A Living Lab Infrastructure for Investigating Activity Monitoring Needs in Service Robot Applications

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ABSTRACT
This paper presents a framework that has been developed for automatic activity recognition and domestic behavior monitoring, towards supporting elderly MCI patients in their daily domestic life. Our framework's infrastructure consists of a network of smart-home sensors and RGB-D cameras that can be adapted and be unobtrusively installed in a variety of indoor living areas, collecting data relative to the human's movement and the state of the home environment. User activities and behavior are then assessed through machine learning algorithms applied on these data. The developed framework has been applied in real house settings and extensive analysis has been performed, so as to investigate how human activity and behavior monitoring needs, in the scope of ICT solutions for supporting active and healthy ageing of MCI patients, can be covered in the scope of corresponding service robot applications.

CCS Concepts
• **Networks → Sensor networks** • **Computing methodologies → Activity recognition and understanding** • **Computing methodologies → Vision for robotics** • **Computing methodologies → Object identification** • **Computing methodologies → Tracking** • **Computing methodologies → Supervised learning** • **Hardware → Sensor applications and deployments** • *Social and professional topics → Seniors*

Keywords
Smart home; elderly behavior monitoring; mild cognitive impairment.

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1. INTRODUCTION
The continuous improvement of living conditions and the subsequent increase in life expectancy during the last few decades, has led to the gradual aging of the world population, resulting in the significant rise of age-related health issues. Medical conditions affecting a person's cognitive abilities, such as Mild Cognitive Impairment (MCI) and Alzheimer's disease (AD), have been proven to lead to functional limitations and impairments in daily life [1][2], while severely affecting an individual's ability to execute everyday tasks and activities. As a result, the research community has turned its attention towards the area of active and healthy ageing, aiming to support the independent living of MCI patients. Moreover, the major advances of recent years in the area of smart-home technologies, have shifted the focus towards living lab designs capable of monitoring the domestic behavior of MCI residents, and supporting their well-being through activity-specific interventions.

Towards activity detection through home state environment monitoring, state-change sensor networks have been extensively examined in the past [3]. In [4] the authors analyzed how the number of the smart-home sensors affects the detection accuracy, concluding that a small set of strategically installed sensors can outperform large-scale sensor networks. The issue of fusing information from heterogeneous sensors was tackled in [5], while [6] presented an extensive analysis of the effectiveness of the use of ambient sensors within the scope of activity detection. In addition to smart-home sensor-based designs, various approaches based on the person's movement within the house have been proposed. In [7], PIR sensors were used to record the occupant's movement, while in [8][9] RGB cameras were utilized towards activity recognition. Moreover, the emergence of low cost RBG-D sensors has led to approaches combining color and depth image features towards computer vision –based activity recognition [10][11]. Efforts have also been made in order to achieve human monitoring and support through the use of sensors mounted on mobile robotic platforms [12] instead of fixed house-wide installations.

Although domestic behavior monitoring has been proven to be feasible and effective in controlled lab environments, several problems arise when trying a similar approach in real home environments. Smart-home sensors and cameras are rarely available in real apartments, while installing such units requires major, and often obtrusive, alterations in the house's interior layout and are usually dismissed by the residents. Small mobile robotic platforms, on the other hand, can provide an alternative approach, as they do not require any prior modifications in the house and can be easily installed without any need for major hardware customization. Moreover, their size and ability to interact with the human, can offer a less invasive, companion-like experience. The current work follows this line, presenting a living lab infrastructure for automatic domestic behavior monitoring and activity detection for elderly MCI patients, aiming to investigate the monitoring needs and challenges of porting such an infrastructure within the scope of service robot applications.

The paper is structured as follows: section 2 presents the design of the preliminary living lab infrastructure, section 3 describes its experimental application in real home environments, section 4 describes the analysis that was performed towards the development of an equivalent human activity monitoring platform based on a mobile service robot and section 5 includes information about the acceptance level of the infrastructure by the elderly.

