A Context-Aware Architecture for Personalized Elderly Care in Smart Environments

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Abstract. Much research has focused recently on the development of smart environments and services for human-centered applications for personalized care and improved quality of life. This is especially relevant to support the elderly to lead an active and independent life. Recent efforts exploited the state of art development in the Internet of Things, Smart Sensors grid, Embedded and Wearable systems as well as Cloud Computing to build mathematical models of personal behavior and lifestyle largely driven by big data analytics. In order to overcome the range of challenges associated with the size and heterogeneity of the related data, hardware and software, as well as of the human and social factors involved, a context-aware architecture appropriate for smart environments is needed. This paper describes ACTiVAGE (ACTiVe AGeing sErvices), a conceptual framework for developing Personalized Elderly Care services that leverage big data analytics for context-awareness in smart environments.

Keywords: smart environment, personalized elderly care, context-awareness, big data analytics, future technology design

1 Introduction

Recent progress in Information Technology, wearable sensors, Internet of Things and Mobile Computing combined with the smart grid technology has given rise to "a world of data" [1] with fast and ubiquitous analytics at scale. In this context, there has been an increasing demand for the processing of heterogeneous data involving different aspects of life such as sport habits and travel records, people interactions, and biometrics. Thanks to the availability of this information, it is possible to define the profile and habits of the end-users and consequently customize market offers and services. Nevertheless, it is still an open question how data should best be acquired, manipulated and shared in order to maximize efficiency and respect human privacy. This particularly apply to applications on elderly care, which is raising up a demanding societal challenge affecting health, demographic change and wellbeing, with intriguing perspective in innovative collaboration on care and cure, independent living and active ageing, prevention screening [1-3]. New markets and opportunities are expected to grow significantly, especially for residential people and therefore a lot of effort is spent in order to support the development of novel data frameworks and technologies as well as pre-commercial procurements to enhance autonomy, choice and control of older adults along with the development of innovative solutions to target assisting elderly people.

Developing technologies which improve elderly independent living and safety is a critical point issue in personalized elderly care; technologies may strongly support, even if a proper strategy have to be designed to involve elderly, develop integrated technical and financial solutions facing the real daily life problems and implement them [4-6]. Current exabytes of data have a promising potential to address the challenge of personalized care and, in particular, of elderly care [7-9].

This work aims to leverage Big Data analytics and smart environments for supporting elderly care within a context-aware architecture: a lifestyle-oriented framework for supporting human-centered elderly care and independent living is proposed. This framework allows the extraction of representations of the end-user lifestyle in order to tailor elderly-care services to individual needs.

2 Developments in Context-Aware Support for Elderly Care

Current technologies for elderly care can be broadly classified into two main classes:

1. *Human activity monitoring* where devices are tracking subject daily activities and alerting medical personnel in case of need or emergency.

2. Technologies for *assistance and rehabilitation*, from simple passive devices (i.e. a wheelchair) to personal robot assistant.

Based on this classification, we present in the remaining part of this section some relevant technologies.

2.1 Smart Ambient Assisted Living

Smart Ambient Assisted Living (AAL) or smart home is “any living or working environment that has been carefully constructed to assist people in carrying out required activities” [10] and can embed a variety of services and tools, from devices for rehabilitation, training, exercises or gaming, to pain treatment systems, social robots and home-based cognitive rehabilitation devices.

Current smart home projects have focused on the development of smart grid and sensor networks, data collection and decision [11]. Applications include '*Telehomecare*' connected with medical services [12], smart room [13], home systems [14-15], rehabilitation platform [16], smart and adaptive house [17].

To facilitate the acceptance of smart home technological architectures, the end-user interface need to be optimized and made highly user-friendly: thanks to novel marker less motion capture systems, smart home solutions can be therefore combined with gesture control systems, voice recognition devices (for TV control, activation and deactivation of goods) and eye tracking devices. These methodologies exhibit advantages in that they do not require expert end-users and or people with a high technological background and therefore can be well suited to applications for the elderly people.

A significant challenge of these systems is that rigorous validation and exploitation processes are needed in order to effectively evaluate the performance of these architectures and 'proof of concepts' in terms of efficiency and improving the life of elderly users and their transferability into the daily life and the market.

