Dem@Lab: Ambient Assisted Living Framework for the Assessment of Dementia in Clinical Trials

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ABSTRACT
Dem@Lab is an ambient intelligence framework, which supports monitoring behavioral aspects of individuals in goal-oriented scenarios, within controlled, pervasive environments. Semantic Web technologies, such as OWL 2, are extensively employed in Dem@Lab to unanimously represent a wide variety of sensor observations and application domain specifics as well as to implement hybrid activity recognition and problem detection solutions. Multi-sensor, activity recognition and interpretation analytics in an Internet-of-Things context, are complemented by clinical applications aimed at assisting technology-aided clinical trials for the assessment of autonomy at different stages of dementia, evaluated over 158 trials.

Keywords
ambient assisted living, sensors, semantic web, ontologies, rules, dementia

1. INTRODUCTION
A key clinical feature of the Alzheimer's disease (AD) is impairment in daily function, reflected on the difficulty to perform complex tasks, such as the Instrumental Activities of Daily Living (IADLs) [15]. IADLs are daily tasks, characteristic of an independent lifestyle, such as making phone calls, shopping, preparing food, housekeeping and laundry. Inability to perform IADLs is notable at early stages of the disease affecting autonomy maintenance and quality of life, leading to loss of independence and increasing the burden of caregivers [1].

Treatment of AD begins with its diagnosis, based on behavioral and cognitive assessment that highlight quantitative and qualitative changes in cognitive functions, behaviors and ADLs. Currently, such methods involve questionnaires and clinical rating scales, which unfortunately, cannot often provide objective and fine-grained information. In contrast, pervasive technologies promise to overcome such limitations using sensor networks and intelligent analysis to capture the disturbances associated with autonomy and goal-oriented cognitive functions. This way, they could extract objective and meaningful information about individuals' condition for timely diagnosis.

This paper presents Dem@Lab, a semantically-enriched framework for monitoring IADLs in goal-oriented scenarios. Dem@Lab aims to provide the means to formally capture and integrate sensory observations, describe domain-specific use case scenarios of IADLs, and support intelligent data analytics, interpretation and assessment services pertinent to each deployment. To this end, Dem@Lab follows an ontology-driven approach to data modelling and analysis, using OWL 2 ontologies to capture deployment-specific properties and sensory observations, while interpretation and assessment are performed, using DL (Description Logic) reasoning and rules.

Dem@Lab is based on DemaWare [18], an Ambient Assisted Living (AAL) framework for activity detection, adapting it to a confined scenario of clinical, goal-driven lab trials. The chosen lab setting aims to provide feedback to clinical experts about IADLs that have been missed, repeated or took excessive amounts of time, helping them assess the autonomy of participants. The scope of this paper is to present the technologies that underpin the deployment of Dem@Lab in a lab, leaving out the clinical procedure to classify individuals as cognitively healthy, MCI (Mild Cognitive Impairment), or AD[1]. Dem@Lab has been deployed in the day center of the Greek Association of Alzheimer Disease and Relative Disorders and already used effectively to monitor and assess hundreds of participants.

The rest of the paper is structured as follows: Section 2 presents relevant work. Section 3 gives an overview of the framework. Sections 4, 5, 6 7 and 8 respectively present each of the framework's layers, namely the infrastructure pulling observations and events, knowledge structures and vocabularies, complex activity recognition and problem detection methods and means for clinical feedback in end-user applications. Section 8 concludes the paper.

2. RELATED WORK
Pervasive technologies have already been employed in several ambient sensing environments [11] [6], traditionally driven by various domain requirements such as sensor modalities and analytics in each existing framework. The proposed framework complements such developments, by integrating a wide range of sensor modalities and high-level analytics to support IADL monitoring towards tailored autonomy assessment.

OWL has been widely used for modelling human activity semantics, reducing complex activity definitions to the intersection of their constituent parts [3]. In most cases, activity recognition involves the segmentation of data into snapshots of atomic events, fed to the ontology reasoner for classification. Time windows [9] and slices [13] background knowledge about the order or duration [12] of activities are common approaches for segmentation. In this paradigm, ontologies are used to model domain information, whereas rules, widely embraced to compensate for OWL's expressive limitations [8,20], aggregate activities, describing the conditions that drive the derivation of complex activities e.g. temporal relations. Dem@Lab follows a hybrid reasoning scheme, using DL reasoning for activity detection and SPARQL to extract clinical problems.

