that generates interventions and incentives for elderly mobilization according to their mobility conditions and a knowledge base which is built incrementally from their behavioral characteristics. The *Interfaces* consist of a set of methods and REST APIs which provide the means to retrieve and update entities of the Ontology and expose the movement sequences as they have been processed by the other components of the agent.

This semantic interoperability agent automatically serves as a middleware which provides knowledge gained during the execution history through the REST APIs. If, for example, a set of movement patterns have been observed, these sequences are stored to a centralized database and shared through all the instantiations of the entire framework by the respective API. The semantic interoperability is realized through the Ontology, Data Alignment and Interfaces that are combined in order to *turn domain specific data into domain agnostic across different services*. Figure 2 shows the functionality of the semantic interoperability agent, how it interacts with the mobility tracking module and how it produces recommendations for personalized exercises and incentives for mobilization through the Interfaces. Therefore, knowledge incrementally gained information is derived by semantic-aware movement sequences, stored in the database and exposed by the Interfaces.

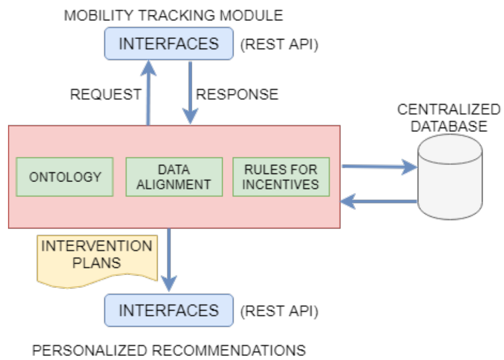

Fig. 2. The Semantic Interoperability Agent.

3.1 Preliminaries

The *input* to the semantic interoperability agent comprises sparse *mobility tracking data* in the form of spatiotemporal sequences. Using linear interpolation between consecutive samples, we derive the mobility tracks of each person. A mobility track is modeled as a list of spatiotemporal points $M = \{p_0, \ldots, p_n\}$ with $p_i = \langle x_i, y_i, t_i \rangle$ and $x_i, y_i \in R, t_i \in R^+$ for $i = 0, 1, \ldots, n$ and $t_0 < t_1 < t_2 < \ldots < t_n$. These tracks are susceptible to noise, as they are affected by a measurement error and a sampling error due to the variable sampling rate. The *output* of the semantic interoperability agent is a set of recommendations R, modeled as a set $R = \{id, ActivityType\}$, where id corresponds to a user identifier and $ActivityType$ corresponds to the category of the personalized activity proposed each time to her. This activity may result in a walking game or a mind game having as a sequence either a light mobilization or a mental exercise in the form of recommendations to elderly people.

3.2 Mobility Tracking Model

The tracking of the user is realized by 3D sensors, happens throughout the day and covers individual tracks. The individual tracks are stored and periodically sent to the semantic interoperability agent for further analysis to gain information of the user's mobility by extracting whenever the person is moving within the room, the duration, distance, type and velocity of her movement. End-users data have been anonymized by removing their personal and identifiable information. The following *information is extracted from the stored tracks* and is taken into account in the rules definition and enforcement for the provision of recommendations in each individual person:

- The *Active Time in Room (ATR)*. The duration of every track is summed up and divided through the estimated time that the user has actually been in the room during the day. This leads to a relative amount of active time within the observed room by also capturing the distance and duration.
- The *Active Time of Day (ATD)*. The observed tracks are divided into timeslots of one hour to give a statistical overview of the user's most active/inactive times during the day in the form of a histogram.

- The *Average Gait Velocity (AGV)*. The observed tracks are segmented and filtered into straight parts to calculate the average gait velocity on straight paths.
- The *Average Stand up Time (AST)*. When the person stands up (i.e. a track is recognized from within the scene) the time from sitting to standing is measured.
- The *Average Walking Time (AWT)*. When the person walks (i.e. a track is recognized from within the scene) the duration of her walking is measured.

This mobility tracking information is analyzed to create a spatiotemporal behavior model which shows where in the room the user stays most of the time. This is analyzed over a long time period (i.e. 3 months) and is compared to previous behavior recordings to determine changes in the user's behavior.