2. LIVING LAB INFRASTRUCTURE

The design of the living lab infrastructure was dictated mainly by the activities that had to be recognized: cooking, eating, dish-washing, sleeping, watching TV and personal hygiene. These activities, also known as Instrumental Activities of Daily Living (IADLs) [13], have been proven to be effective towards evaluating cognitive ability and detecting MCI in elders [1]. The collected data had to provide strong indications about the executed activity, while simultaneously protecting the privacy of the user. As a result, a set of main household objects was defined for each activity (i.e. watching tv – TV, cooking – stove, sleeping - bed etc.), whose working state would provide the main indication for the execution of the activity. Similarly, a set of secondary objects, related to the room that the activity was usually executed (i.e. cooking – lights in kitchen), was also defined, further supporting the activity recognition process. Moreover, based on the work of [14], it was decided for all the activities to incorporate vision-based information extracted from the user's silhouette, including his/hers location, body posture and upper body activity level. Taking into consideration these monitoring requirements, a set of monitored features for each activity was defined, using both the sensor-based and vision-based data collection modalities. A detailed description of these features is presented in Table 1 and Table 2.

The whole system had to be adaptive, in order to allow easy and relatively unobtrusive installation in diverse apartments. Towards meeting these requirements, it was decided to use a network of small-form-factor smart-home sensors along with RGB-D cameras in order to extract information relative to the home environment state and the state of the monitored human.

The smart-home sensors network consisted of ambient sensors which provided information about the environmental conditions around points of interest within the house (i.e. temperature at stove) and the relative position of objects of interest (i.e. fridge door open / closed), based on the activity specific features defined above. It should be noted that a major factor driving the selection of our infrastructure's sensors was to minimize the interventions that would be necessary in order to install the framework in different house environments. In this scope, our framework was for instance capable to monitor the operating state of the user's oven, while the exact sensor used to this end could differ among different house setups. Indicatively, either an AC sensor was used when the power line of the oven was easy to reach, or a temperature sensor near the oven otherwise, while different sensors were used for different tap types. Overall, a series of alternatives for monitoring the same characteristics of the environment were prepared, so as to allow us to easily monitor the same environment attributes through different setups, with the minimum needed interventions.

Table 1. Sensor-based activity-specific monitored features

• SLEEPING	
Bed state	Person is on/off the bed
Bedroom lights state	Lights in the bedroom are turned on/off
TV state	TV is turned on/off
Other lights state	Lights in other rooms are turned on/off
• PERSONAL HYGIENE	
Bathroom lights state	Lights in the bathroom are turned on/off
Bathtub state	Water in the bathtub is/is not running
Sink state	Water in the bathroom sink is/is not running
• WATCHING TV	
TV state	TV is turned on/off
TV remote controller state	Frequency of channel changes through the remote controller
TV room lights state	Lights in the room of the TV are turned on/off
Other lights state	Lights in other rooms are turned on/off
• COOKING / DISHWASHING / EATING	
Stove state	The stove is turned on/off
Kitchen lights state	Lights in the kitchen are turned on/off
Other lights state	Lights in other rooms are turned on/off
Sink state	Water in the kitchen sink is/is not running
Cupboard/fridge doors state	Frequency of cupboard and fridge doors opening/closing
TV state	TV is turned on/off

Table 2. Vision-based monitored features

Location	Person's location in the monitoring area
Body posture	Standing / Bending / Sitting / Lying
Upper body geometry	Head - Hand distance Hands distance Head – Shoulder – Hand angle

The heterogeneity of the available sensing units of our infrastructure allowed the installation of the sensor network in different apartments, as the data collection process was independent of the monitoring space layout. For the implementation of the infrastructure, Phidgets[1] sensors were selected, as they provided a large variety of small-form-factor sensors, along with a comprehensive API which simplified the data collection process. Table 3 outlines the smart-home sensors that were used, along with their position and measured variables, while Figure 1 presents an indicative sensor setup in a real apartment.