[1] More details about clinical validation can be found in [7].

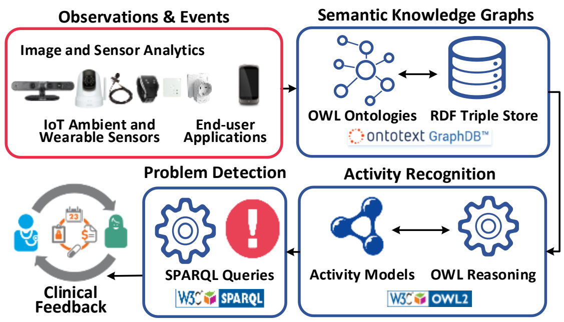


Fig. 1. Dem@Lab conceptual architecture.

Focusing on medical care and ambient sensing, the work in [16] uses web cameras to monitor IADL in home. The framework presented in [5] evaluates activity performance i.e. completion of a task based on sensor data in a smart home. The work in [19] has deployed infrared motion sensors in clinics accurately identifying sleep disturbances according to questionnaires. However, it reveals some limitations of using a single, only, sensor. Similarly, the work in [2] is a sensor network deployment in nursing homes in Taiwan to continuously monitor vital signs of patients, lacking the ability to fuse more sensor modalities, with limited interoperability. Such concepts have been described in the E-monitor framework for ambient sensing and fusion in a clinical context [4]. Dem@Lab implements and extends these concepts in a unified framework for sensor interoperability.

3. DEM@LAB OVERVIEW

Dem@Lab supports a rich selection of ambient and wearable sensors, listed on Table 1, which introduce multiple data modalities, such as image and video for specialized analysis, and more self-contained measurements, such as physical activity and object motion. A core objective of Dem@Lab is to recognize activity events which may be relevant to direct sensor outputs, e.g. activation of motion sensors, or even require intermediate data analysis, e.g. posture recognition on video data. Its conceptual architecture, as depicted in Fig. 1, consists of five core layers:

- **Observations & Events:** This layer hosts the interconnected Internet of Things (IoT) hardware in Dem@Lab. It consists of ambient and wearable sensors, image and sensor analysis methods and end-user applications that all generate observations and events, serving as inputs for the upper layers of the system.
- **Semantic Knowledge Graphs:** OWL vocabularies are used to build semantic knowledge graphs capturing (i) domain protocols, (ii) sensor and analysis observation types and (iii) IADL contextual models. The GraphDB[2] triple store is used for persisting ontologies and data.
- **Activity Recognition:** IADL models are fed to an OWL 2 RL reasoner provided by GraphDB (or any other, e.g. a DL reasoner) for activity recognition.
- **Problem Detection:** A set of SPARQL queries implement activity-related problem detection, e.g. activities with long duration, or incomplete ones.
- **Clinician Feedback:** As the uppermost layer of Dem@Lab, this layer contains end-user applications, i.e. a clinician interface, that collectively present gathered knowledge and detected problems to clinicians, serving as a basis for on-going interactions between clinicians and people under their care.

[2] http://ontotext.com/products/ontotext-graphdb/

Table 1. Sensor types currently supported in Dem@Lab.

Sensor	Type	Data Type	Modality
Kinect	Ambient	Image, Depth	Posture, Location, Event
Camera	Ambient	Image	Posture, Location, Event
GoPro	Wearable	Video	Objects, Location
DTI-2	Wearable	Accelerometer	Moving Intensity
Plugs	WSN	Power Usage	Objects
Tags	WSN	Object Motion	Objects

The following sections describe in detail underlying technologies and methods in each layer.

4. OBSERVATIONS & EVENTS

The sensors currently included in the framework are non-intrusive, ambient or wearable low-cost devices that support a variety of modalities. Each lab deployment consists of cameras, lifestyle and wearable sensors. An ambient depth camera[3] is placed to survey the whole room, capturing images and depth information. Smart plugs[4] are attached to electronic devices, e.g. the tea kettle, radio etc., measuring their consumption, while smart tags[5] measure the movement of objects, e.g. the kettle, teacup, watering can, drug-box, phone etc. A wearable sensor measures moving intensity per minute[6].