2.2 Smart Sensors for Activities of Daily Life Monitoring

Activities of Daily Life (ADL) monitoring can cover outdoor and indoor monitoring, through the employment of GPS (Global Positioning System) technologies combined with fall detection system and phone or computer support. In particular, phone devices have strong potentials on supporting activity classification, indoor localization and even scene recognition (by using, for instance, their embedded microphone); with proper data analysis and interpretation, behavioral and contextual information can be also inferred with these set-up, which may even infer the recognition of some pathologies (for instance, people may be monitored at home for multiple days and distribution of positions will be more regular if the elderly person is not affected by dementia).

Fall detection systems have been also largely applied and investigated: in the European Community context, diverse projects about fall prevention have been designed and implemented, based on development of insoles which are positioned in the shoes of the elderly, long-term analysis of data collected via smart phones, ICT-based system predicting and preventing falls. Other approaches have focused on monitoring specific physiological and behavioral parameters through set of home sensors combined with robot caregiver, wearable systems or combination of sensors for the estimation of short and long term unexpected behaviors [18-21].

In conjunction with fall detection systems, other critical situations have been identified and studied with visual sensor which can be used to recognize them. In this context and by using structured environments and set of sensors distributed at home, acute and gradual changes of daily life activity may also support the prompt detection of coming impairments like dementia.

2.3 Robotic Rehabilitation and Assistance

Robotic assistance and rehabilitation inherently involves human robot (HRI) interaction issues, namely, how the robot may 'intelligently' react to end-user action, embeds 'social intelligence', and cooperate with the user and incorporates reasoning, recognition, understanding and planning. From the end-user viewpoint, the development of interaction-oriented robots have also to take into account the way we perceive and relate with these devices, especially in the case of an elderly person. Therefore it is critical to understand how to improve the relationship between the human subject and the machine through the introduction of "human-like" skills within the latter. Interestingly, an underestimation of the psychological and cognitive impact can partially explain why these systems did not yet successfully enter in the market and overcome the problem of having something properly performing.

3 Personalized Elderly Care in Smart Environments

As noted in Section 2, embedded sensors and devices in existing technologies have led to large data of heterogeneous types: from sensor data of smart home to miscellaneous information coming out from a robotic caregiver, giving rise to zettabytes of data (i.e. 10^{21} gigabytes, [22]) characterized by an huge heterogeneity, [23]. However, the efficiency of an elderly care system is mainly dependent on how properly these data are processed and information are extracted, manipulated and used to infer knowledge and support care. Although, the availability of data presents a unique opportunity to analytically classify human subjects' activities, perform behavioral studies and correlate information of different nature [24], but poses huge challenges from engineering and computational design perspectives.

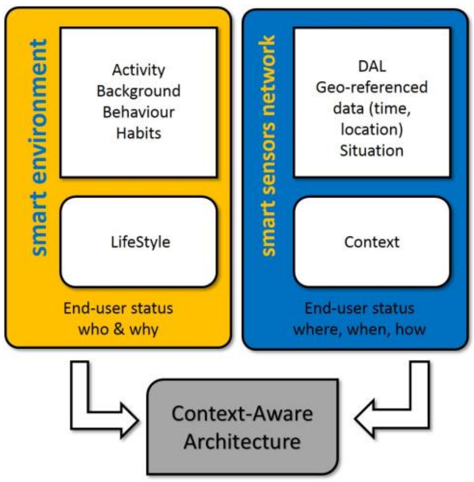

Fig. 1. The *ACTiVAGE* Context-Aware framework for Personalized Elderly Care

We present the conceptual framework of *ACTiVAGE* (ACTiVe AGeing sErvices), a context-aware framework for supporting personalized elderly care and independent living. As shown in Figure 1, the proposed framework combines knowledge about user lifestyles, personal preferences and beliefs, as well as knowledge of user context to offer a model of ICT-enabled support for independent living. The framework leverages research in context-aware user support, particularly the works of [25], [26] and building on the unique capabilities of big data analytics in aggregating and analyzing large-scale data about individual behaviors and lifestyles. Because of the inter-subject variability of human data and especially of physiological data, personalized applications and services of elderly subjects are highly dependent on their execution contexts [27], [28]. Context awareness is not an optional feature in elderly care systems, but a major one since it allows controlling the health status of the subject, the activity he or she is performing, the condition of the surrounding environment. The concept of situational awareness, namely the capacity to infer knowledge of one's surrounding environment has been an active research focus [27], [29]. Integrating context awareness can provide metadata for interpreting Big Data and making sense of data entities [29].

