Real-Time Anomaly Detection in Elderly Behavior

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ABSTRACT

The rapid growth of the aging population and the increasing cost of the hospitalization are arousing the urgent need of the remote health monitoring system. Using the physiological sensing devices enable early detecting of health issues and allow for prompt treatment to help elderly towards changing their anomalous behavior and having a healthy lifestyle. Our approach, exploited task models to produce scenarios (which is the expected user behavior) and a middleware software, Context Manager to detect the events happened in the real context. Later, our real-time algorithm compares the expected user behavior to the real one detected in user context to find the anomalies if there is any. Finally, we validated our approach via a simulator, which automatically generates the anomalous sequences of user activities. The experimental results show that our system can detect abnormal user behavior precisely and effectively. Besides, the system should be able to generate proper action based on the detected deviation to motivate older people towards a healthy lifestyle.

CCS CONCEPTS

• **Human-centered computing** → *HCI theory, concepts and models*;

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KEYWORDS

Elderly behavior analysis; deviations in task performance; ambient assisted living.

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INTRODUCTION

A World Health Organization (WHO) study [1] estimates that between 2000 and 2050, the number of people over 60 years of age will grow to double and one in four people in the world will be over 60. In contrast, the quality of life of the elderly is not increasing at the same pace as the previously referenced growths. Consequently, health systems are predicted to face an array of challenges to meet an increasing demand for aged care health services. Recently, researchers have developed a variety of Ambient-Assisted Living (AAL) tools like remote assistance applications which support various techniques such as monitoring the daily user activities, modeling the user context and detecting the anomalous behavior. Based on the fact that elderly prefer to remain living in their home, with some level of independence, instead of residential care [13], remote assistance applications should enable elderly users to receive remote assistance and support by both family and care providers directly in their own homes with the goal to improve quality of life, decrease health care delivery cost, extend the time older people can live in their home environment and increase their autonomy and assisting them in carrying out activities of daily living. Meanwhile, observing any change in the elderly daily routine and detection the anomalous behavior of older adults is highly critical, because any change in the user routine may reveal vital clues to underlying health conditions. In addition, the detection of the elderly anomalous behaviors can be beneficial to act upon in risky situations, both for the experts and the family members (or caregivers). Although, based on the changes in the elderly routine, they should receive relevant notifications, helping them to carry out their activities in a proper way and encourage them to improve their lifestyle.

[1] http://www.who.int/mediacentre/factsheets/fs404/en/

RELATED WORK

In the remote assistance tools, in order to understand changes and abnormal behaviors, the system needs to model the user "normal" daily routine and current contextual events. Task analysis is a way to identify a set of user activity and goals and it is useful meant for gathering a huge amount of disorderly information. Task Models have been successfully applied in various fields such as modeling erroneous behavior to improve the safety of human-interactive systems based on where and how human behavior diverges from a task model [1], designing and assessing interactive systems [11],

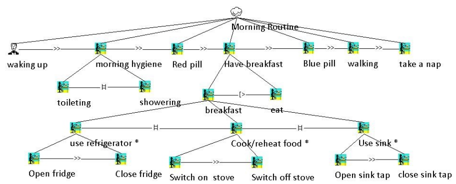

Figure 1: The task model of the example.

Choice	**[]**
Order Independence	**|=|**
Interleaving	**|||**
Synchronization	**|[]|**
Disabling	**[>**
Suspend-Resume	**|>**
Sequential Enabling	**>>**
Sequential Enabling Info	**[]>>**
Iteration	**T***
Optionality	**[T]**

Figure 2: Temporal Operations.

providing the backbone of educational programmes [7], describing human behavior abstractly and mapped this abstract expression to humanoid robots [10]. Bolton et al. presented a method for automatically generating formal task analytic models encompassing both erroneous and normative human behavior from normative task models (EOFM) [2] and illustrated the method with a case study in the programming of a patient-controlled analgesia pump. By using task analytic behavior models they evaluate their impact on the system using model checking. In their method, they focused on generating erroneous human behaviors using Hollnagel’s [5] zero-order phenotypes of erroneous action.

Nowadays, there is a strong focus on detection anomalies in elderly behavior . However, a few of them focused on finding anomalies in the routine of the elderly daily activities. Hajihashemi et al. [4], propose a new illness recognition framework, MFA, based on detecting a missing frequent activity from the daily routine. Their strategy for detecting the anomalies is to exploit the similarity between sensor sequences using a frequent temporal pattern detection algorithm. The authors [3] have developed a system using 1-class HMM and 2-HMM (based on the availability of the training data) to detect the anomalies in the daily activities and future behaviors which is based on the long-term context histories. Later, they send the final outcomes to the Fuzzy rule-based model for final prediction and send the proper alert to the experts. Moreno et al. [8] present a method to detect anomalies in the user daily living by using the user location at a given time instance. They used a hybrid system of classifiers to model the input data, such as the day, week, hour of earlier user states to predict the current user situation, teach the system the pattern of the user and consequently identify if there is something different from user routine or not. Most of the researchers on anomaly detection can define if there are anomalies in the user daily activity or not, while in our work, we classify the anomalies in more systematic categories and we provide more details about the time that anomaly happened and which user behavior triggered the detected anomaly.