The Dem@Lab middleware incorporates one core module per sensor, dealing with each device's API and requirements for interoperable integration. Sensor data is retrieved and processed accordingly to be transformed into meaningful atomic events. E.g. plug and tag data are transformed to utility and object usage events, while computer vision techniques are employed for images to extract the location within pre-defined zones, posture and activity recognition of humans in the scene [14]. All events are mapped using semantic knowledge graphs and stored in the Knowledge Base.

5. KNOWLEDGE STRUCTURES AND VOCABULARIES

Dem@Lab allows end users to model domain knowledge about (i) goal-oriented protocols, (ii) domain observation entities and events and (iii) IADL contextual models i.e. semantics of complex activities involved in each scenario.

[3] ASUS Xtion PRO Live - https://www.asus.com/us/Multimedia/Xtion_PRO_LIVE/

[4] Circle, Cirlce+ and Stealth products by Plugwise.nl - https://www.plugwise.nl/

[5] Tags, PIR KumoSensor, Reed KumoSensor of the Wireless Sensor Tag System - http://wirelesstag.net/

[6] Philips DTI-2 non-commercial wristwatch kindly provided by Philips Research NL - http://www.philips.nl/ [10]

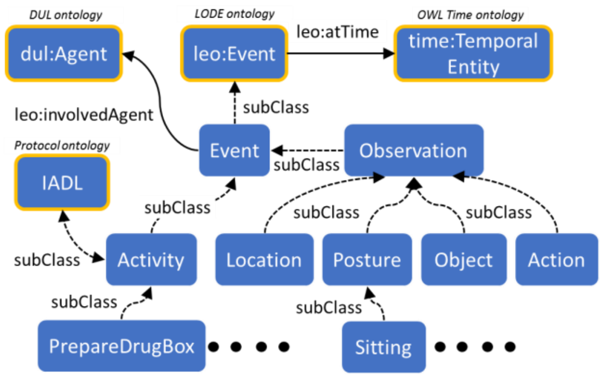


Fig. 2. Capturing observations and activities in Dem@Lab.

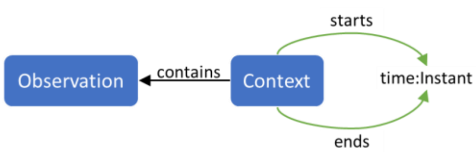


Fig. 3. Lightweight pattern for capturing IADL context.

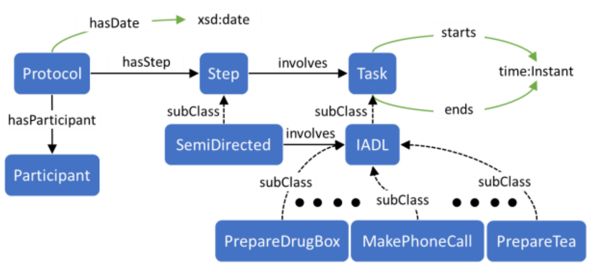


Fig. 4. Vocabulary for modelling goal-oriented protocols in Dem@Lab.

5.1 Goal-oriented Protocols

A protocol (or scenario) is represented as instance of the `Protocol` class and is used to store information about its date, the participating individual and the involved steps (Fig. 4). The `Participant` instances allow profile-related assertions about participants to be defined, such as demographic, clinical and experimental records. A protocol step involves some tasks and has a start and an end timestamp. Our deployment implements three protocol steps, relevant to directed activities, semi-directed activities and discussion with the clinicians. Fig. 4 depicts the conceptualization of the semi-directed task step, along with some examples of IADL tasks involved.

5.2 Observations and Activities

Sensor observations, intermediate analysis results (e.g. posture) and recognized activities are captured by extending the `leo:Event` class of LODE [17] (Fig. 2). The agents of the events and the temporal context are captured using constructs from DUL[7] and OWL Time[8], respectively. In the current deployment, Dem@Lab allows end-user to model information about location, posture, actions and objects as subclasses of the `Observation` class, while complex activities are defined as subclasses of the `Activity` class. Instances of the `Activity` class are also instances of the `IADL` class in Fig. 4 (and vice versa), which is captured as a mutual subclass relationship `Activity` ≡ `IADL`.