3.3 Ontology

UniversAAL [18] is an open source platform that enables seamless interoperability of devices, services and applications on a large scale. It provides an efficient framework for communication in an ensemble of networking-enabled nodes by hiding distribution and heterogeneity, acting as a broker between the communicating services. It supports the integration of software components distributed on different nodes and the collaborative communication among them. In this work, we extend the *ont.handgestures* ontology which describes concepts related with person's gestures.

As an outcome of this stage, a formal conceptual model to define individual elderly profiles is achieved in which data provided by the different sources participating in the mobility tracking process can be mapped. This is achieved through a flexible and extendable model for both data-in-motion and data-at-rest, which can be further exploited across multiple processing components.

The main purpose of the Ontology is to model all possible movement sequences that are of interest to the semantic interoperability agent and thus the entire framework. The ontology is developed in order to cover sequences of movements and has been designed in such a way to allow easy extension, thus facilitating easy future modeling of different movement sequences, that are needed due to the discovery of new efficient movement patterns.

All the implemented classes follow the hierarchical structure proposed by UniversAAL [18]. Each movement sequence is modeled after the class MovementSequence. An instance of MovementSequence consists of set of Movements (e.g. walking, stand up, etc.) which are considered important to be captured by the agent based on some criteria (e.g. the person is alone in the room). Each one of these movements is an instance of the class Movement. A Movement can be a *Walking*, a *Stand up* or an *Active* movement. In addition to MovementSequence and Movement, the entities of Game and GameCategory are included in the ontology; these entities are used to encode information that is based on data stored in the movement entities (e.g. proposed games based on the movement history of the user). PeoplePresence class is defined for facilitating the proposition of interesting incentives for mobilization. More specifically, it represents how many persons are actually in the room (e.g. physiotherapists, care-givers, etc.), so that the agent can use this information to determine when the user's movements should be tracked. Figure 3 illustrates the main classes and properties of the Ontology and the relations among the entities.

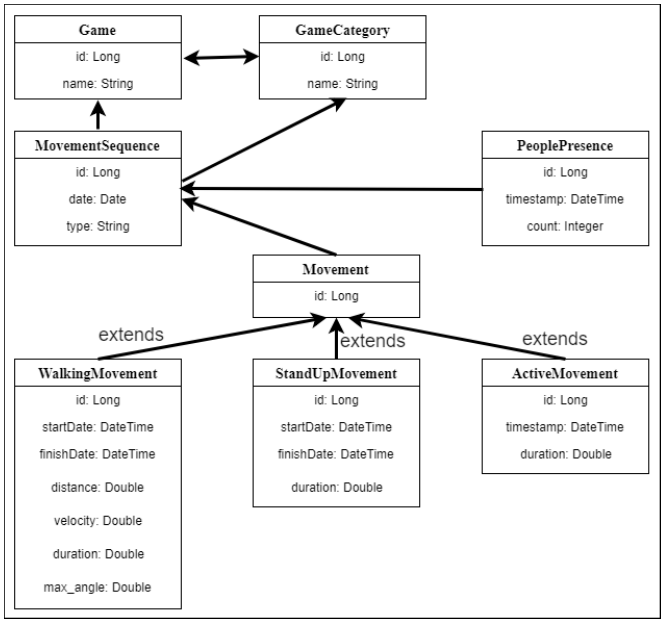

Fig. 3. Extension of universAAL Handgestures Ontology.

The OWL-DL language (an OWL – Ontology Web Language – sublanguage) was chosen to describe the ontology model [19]. OWL is a vocabulary extension of RDF (Resource Description Framework) [20]. It describes the structure of a domain in terms of classes and properties and provides a set of axioms to express assumptions or equivalences with respect to classes and properties. In our case, OWL-DL provides the maximum expressivity that can be offered while guaranteeing total computational capacity. The ontology was implemented by using the Protégé-OWL v.5.2.0 ontology editor and its consistency was checked using the Pellet reasoner [25].

3.4 Data Alignment

The main purpose of the *Data Alignment* is to map the mobility tracking data provided as input to each class of the Ontology and finally to JAVA objects of the semantic interoperability agent. The JAVA objects contain the relevant fields and methods needed for representing the corresponding classes and some helper methods. They are all serializable, so that they can be promptly converted to JSON format and communicated via the endpoints of the Interfaces. Except from the mapping of Ontology classes to JAVA objects the mapping of JAVA objects to database tables is needed as well, in order to store all the required information into the centralized database. A JAVA API serves as consumer which acquires data that are generated by a scheduler and stores them in the centralized database for further process and usage by the facets of the Interfaces. Mapping JAVA objects to database tables is implemented via the JAVA Persistence API (JPA). The JPA API allows to map, store, update and retrieve data from the centralized database to JAVA objects and vice versa.