METHOD AND THE ARCHITECTURE OF THE SYSTEM

We set up our study on prior work by Manca et al. [6] but generalize their algorithm (which was an offline algorithm) to the real-time algorithm which also has the ability to address a greater range of anomalies. In our method, we feed the system with user task model (which is the expected user routine daily activity) and compare the user expected behavior with the data received from the real context to find the anomalies and consequently act upon them. The task models (Figure 1) considered in this approach are specified according to the ConcurTaskTrees (CTT) language [9] and can be created by the elderly themselves or their caregivers. Tasks in the task model contain information, such as name, execution time interval, number of iteration, optionality and criticality level. In our approach, we considered just the elementary tasks in the task model which are the task without any further detailed activity. Temporal operators (presented in Figure 2) are used to represent temporal

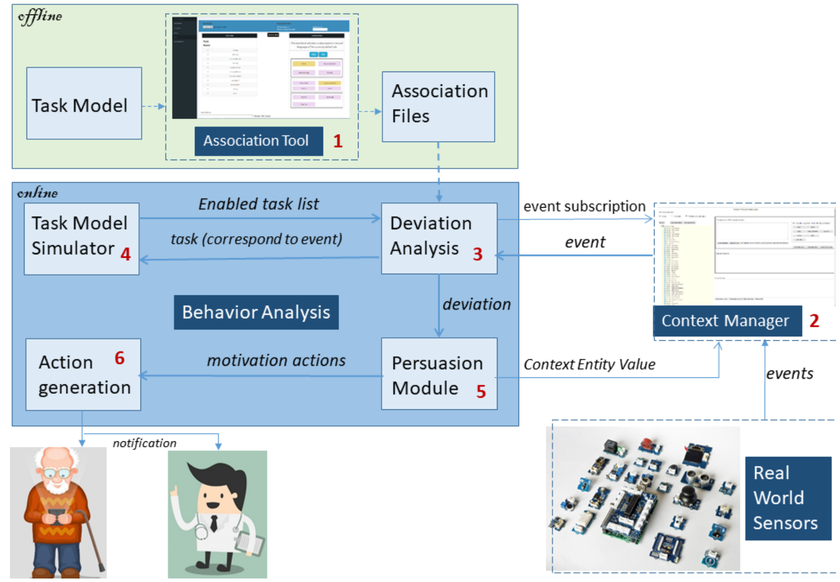

Figure 3: The Architecture of the Solution.

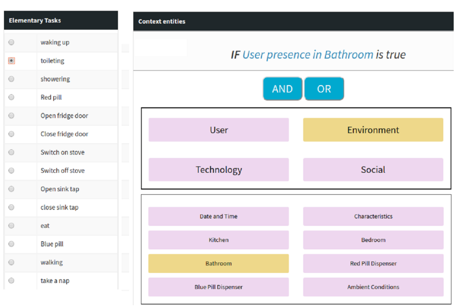

Figure 4: association tool.

relationships between tasks in the task model. Then, by using the Association Tool, each elementary task can be associated with one or more events in the user context based on the available sensors in the elderly house (Figure 4). Later, the deviation Analysis module subscribes these associated events to the Context Manager (CM) in order to receive the events which are related to the user daily routine (defined in task model). The Context Manager (number 2 in Figure 3) is a software which is able to detect relevant contextual events determined by the actual elderly behavior. As soon as the CM received such an event, sends a JSON notification to the Deviation Analysis. In turn, the Deviation Analysis (number 3 in Figure 3) analyses the JSON file, find the elementary task associated to the received event(s) and pass it to the Task Model Simulator (number 4 in Figure 3). The Task Model Simulator is a module that takes the task in input and outputs the list of currently enabled tasks (based on the temporal operators between the tasks). Further, based on the information provided by the Task Model Simulator, time and the duration of the task (correlated to event), the real-time anomaly detection algorithm in Deviation Analysis module controls whether the sequence of events detected by the CM matches to the path of the elementary tasks contained in the task model based on the temporal relationships. Besides, the algorithm analyses the time and the duration of the event and refers to the output of Task Model simulator to detect the anomaly in the received sequence of events and determines in which category the anomaly placed. As already mentioned, an anomaly is outlined by the differences between the received data from sensors and the expected user behavior. Based on the severity degree of the deviations, each anomaly can be an initial sign of health issues and based on the anomaly classification, the system may consider a different strategy for issuing actions which help elderly to improve their abnormal behavior. For having more precise decision about the deviations in the user behavior, we classified the possible task-related anomalies in a systematic categorization.

- **Less**: A task that was expected has not been performed.
- **More**: A task has been performed more than permitted time, which later will be extended to More-Number and More-order based on the order and the time of the task performance.
- **Difference**: A task has been performed differently from the expected one in terms of time and the order, which later will be classified in Difference-Early-time, Difference-Later-Time, Difference-Order and Difference-Order-Time.