[1] http://www.phidgets.com/

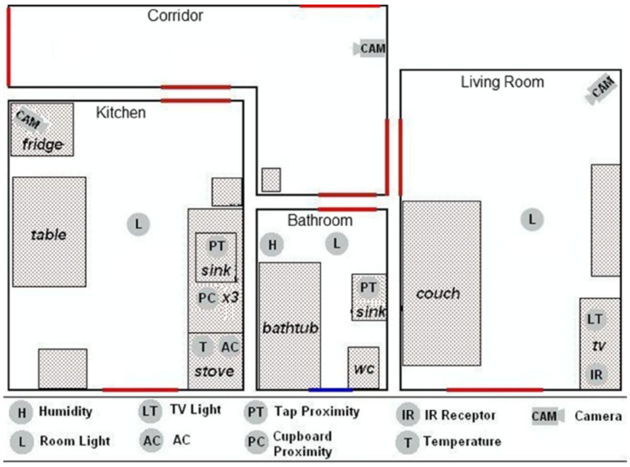

Figure 1. Indicative sensor setup in apartment

Table 3. Set of sensors used for monitoring the home environment state

Sensor type	Position	Measurement
Temperature	Near stove	Local ambient temperature
Humidity	Inside bathroom	Local ambient relevant humidity
Light (I)	Inside each room, near the main light source	Ambient luminance
Light (II)	On TV Screen	Luminance of the TV screen
AC Current	On supply cord of electric appliances	RMS value of the appliance's AC current
Accelerometer	On tap handle	Tap state (open / close)
Proximity (I)	On cupboard/fridge door	Door state (open / close)
Proximity (II)	On round tap handle	Tap state (open / close)
IR Receiver	Next to TV	IR TV codes sent by the remote
Pressure	Under the bed's mattress	Pressure on the bed

For tracking the human within the house and extracting silhouette-based information, a network of interconnected low-cost RGB-D cameras (Microsoft Kinect v1 & v2[2]) was utilized. Each room was monitored using one or two cameras, depending on the room's dimensions, which were installed close to the ceiling, in order to maximize the cameras' field of view. The RGB-D cameras were calibrated with reference to the top-down layout of the apartment and were able to track the human in real time, provide her/his exact position within the monitoring area and extract information on body posture and relative body movement. In order to protect the person's privacy, only the depth stream of the cameras was utilized, while the RGB data were discarded. Moreover, some areas (bathroom, bedroom) were excluded from monitoring in order to reduce the obtrusiveness of the system and offer the human a private safe space.

[2] https://dev.windows.com/en-us/kinect

Both the smart-home sensors and the RGB-D cameras were controlled by small-factor PCs, which were installed within the house and were connected to a secure local network. One of the PCs was selected as an aggregator PC while the rest were designated as client PCs. Each client PC would collect the raw data provided by the sensors and cameras connected to it, and would transfer it to the aggregator PC were they were stored locally. The data collection process was fully automated and was active for 20 hours per day. During the night, while there was no activity detected in the monitoring areas, the data collection would stop in order for the aggregator PC to analyze all the recorded sensor and trajectory data, perform activity detection and extract the activity-related information. Once the activity detection process was complete, the data recording process would restart automatically. An overview of the data collection setup is presented in Figure 2.

Figure 2. Overview of the data collection network

3. INFRASTRUCTURE APPLICATION IN REAL HOME ENVIRONMENTS

In order to test and evaluate the proposed infrastructure, four pilot experiments were performed in the apartments of single elderly MCI patients. The main goal of the experiments was to investigate and define the monitoring needs for detecting and recognizing ADLs of interest such as cooking, dish-washing, eating, sleeping, personal hygiene, watching TV, as they were executed by the residents. Moreover, the pilots contributed towards streamlining the installation process, while reducing the obtrusiveness of the system. It should be noted that, in order to ensure the residents' privacy, depth cameras were not installed in personal areas of the house, such as the bedroom and the bathroom, while any sensors deemed obtrusive by the residents, were also removed.

The first pilot was set up in a 90m^2 apartment. Five RGB-D cameras, monitoring three areas (living room, corridor, kitchen), and 14 sensors were installed. The resident was a 74 year old female MCI patient and data was collected for 15 days.

The second pilot was set up in a 60m^2 apartment. Three RGB-D cameras, monitoring three areas (living room, corridor, kitchen), and 13 sensors were installed. The resident was an 83 year old female MCI patient and data was collected for 8 days.

The third pilot was set up in a 50m^2 apartment. Two RGB-D cameras, monitoring two areas (living room, kitchen), and 11 sensors were installed. The resident was a 68 year old female MCI patient and data was collected for 7 days.

The fourth and final pilot was set up in a $90m^2$ apartment. Three RGB-D cameras, monitoring two areas (corridor, kitchen), and 13 sensors were installed. The resident was an 80 year old female MCI patient and data was collected for 8 days. Figure 3 presents the design of the apartments used in these pilot installations.