5.3 Activity Models

Dem@Lab provides a simple pattern (Fig. 3) for modelling the context of complex activities (IADL) i.e. semantics for activity recognition. Each activity context is described through class equivalence axioms that link them with lower-level observations.

The instantiation of this pattern is used by the underlying reasoner to classify context instances, generated during the execution of the protocol, as complex activities. The instantiation involves linking IADLs with context containment relations through class equivalence axioms. For example, given that the activity `PrepareTea` involves the observations `KettleOn`, `CupMoved`, `KettleMoved`, `TeaBagMoved`, `KettleOff`, `TeaZone`, its semantics are defined as:

$$\begin{aligned} PrepareTea \equiv Context &\sqcap \exists contains.KettleOn \\ &\sqcap \exists contains.CupMoved \\ &\sqcap \exists contains.KettleMoved \\ &\sqcap \exists contains.TeaBagMoved \\ &\sqcap \exists contains.KettleOff \\ &\sqcap \exists contains.TeaZone \end{aligned}$$

6. ACTIVITY RECOGNITION

Dem@Lab implements a location-driven context generation and classification approach. The deployment room is divided into zones, according to the location each activity takes place (Fig. 5 (a)). When a participant enters a zone, Dem@Lab generates a `Context` instance and starts associating it with collected observations using `contain` property assertions, until he leaves it. The resulting context instances generated in each session are fed into the ontology reasoner to classify them in the activity hierarchy.

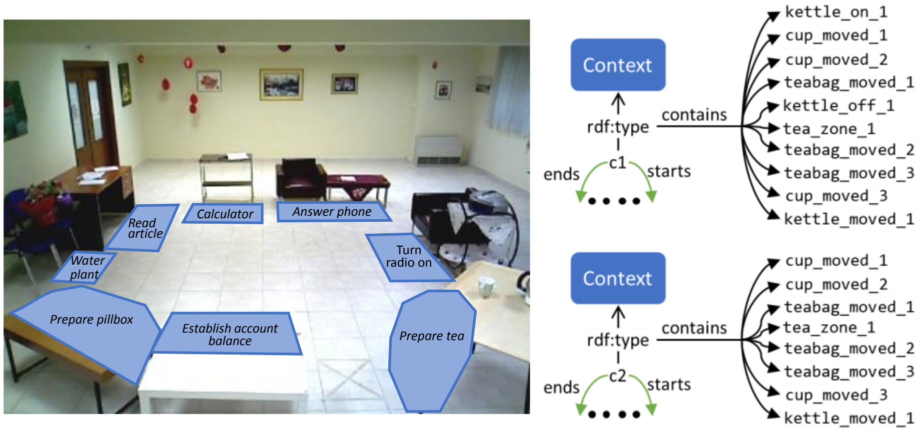
Fig. 5 (b) depicts two example context instances associated with a set of observations relevant to tea preparation. Based on the semantics of `PrepareTea` described in Section 5.3, `c1` will be classified in this class, since all existential restrictions are satisfied. However, `c2` will not be classified as tea preparation, since the context is not associated with any observation of type `KettleOn`, but rather translated into an incomplete activity, as described in Section 7.

Table 2 summarizes the performance on Dem@Lab on a dataset of 50 participants. TP is the number of IADLs correctly recognized, FP is the number of IADLs incorrectly recognized and FN is the number of IADLs that have not been recognized. Our approach achieves the best accuracy for “Prepare tea”, “Answer phone”, “Watch TV”, “Water the plant”, and “Write check”, whose activity models encapsulate richer contextual information, compared to “Prepare pill box” and “Read article”. On the other hand, the recall of these activities is relatively low, as they entail richer contextual dependencies and are, therefore, more susceptible to false negatives.