On the other hand, there is a big need to encourage elderly to improve their behavior for having a healthy lifestyle [12]. Consequently, the Deviation Analysis sends the anomalous task, time of occurrence and the anomaly type to the Persuasion Module. In turn, the Persuasion Module (number 5 in Figure 3) based on the detected deviation and the user contextual aspects (e.g., current time, location, etc.) which retrieves from CM, selects the proper motivation actions and passes them to the Action Generation module. The Action Generation module (number 6 in Figure 3) delivers the suitable actions in a proper way (depend on the user contextual aspects) to motivate older people in order to help them improve their well-being. Applying persuasive techniques increases the chance of acceptance of the proposed interventions by older adults.

Result:
In order to systematically validate our approach, we simulated the event notifications received from the Context Manager. By using the simulated events, we generated 30000 anomalous sequences, which 10000 of them contain one and another 20000 sequences contain two or more types of anomaly. Later, the simulator sent the events in the generated sequences, one by one, to the real-time anomaly detection algorithm. The algorithm in turn hands out the anomalous events with their anomaly type and the time of occurrence. The result is promising and shows that our real-time algorithm can obtain 95% of accuracy.

CONCLUSIONS AND FUTURE WORK

In this paper, We proposed a real-time solution to detect the anomalies in the user behavior by comparing the planned user behavior which is specified using a CTT task model, with the real one happens in the user context. For validating our method, we simulated the anomalous sequences and send it to the Deviation analysis. The results show the 95% of accuracy. However, the complete implementation of the framework will be performed in future work. For the future work, we plan to validate our algorithm by the data from the real user. Moreover, The persuasion module will provide some advice based on anomalous behavior, vital signs and the agenda of the elderly. For example, it could present reminders and give motivational messages for a healthy lifestyle and caregiver or health providers can be immediately alerted if a problem is detected to ensure timely support.

REFERENCES

[1] Matthew L Bolton. 2017. A task-based taxonomy of erroneous human behavior. *International Journal of Human-Computer Studies* 108 (2017), 105–121.
[2] Matthew L Bolton, Radu I Siminiceanu, and Ellen J Bass. 2011. A systematic approach to model checking human–automation interaction using task analytic models. *IEEE Transactions on Systems, Man, and Cybernetics-Part A: Systems and Humans* 41, 5 (2011), 961–976.
[3] Abdur Rahim Mohammad Forkan, Ibrahim Khalil, Zahir Tari, Sebti Foufou, and Abdelaziz Bouras. 2015. A context-aware approach for long-term behavioural change detection and abnormality prediction in ambient assisted living. *Pattern Recognition* 48, 3 (2015), 628–641.
[4] Z. Hajihashemi and M. Popescu. 2014. A new illness recognition framework using frequent temporal pattern mining. In *Proc. Pervasive and Ubiquitous Computing*. ACM Press, 1241–1247.
[5] Erik Hollnagel. 1993. The phenotype of erroneous actions. *International Journal of Man-Machine Studies* 39, 1 (1993), 1–32.
[6] M. Manca, P. Parvin, F. Paternò, and C. Santoro. 2017. Detecting anomalous elderly behaviour in ambient assisted living. In *Proc. EICS*. ACM, 63–68.
[7] Jeroen JG Merrienboer and Diana HJM Dolmans. 2015. Research on instructional design in the health sciences: from taxonomies of learning to whole-task models. *Researching medical education* (2015), 193–206.
[8] Aitor Moreno-Fernandez-de Leceta, Jose Manuel Lopez-Guede, Manuel Graña, and Juan Carlos Cantera. 2016. Real Prediction of Elder People Abnormal Situations at Home. In *Proc. SOCO'16-CISIS'16-ICEUTE'16*. Springer, 31–40.
[9] Giulio Mori, Fabio Paternò, and Carmen Santoro. 2002. CTTE: support for developing and analyzing task models for interactive system design. *IEEE Transactions on software engineering* 28, 8 (2002), 797–813.
[10] Masaya Ogawa, Katsuya Honda, Yoshihiro Sato, Shunsuke Kudoh, Takeshi Oishi, and Katsushi Ikeuchi. 2015. Motion generation of the humanoid robot for teleoperation by task model. In *Proc. RO-MAN*. IEEE, 71–76.
[11] Philippe Palanque, Célia Martinie, and Marco Winckler. 2017. Designing and Assessing Interactive Systems Using Task Models. In *Proc. HCI*. Springer, 383–386.
[12] Marcela D Rodríguez, José R Roa, Alberto L Morán, and Sandra Nava-Muñoz. 2012. Persuasive strategies for motivating elders to exercise. In *Proc. PervasiveHealth*. IEEE, 219–223.
[13] Leibing A. Guberman N. Reeve J. Wiles, J.L. and R.E. Allen. 2012. The meaning of "aging in place" to older people. *The gerontologist* 52, 3 (2012), 357–366.