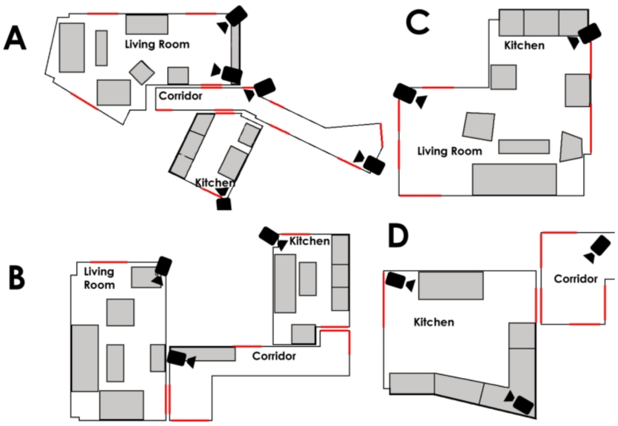

Figure 3. The four apartments of the pilot experiments

The home environment state data collected from the smart-home sensors network, and the human tracking data collected from the RGB-D cameras were both used in order to evaluate the infrastructure's potential towards effective activity detection. By employing HMMs to model human trajectories during the monitored ADLs, and by using their output as input to SVMs, along with features extracted from the smart-home sensors data, we achieved average precision and recall rates above 80% when using only sensor or tracking data. Meanwhile, the fusion of both data modalities increased the average precision rate to over 90% [15]. Additionally, in order to test the activity detection potential of a sensor-less infrastructure design, an HCRF-based approach was employed, using only the vision-based features described in section 2. Specifically, HCRFs were used to detect user activities, utilizing data sequences extracted from the occupant's movement, body posture and upper-body geometry, leading to a precision rate of 90.5% [16].

The high detection rates achieved in the pilot applications, demonstrated the effectiveness of the developed infrastructure, as well as the activity detection potential of vision-only methods that can be used when smart-home sensors are not available.

4. ACTIVITY MONITORING NEEDS IN SERVICE ROBOT APPLICATIONS

The main goal of the presented work was to investigate the activity monitoring needs and understand differences and problems that arise when trying to transfer the capabilities of such an infrastructure, in the scope of robotic applications, specifically on service robots that are designated to monitor and support MCI patients at home, being thus in need of user activity and behavior monitoring and assessment, as in the case of RAMCIP service robot[3].

[3] http://www.ramcip-project.eu/ramcip/

Since smart-home sensors and statically mounted RGB-D cameras are not available in the majority of apartments, and taking into consideration the fact that any major alterations within the house (sensors installation, PCs, cameras etc.) should be avoided, as they may have a negative impact on the emotional state of the patients, it becomes apparent that a series of problems must be overcome in order to fulfill the activity monitoring needs using a robotic platform.

One major issue arises from the lack of a smart-home sensor network within the house. Since the robotic platform is usually equipped only with a RGB-D camera, the home environment state recognition must be achieved through vision-based techniques. In order to extract the activity-specific monitoring features presented in Table 1, the working state of all the main and secondary activity-related household objects, described in section 2, must be detected. For objects/appliances operated using knobs or handles (stove, kitchen/bathroom sink), the working state can be recognized by detecting the state of the controlling knob. Through RGB-based object recognition, utilizing a latent SVM [17], the handle is located within the camera view, and its relative rotation provides information about the state of the appliance. A similar approach is employed for appliances that use remote controllers. The controlling unit is recognized within the scene through an RGB-D based small object detection algorithm [18], and the user's interaction with it is used to infer the appliance's state. For objects with large movable parts (fridge, cupboards), custom 3D articulated models are utilized [19] in order to calculate the position of the movable part relative to the main body of the object. Appliances that provide major optical cues regarding their operating state (TV, room lights) can be easily handled through thresholding-based approaches. Finally, the use of large furniture, specifically the sofa, armchairs and the kitchen table, is infered by taking into consideration the occupant's position relative to the furniture and his body posture. For example, if a person is located on or in very close proximity to the sofa and his body posture is detected as "sitting", then the sofa is considered "in use".