Dem@Lab’s performance is strongly dependent not only on its activity recognition layer, but also on the underlying observations layer. Namely, sensor observations in the lab have been found to be quite reliable, always detecting a sensor event (object movement and utility usage) with an acceptable delay for

[7] http://www.loa.istc.cnr.it/ontologies/DUL.owl

[8] http://www.w3.org/TR/owl-time/



(a) (b)

Fig. 5. (a) Activity zones, (b) example context instances with associated observations.

the setting, of 0-10s, using two to five sensors per activity. Scaling up the deployment to more sensors than that, exponentially increases delay beyond acceptable levels. On the other hand, image recognition methods e.g. for posture and location are slightly less reliable, being an active field of research. Extensive attribution of performance to the underlying framework components is subject of future studies.

Notably, the activity contexts do not involve temporal restrictions. E.g. the semantics of `PrepareTea` in Section 5.3 do not involve temporal relations[9]. As activities do not usually appear in a predefined order, Dem@Lab uses loosely coupled activity models, based on containment relations, instead of highly structured ones. Detected activities constitute aggregations of atomic events in time. Therefore, they do reflect clinical symptoms of participants related to event duration e.g. when taking too long to prepare tea, but do not examine event order e.g. when grabbing a tea bag before boiling water.

7. PROBLEM DETECTION

The clinical experts highlighted the fact that, apart from recognizing protocol activities, the derivation of problematic situations would further support them for the diagnosis/assessment. Towards supporting this requirement, Dem@Lab has been enriched with a set of SPARQL queries to detect and highlight situations of possibly problematic behavior and of critical value to the clinical experts. Currently, abnormal situations detected include highly repeated, excessively long, incomplete and missed (absent) activities. The closed-world reasoning (e.g. instance counting or negation as failure) required to detect them, was implemented with SPARQL queries.

Activity repetitions correspond to the number of context instances classified into each activity type, highlighting a problem if there is more than one of them. Activity duration, computed from start and end activity timestamps, is compared to a reference duration per IADL suggested by the clinical experts. Missed activities correspond to IADLs not performed i.e. absent in the knowledge base while incomplete activities correspond to orphan context instances, i.e. those with more than one `contains` property assertion, but with no pertinent `Activity` classification.

```
1: select ?x ?s ?e
2: where {
3:   {
4:      select (count(?o) as ?n) ?x ?s ?e {
5:           ?x a :Context; :contains ?o; :starts
?s; :ends ?e.
6:         FILTER NOT EXISTS {?x a :Activity.}
7:      }
8:   }
9:   FILTER (?n > 1)
10:}
```

The above query in SPARQL defines a nested graph pattern (lines 3 to 8) to retrieve context instances `?x` not classified as activities (line 6), while counting their `contains` property assertions (line 4). In order for the query to be successfully pattern matched, there should be more than one associated observations (line 9) apart from the location-related observation associated with all context instances. This helps eliminate cases where participants just enter zones without performing any action. In case of a match, the query returns the context instance `?x` along with its start and end timestamps, used to provide pertinent feedback to the end users. The use of SPARQL allows expressivity beyond native OWL, e.g. temporal relation, and the

Table 2. Recall and precision results for seven IADLs.

	TP	FP	FN	Recall	Precision
PreparePillBox	45	10	5	90.00	81.82
PrepareTea	38	3	12	76.00	92.68
AnswerPhone	36	4	14	72.00	90.00
TurnRadioOn	41	3	9	82.00	93.18
WaterPlant	41	3	9	82.00	93.18
AccountBalance	40	4	10	80.00	90.91
ReadArticle	45	8	5	90.00	84.91

[9] The native OWL semantics do not support temporal reasoning. However, it can be simulated using custom property assertions, as described in [13].