3.1 Architectural Design

The system architecture consists of four layers, namely the data layer, the analytics layer, the context-awareness layer, and the services layer (see Figure 2). The approach will combine systematic data capture and rigorous analytics to uncover the actual and complete picture of the elderly person's lifestyles, and build a formal representation of the lifestyle concept for system design. The lifestyle is integrated with context-aware services that dynamically configurable using the user's location, identity, time, and an understanding of user activities of daily living in order to provide personalized user requirements recommendation. Based on the recommendation, e-services are developed, using the capabilities of mobile devices and cloud-based services, to offer individually-tailored and lifestyle-oriented services for active ageing and independent living, including social networking, self-diagnosis and monitoring, advisory, entertainment, exercise and dietary, reminder and local events services. The e-services will leverage on advances in ICT, including pervasive computing and usability engineering, for the provisioning of rich and platform independent e-services.

A key focus of the architectural model of the ACTiVAGE is the specification of a user lifestyle profile model. This is achieved by aggregating data about users and transforming them in a formal model for computer-based design. This involves the use of modelling and simulation tools, including rule-based systems, as well as cognitive methods and the specification of a lifestyle ontology to enable proper representation of the lifestyle concept. The lifestyle ontology will be integrated with context ontology for the creation of person-centered and context-aware e-services for the elderly patient that enables quality and independent living. Figure 3 shows an activity context model for building a context ontology, which draws upon the CAPIM context [26], and aggregates all the information – location, time, and actor –

necessary to detect the relevant attributes of a past activity into a unique set of data. In the model, we use the term, actor, to represent an elderly person or user to be supported. Information about the actor's history of events, social interests, beliefs, and personal attributes is used to context the actor's lifestyle profile. Lifestyle profile will be implemented as lifestyle graph, where vertices represent life events (e.g. marriage, an instance of a sport event, etc.), and edges represent relationships between life events. The vertices will consist of two types of life events: atomic events and composite events, where composite events are derivable from atomic events.

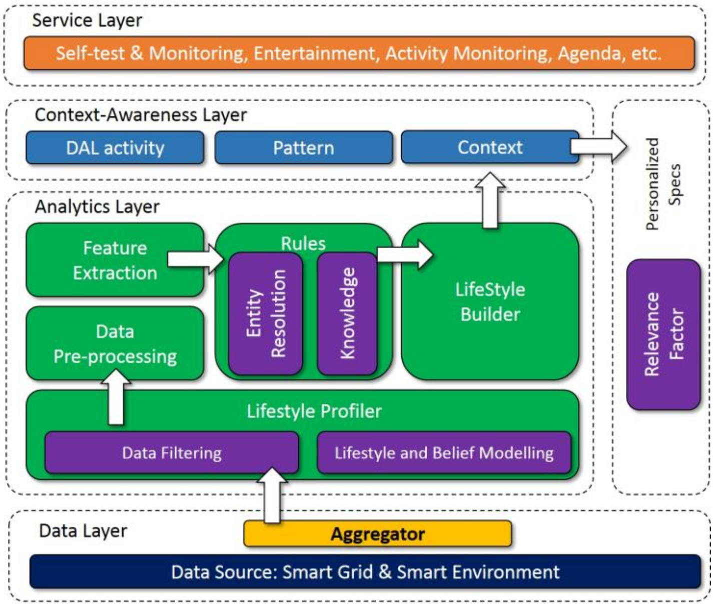

Fig. 2. The *ACTiVAGE* System Architecture performing context awareness from smart grid and smart environmental sensors.

3.2 A 'Walk-through' Application Example

To explore the proposed architecture, a walk-through scenario illustrating the use of *ACTiVAGE* to provide recommendation services to an elderly person in described below. The following assumptions underlie the scenario example:

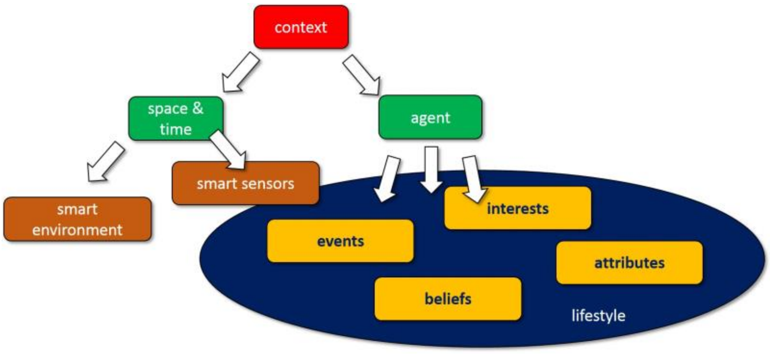

Fig. 3. The *ACTiVAGE* Lifestyle-Oriented Context Model.