3.5 Personalized Recommendations

In order to provide personalized recommendations, apart from an instance of the elderly movement ontology, a number of rules are individually defined for each person. These rules take into account the duration, the distance, the velocity and the kind of elderlies activity extracted from the stored tracks (i.e. active time, gait velocity, stand-up or walking time), as presented in Section 3.2. By using these rules, the behavior of individuals are expressed inside the domain and thus can be used to express individual recommendations according to their movement conditions. In fact, rule-based systems have been extensively used in applications that require personalized services [3]. Specifically, the SPARQL (SPARQL Protocol and RDF Query Language) language was selected to express rules to be applied over the elderly profile instances. Although SPARQL is a query language, it offers substantial power to filter individuals with specific characteristics. Then, SPARQL rules are used to define personalized care tasks according to elderly movement conditions.

The steps of the algorithm are listed in Algorithm 1. Specifically, the Semantic Interoperability Agent takes as input Mobility Tracks M and gives as output a set of Personalized Recommendations R. For each mobility track (Lines 3 - 18), the algorithm looks for people's presence in a room and a set of movements by using specific temporal criteria (e.g. dates) (Lines 4 - 7). Then, the algorithm records in the $MovingSequence$ the set of walking movement, dates and types (Line 8). If the set of $MovingSequence$ is empty, the algorithm returns a set of personalized recommendations regarding games which include walking exercises in order to mobilize the elderly people (Line 13). On the contrary, if the set of $MovingSequence$ is not empty, the algorithm returns a set of personalized recommendations regarding mind games (Line 16).

Algorithm 1: Semantic Interoperability Agent

```
   Input: A set of Mobility Tracks M
   Output: A set of Personalized Recommendations R
1  begin
2      /*The Semantic Interoperability Agents receives Mobility Tracks as input*/
3      foreach (M_i ∈ M) do
4          P ← LookupPeoplePresence(M_i)
5          W ← LookupWalkingMovement(M_i)
6          foreach (P_i ∈ P) do
7              if OnAlone(Date(P_i)) ∈ Date(W) then
8                  MovingSequence ← Concat(W, Date(R_i), type)
9              end
10         end
11         /*Personalized Recommendations are sent as output*/
12         if IsEmpty(Lookup(MovingSequence, P)) then
13             return(R ← WalkingGame(ActivityType))
14         end
15         else
16             return(R ← MindGame(ActivityType))
17         end
18     end
19 end
```

4 Experimental Evaluation

As interoperability and personalized services are one of the primary design and evaluation goals, we need to ensure that the Semantic Interoperability Agent achieves abundant communication and interfaces among sensors, software and tools. This is related with all the data needed to support the respective decision support systems. Also, it achieves interoperability of the solution with external services as the data are made available in a standardized format that can be read and used by other systems.

The efficiency of the Semantic Interoperability Agent has been evaluated in terms of technology acceptance and incentives for exergaming. We conducted a survey interviewing end-users by both using quantitative and qualitative questions. In this section, we focus on the respective questions which concern the Semantic Interoperability Agent and especially the technology use and acceptance, their attitude towards exergaming, the accuracy of personalized recommendations and the efficiency of motives for physical activities. We also denote some evaluation criteria regarding mental, functional and general health of end-users. Mental health refers to psychological and social well-being condition of end-users, functional health refers to the ability of end-users to do the activities they need to do and general health refers to end-users who are generally healthy. We interviewed 201 end-users who are coming from Austria (i.e 100) and Netherlands (i.e. 101). Their average age is approximately around 77 years old where 33% of them are men and 67% of them are women. Also, 55% of end-users live in single households. All the end-users gave their consent for the participation in the survey and no personal data were collected. We used a 5-points scale questionnaire in which we either measured and evaluated end-users agreement (from 1 to 5, e.g. ranging from strongly disagree to strongly agree), or satisfaction (from 1 to 5, e.g. ranging from very dissatisfied to very satisfied).