Figure 4. RGB-D camera viewpoint: Top – wall-mounted fixed camera, bottom - robot-mounted camera

Another challenging aspect of the adaptation of the monitoring infrastructure to a service robot application is the selection of a suitable viewpoint depending on the task in hand. In the infrastructure described in section 2, the RGB-D cameras were installed around the apartment, on relatively high positions, ensuring the coverage of all the monitoring areas, while also minimizing any potential occlusions due to obstacles in the camera FOV. On the other hand, the single, low-height camera viewpoint of a robotic platform (Figure 4), offers a limited partial view of the monitoring space, making it necessary to employ an autonomous navigation strategy in order to achieve optimal camera viewpoints during each task. Since the apartment set up and the areas relative to each activity are known beforehand, the robot is provided with a set of predetermined monitoring positions, called "parking positions", which offer the best possible field of view for each activity [20]. Similarly, a set of parking positions is provided for each activity-related household object (either the object itself or the surface that supports it, i.e. kitchen table, coffee table etc.), in order to maximize the object recognition accuracy. A list of the defined parking positions along with a short description is presented in Table 4, while a set of indicative parking positions for kitchen-related activities is presented in Figure 5.

Table 4. Detailed list of parking positions within a typical apartment

• AREAS	
Living room	Overall view of the sofa, armchairs, TV and coffee table
Kitchen	Overall view of stove, sink, kitchen table, fridge and kitchen cupboards
• SURFACES	
Kitchen table Coffee table Kitchen deck	Close up view of the surface in order to recognize and interact with objects placed on it
• OBJECTS	
Fridge Cupboards	Close up view of the object in order to recognize the position of its movable part and interact with it
Stove Sink TV	Close up view of the object in order to recognize its working state and change it if necessary
Sofa Armchairs	Close up view of the object in order to interact with human using it
Light switches	Close up view of the switch in order to interact with it

Finally, in order to achieve efficient robot navigation within the house, when moving between parking spots or following the human, a detailed map of the apartment is utilized to generate an optimal trajectory between the start and end point [20]. Simultaneously, a local obstacle detector is used to alter the trajectory in real time, so as to avoid any obstacles not present in the map, while also updating the map with the newly discovered obstacles. Moreover, as it is very important to make sure that the robot will not obstruct the occupant when moving around the house or performing everyday tasks, the trajectory planner takes into consideration the position and movement pattern of the human, and further alters the generated trajectory, ensuring that the robot will not violate the human's personal space, unless explicitly asked to do so (i.e. hand over an object).

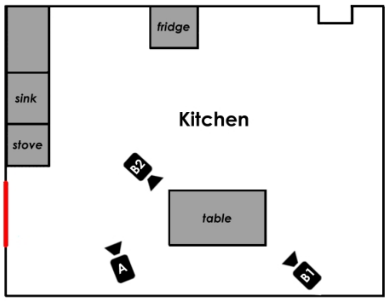

Figure 5. Indicative parking positions: A - Parking position for cooking monitoring, B1,2 – Parking positions for detection of objects on the kitchen table

The techniques described above offer feasible solutions to the challenges presented by a vision-only mobile platform design. However, they also pose an important problem that has to be tackled: Vision-based identification algorithms tend to be computationally intensive, as the identification process usually includes the point-by-point comparison of the viewed object with a large database of similar objects, leading to longer execution times and higher energy consumption, two features that are incompatible with an autonomous and responsive robotic platform design. In order to overcome these obstacles, a hierarchical approach is used towards the execution of the various vision algorithms. Tasks with lower processing needs, such as robot navigation and human localization, are given a high priority and are executed continuously. On the other hand, computationally intensive algorithms, which usually include the initial object identification tasks, are given a lower priority and are executed on demand, when deemed necessary depending on the task in hand. It becomes clear that a tradeoff between accuracy and processing speed is unavoidable, making it necessary to find a balance between these two aspects in order to fulfil the activity monitoring requirements.

5. INFRASTRUCTURE ACCEPTANCE

The seniors that participated in the pilot experiments showed, in general, a positive attitude towards the installation of the infrastructure in their residences, as they comprehended that it was a tool aiming to improve their quality of life. Before the equipment setup, each participant was given a thorough briefing on the experiment's goals and the installation process. Focus was given on the voluntary nature of the experiments, and it was clearly stated that the participants could forfeit the experiments at any time without any implications. A short live demonstration of both the depth cameras and the smart home sensors was also given, pointing out to the privacy-preserving nature of the data collected. These features, along with the inclusion of non-monitored private areas, such as the bedroom and bathroom, helped to overcome any hesitations that the participants may initially have had, leading to a high acceptance level of the infrastructure, as we did not receive any requests for equipment removal or monitoring interruption during the pilot experiments. However, some of the participants noted that they were hesitant to have guests during the experiments, as they were afraid that the presence of the monitoring equipment and their participation, in general, in a mental health-related experiment could create misconceptions about their mental health in their social circle.