- It is assumed that the end-user is an elderly subject with memory difficulties who is living in a smart home allowing the collection of real-time information (Figure 4).
- In this scenario, smart home sensor network and body area network are simultaneously gathering activity-related and environmental-related parameters through distributed transducer within the house and wearable sensors embedded in the garments of the user and his/her smart phone;
- Raw data of the smart phone accelerometer are locally processed and features of subject motion, such as the type of activity, motion intensity and estimates of calories consumption, are wirelessly sent to the aggregator.

  Physiological status parameters acquired through wearable sensors - heart rate, breathing rate, body temperature, etc.

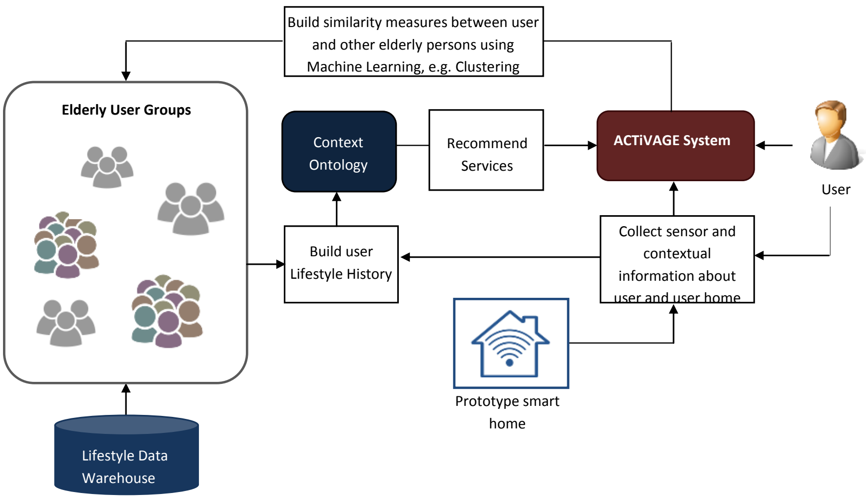

Fig. 4. Recommendation procedure in *ACTiVAGE*.

- Environmental conditions - indoor position of the subject, activated white goods, relative position of subject, etc. - are pre-processed and received from the aggregator to infer alert condition, detect execution of repetitive tasks, inconsistencies and dementia-related events.
- Data are also normalized according to personalized physiological profile of the subject, especially their resting heart rate & breathing rate and baseline activity profile.
- Lifestyle history is built in a day by day process collecting information and inferring main subject behaviors.

The recommendation procedure is depicted in Figure 4. The goal is recommend active ageing services to a new user based on in-depth mining of aggregated data from large volumes and different sources of data in Big Data that describes an individual's lifestyles. Data about users' lifestyles are preprocessed into a set of features suitable for the design of active ageing services. To provide a new user with appropriate service recommendation, the system uses clustering and collaborative filtering algorithms to determine people that have similar features and preferences with the user based on background and lifestyle experiences.

4 Conclusion

This paper proposed a framework to enable the delivery Personalized Elderly Care services in smart environments, leveraging Big Data analytics for context-awareness and therefore for 'smart' services informed by user lifestyle and behavior. Big Data and data analytics can potentially play a vital role in capturing, processing, and analyzing user social and behavioral data in highly connected and sensor-rich environments, and has thus providing 'context awareness' for personalized elderly care. The proposed framework denotes a combination of context-aware computing and the notion of lifestyle modeling in order to facilitate the provision of personalized services for elderly care and independent living. The paper has focused on a high-level description of the *ACTiVAGE* framework, and lacks specific details about a number of the techniques included in the proposed framework, e.g. life event modeling, ontology development, graph analytics, context information processing, and service composition. Future work will focus on developing specific details of the framework as well as prototype and evaluate systems based on it within a real world application context. Our goal here has been to highlight a number of issues from the perspectives of analytics, context-awareness, and cognitive computing that need to be addressed for the design of computer-based systems that combine knowledge of user lifestyle and knowledge of user activity context for personalized elderly care. By developing a set of lifestyle-oriented active ageing e-services, this approach will make a novel contribution to healthcare for the elderly through an approach that exploits the lifestyle concept integrated with context-aware computing as a foundation for informing the design of ICT-enabled active ageing services and products.

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