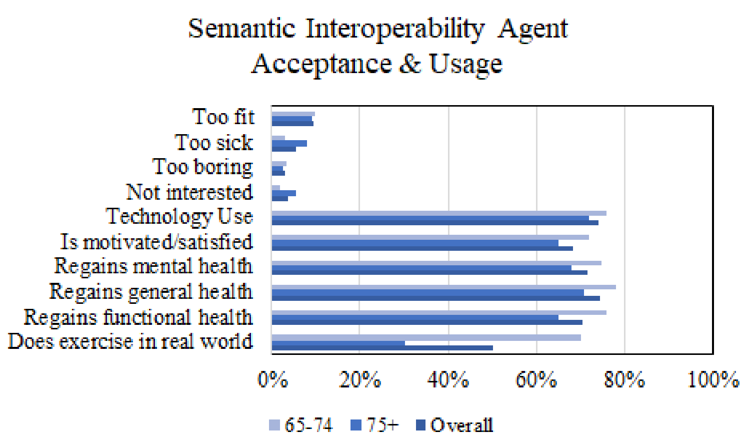

Fig. 4. Quantitative and Qualitative Results.

Figure 4 shows that the end-users exhibit wide acceptance (more than 68.5%) of the system and believe that its use has significantly contributed in their mental, functional and general health (more than 72%). However, the greater incentives have been received by persons who do not exercise in their real life, so the agent demonstrates a better potential in the elderly people of 75 years old or more (30%). At the same time, the end-users who would not adopt exergaming are either too fit and already prefer a more active way of life or too sick and thus an alternative option should be taken into account. Besides, the end-users who proved not be such motivated (i.e. not interested, too boring) by exergaming concern a small part of the interviewed of about 3%.

5 Conclusions and Future Directions

The purpose of this work is to offer an interoperability solution which is easily accessible and stores meaningful information driven by ontologies to provide personalized recommendations to elderly people in exergaming. We extended a data model described by a standardized ontology which is familiar to domain experts. Having a clear model contributed to identify rules and provide personalized interventions.

In a nutshell, the semantic interoperability agent exposes data in a standardized format and supports interoperability with existing AAL systems and external services. The agent serves as middleware by taking into consideration mobility behaviors. It drives personalized recommendations to the end-users in their private homes by increasing their self-esteem and thus their quality of life.

In the near future, we plan to experiment with the proposed agent in the context of online methods. As it is becoming increasingly easier to gain access to mobility data sources, such an agent could improve the process of enhancing, combining and enriching disparate data sources and optimize the every day life of elderly people through interactive interventions. To this effect, we are investigating automatic methods to infer useful semantic knowledge from diverse data sources with variable characteristics.

Acknowledgements

This work was supported by EnterTrain project which received fund under the AAL Programme (Project No. AAL-2015-056).

References

1. Martin Floeck, Lothar Litz. Activity- and Inactivity-Based Approaches to Analyze an Assisted Living Environment. In: Second International Conference on Emerging Security Information, Systems and Technologies, pp. 311-316, 2008.
2. Pedro F. Felzenszwalb, Ross B. Girshick, David McAllester, Deva Ramanan. Object Detection with Discriminatively Trained Part-Based Models. Transactions on Pattern Analysis and Machine Intelligence, 32(9), pp. 1627-1645, (2010).
3. Federica Paganelli and Dino Giuli. An ontology-based system for context-aware and configurable services to support home-based continuous care. IEEE Transactions on Information Technology in Biomedicine, 15(2), pp. 324-33, (2011).
4. David Riaño, Francis Real, Joan Albert López-Vallverdú, Fabio Campana, Sara Ercolani, Patrizia Mecocci, Roberta Annicchiarico, Carlo Caltagirone. An ontology-based personalization of health-care knowledge to support clinical decisions for chronically ill patients. Journal of Biomedical Informatics 45, pp. 429-446, (2012).
5. Nelia Lasierra, Alvaro Alesanco, S. Guillén, Jose García. A three stage ontology-driven solution to provide personalized care to chronic patients at home. Journal of Biomedical Informatics, 46(3), pp. 516-529, (2013).
6. Rainer Planinc and Martin Kampel. Detecting Unusual Inactivity by Introducing Activity Histogram Comparisons. In: Proceedings of the International Conference on Computer Vision Theory and Applications, pp. 313-320, Lisbon, Portugal, 2014.
7. Ying-Yu Chao, Yvonne K. Scherer, Carolyn A. Montgomery. Effects of Using Nintendo Wii Exergames in Older Adults. A Review of the Literature. Journal of Aging and Health, pp. 1-24, (2014).