Following the conclusion of the monitoring experiments, the participants were also introduced to an initial simplified version of a monitoring service robot (Figure 6) within their houses, and were asked to execute a few predetermined short activity-related scenarios while being monitored by it. The robot was radio-controlled by a human operator and would move and interact with its environment in a manner similar to the autonomous navigation scheme described in section 4. The goal was to capture the initial reactions of the elderly towards the robotic platform and integrate their feedback in the robot design process. The small robotic platform was generally well received by the participants. Its small size and responsive nature gave the impression of a smart gadget-like assistant, rather than a surveillance system, which all the participants agreed they would feel comfortable to have in their house, whether they were alone or had guests.

Figure 6. Initial version of the service robot used for demonstration

6. CONCLUSIONS

In this paper, an adaptive living lab infrastructure design was presented. The main goal of this work was to evaluate the infrastructure's efficiency in the scope of domestic behavior monitoring, while simultaneously addressing the technical issues that arise when trying to adapt the sensor/camera-based design to the constraints of a vision-only based robotic service platform. The experimental results presented in section 3 validate the activity detection effectiveness of the proposed infrastructure. Moreover, the computer vision techniques described in section 4 offer robust solutions to the limitations presented by the robotic platform design, enhancing the feasibility of such a design in the scope of activity detection and behavior monitoring. The next steps include the implementation and experimental evaluation of the robot service application, in order to test and further improve the proposed approach, as well as examine the hardware processing limitations in various environments.

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8. REFERENCES

[1] Ahn, I. S., Kim, J. H., Kim, S., Chung, J. W., Kim, H., Kang, H. S., et al. 2009. Impairment of instrumental activities of daily living in patients with mild cognitive impairment. *Psychiatry Investig.* 6, 3 (Sep. 2009), 180-184. DOI= http://dx.doi.org/10.4306/pi.2009.6.3.180

[2] Wadley, V. G., Okonkwo, O., Crowe, M., and Ross-Meadows, L. A. 2008. Mild cognitive impairment and everyday function: evidence of reduced speed in performing instrumental activities of daily living. *Am. J. Geriatr. Psychiatry*, 16, 5 (May 2008), 416-424. DOI= http://dx.doi.org/10.1097/01.JGP.0000310780.04465.13

[3] Tapia, E. M., Intille, S. S., and Larson, K. 2004. Activity recognition in the home using simple and ubiquitous sensors. *Pervasive Computing,* 3001, 158-175.

[4] Kasteren, T. and Krose, B. 2007. Bayesian activity recognition in residence for elders. In *Proceedings of the 3rd IET International Conference on Intelligent Environments* (Ulm, Germany, September 24-25 2007). IE '07. IET, 209-212. DOI= http://dx.doi.org/10.1049/cp:20070370

[5] Medjahed, H., Istrate, D., Boudy, J., and Dorizzi, B. 2009. Human activities of daily living recognition using fuzzy logic for elderly home monitoring. In *Proceedings of the IEEE International Conference on Fuzzy Systems* (ICC Jeju, Jeju Island, Korea, August 20-24 2009). FUZZ-IEEE 2009. IEEE, 2001-2006. DOI= http://dx.doi.org/10.1109/FUZZY.2009.5277257

[6] Liming, C., Hoey, J., Nugent, C. D., Cook, D. J., and Zhiwen, Y. 2012. Sensor-Based Activity Recognition. *IEEE Transactions on Systems, Man, and Cybernetics, Part C: Applications and Reviews*, 42, 6 (Nov. 2012), 790-808. DOI= http://dx.doi.org/10.1109/TSMCC.2012.2198883

[7] Le, X. H. B., Di Mascolo, M., Gouin, A., and Noury, N. 2008. Health smart home for elders - a tool for automatic recognition of activities of daily living. In *Proceedings of the 30th Annual International Conference of the IEEE Engineering in Medicine and Biology Society* (Vancouver, Canada, August 21-24 2008). EMBS 2008. IEEE, 3316-3319. DOI= http://dx.doi.org/10.1109/IEMBS.2008.4649914

[8] Duong, T., Phung, D., Bui, H., and Venkatesh, S. 2009. Efficient duration and hierarchical modeling for human activity recognition. *Artificial Intelligence*, 173, 78 (May 2009), 830-856. DOI= http://dx.doi.org/10.1016/j.artint.2008.12.005

[9] Park, S.and Kautz, H. 2008. Hierarchical recognition of activities of daily living using multiscale, multi-perspective vision and rfid. In *Proceedings of the 4th IET International Conference on Intelligent Environments* (Seattle, USA, July 21-22 2008). IE '08. IET, 1-4. DOI= http://dx.doi.org/10.1049/cp:20081157

[10] Cheng, Z., Qin, L., Ye, Y., Huang, Q., and Tian, Q. 2012. Human daily action analysis with multi-view and color-depth data. In *Computer Vision-ECCV 2012. Workshops and Demonstration,* 7584, 52-61. DOI= http://dx.doi.org/10.1007/978-3-642-33868-7_6

[11] Zhao, Y., Liu, Z., Yang, L., and Cheng, H. 2012. Combining rgb and depth map features for human activity recognition. In *Proceedings of the Asia-Pacific Signal and Information Processing Association Annual Summit and Conference* (Hollywood, USA, December 3-6 2012). APSIPA ASC 2012. IEEE, 3-6.

[12] Zhang, H., Parker, L. 2011. 4-dimensional local spatio-temporal features for human activity recognition. In *Proceedings of the IEEE/RSJ International Conference on Intelligent Robots and Systems* (San Francisco, USA, September 25-30 2011). IROS 2011. IEEE, 2044-2049. DOI= http://dx.doi.org/10.1109/IROS.2011.6094489

[13] Lawton M.P and Brody E.M. 1969. Assessment of older people: self-maintaining and instrumental activities of daily

living. *The Gerontologist* 9, 3 (Autumn 1969), 179-186. DOI= http://dx.doi.org/10.1093/geront/9.3_Part_1.179

[14] Zhou Z., Chen X., Chung Y.C., He Z., Han T., and Keller J. 2008. Activity analysis, summarization, and visualization for indoor human activity monitoring. *IEEE Transactions on Circuits and Systems for Video Technology*, 18, 11 (November 2008), 1489-1498. DOI= http://dx.doi.org/10.1109/TCSVT.2008.2005612

[15] Papamakarios G., Giakoumis D., Vasileiadis M., Drosou A., and Tzovaras D. 2016. Human Computer Confluence in the smart home paradigm: Detecting human states and behaviors for 24/7 support of mild-cognitive impairments. In *Human-centric Computing and Information Sciences*. In press.

[16] Giakoumis D., Stavropoulos G., Kikidis D., Vasileiadis M., Votis K., and Tzovaras D. 2014. Recognizing Daily Activities in Realistic Environments through Depth-Based User Tracking and Hidden Conditional Random Fields for MCI/AD Support. In *Computer Vision – ECCV 2014 Workshops*, 8927, 822-838. DOI= http://dx.doi.org/10.1007/978-3-319-16199-0_57

[17] Felzenszwalb, P. F., Girshick, R. B., McAllester, D., and Ramanan, D. 2010. Object detection with discriminatively trained part-based models. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 32, 9, (September 2010), 1627-1645. DOI= http://dx.doi.org/10.1109/TPAMI.2009.167

[18] Doumanoglou, A., Kouskouridas, R., Malassiotis, S., and Kim, T. K. 2016. Recovering 6D Object Pose and Predicting Next-Best-View in the Crowd. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition* (Las Vegas, USA, June 27 – 30, 2016). CVPR 2016. In press.

[19] Pellegrini, S., Schindler, K., and Nardi, D. 2008. A Generalisation of the ICP Algorithm for Articulated Bodies. In *Proceedings of the British Machine Vision Conference* (Leeds, UK, September 1-4 2008). BMVC 2008. BMVA Press, 87.1-87.10. DOI= http://dx.doi.org/10.5244/C.22.87

[20] Kostavelis I., Giakoumis D., Malasiotis S., and Tzovaras D. 2016. Human Aware Robot Navigation in Semantically Annotated Domestic Environments. In *Proceedings of the 18th International Conference on Human-Computer Interaction* (Toronto, Canada, July 17 – 22, 2016). HCI 2016. In press.