8. Xhemal Zenunia, Bujar Raufia, Florije Ismailia, Jaumin Ajdaria. State of the Art of Semantic Web for Healthcare. Procedia - Social and Behavioral Sciences, 195, pp. 1990-1998, (2015).
9. Rainer Planinc and Martin Kampel. Local Behavior Modeling based on Long-Term Tracking Data. In: Proceedings of the IAPR International Conference on Machine Vision Applications, Tokyo, Japan, 2015.
10. Carlos F. Crispim-Junior, Vincent Buso, Konstantinos Avgerinakis, Georgios Meditskos, Alexia Briassouli, Jenny Benois-Pineau, Yiannis Kompatsiaris, François, Brémond. Semantic Event Fusion of Different Visual Modality Concepts for Activity Recognition. IEEE Transactions on Pattern Analysis and Machine Intelligence, 38(8), pp. 1598-1611, (2016).
11. Dale M. Harris, Timo Rantalainen, Makii Muthalib, Liam Johnson and Wei-Peng Teo. Exergaming as a viable therapeutic tool to improve static and dynamic balance among older adults and people with idiopathic Parkinson's disease: a systematic review and meta-analysis. Frontiers in Aging Neurosciences, 7(167), pp. 1-12, (2015).
12. Stephanie Vernon, Kade Paterson, Kelly Bower, Jennifer McGinley, Kimberly Miller, PhD, Yong-Hao Pua, Ross A. Clark. Quantifying Individual Components of the Timed Up and Go Using the Kinect in People Living With Stroke. Neurorehabilitation and Neural Repair, 29(1), pp. 48-53, (2015).
13. Nikolaos Sarafianos, Bogdan Boteanu, Bogdan Ionescu, Ioannis A. Kakadiaris. 3D Human pose estimation. A review of the literature and analysis of covariates. Computer Vision and Image Understanding, 152, pp. 1-20, (2016).
14. Ahlem Rhayem, Mohamed Ben Ahmed Mhiri, Mayssa Ben Salah, Faiez Gargouri. Ontology-based system for patient monitoring with connected objects. Procedia Computer Science, 112, pp. 683-692, (2017).
15. Thassyane Silva dos Santos, Thais Alves Brito, Francisco Sadao Yokoyama Filho, Lara de Andrade Guimarães, Caroline Sampaio Souto, Samara Jesus Nascimento Souza, Luiz Eduardo Barreto Martins, Karla Rocha Pithon. Development of an application for mobile devices to identify the frailty phenotype among the elderly. In: Proceedings of Revista Brasileira de Geriatria e Gerontologia, 20(1), pp. 67-73, Rio de Janeiro, 2017.
16. Amandine Dubois, François Charpillet. Measuring frailty and detecting falls for elderly home care using depth camera. Journal of ambient intelligence and smart environments, 9(4), pp.469-481, (2017).
17. Anna Wanka and Vera Gallistl. Doing Age in a Digitized World — A Material Praxeology of Aging With Technology. Frontiers in Sociology, 3(6), pp. 1-16, (2018).
18. UniversAAL IoT. Available Online: https://github.com/universAAL/ontology/wiki
19. Michael K. Smith, Chris Welty, Deborah L. McGuinness. OWL web ontology language guide. W3C recommendation; 2004. Available Online: http://www.w3.org/TR/owl-guide/
20. Ora Lassila, Ralph R. Swick. Resource description framework (RDF) model and syntax specification. W3C recommendation; 2004. Available Online: http://www.w3.org/TR/REC-rdf-syntax
21. Exergaming. Available Online: https://en.wikipedia.org/wiki/Exergaming
22. Home Care. Available Online: https://en.wikipedia.org/wiki/Home_care
23. Microsoft Kinect. Available Online: https://en.wikipedia.org/wiki/Kinect
24. Nintendo Wii. Available Online: https://en.wikipedia.org/wiki/Wii
25. Protégé-OWL editor. Available Online: http://protege.stanford.edu
26. Semantic Interoperability. Available Online: https://en.wikipedia.org/wiki/Semantic_interoperability