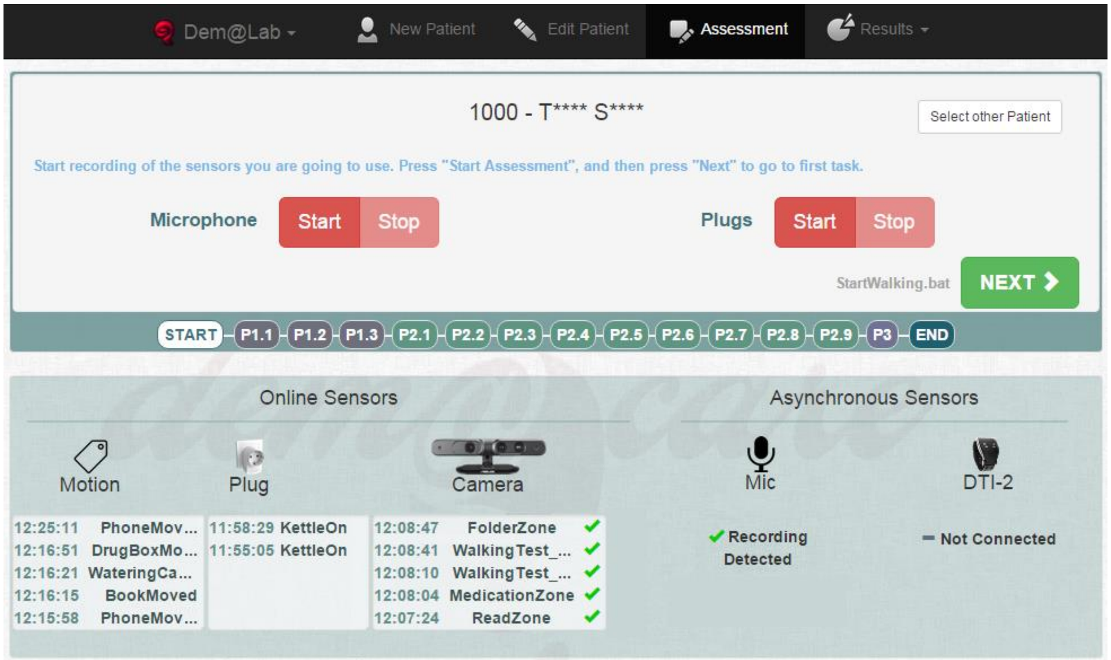


Fig. 6. Dem@Lab assessment application with real-time data collection

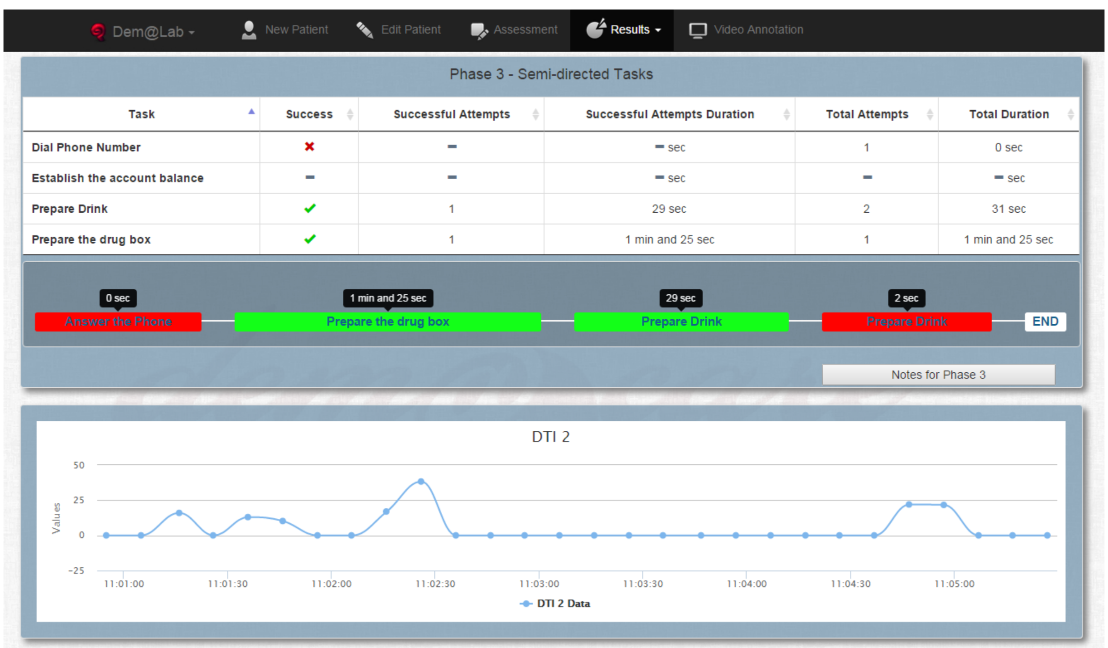


Fig. 7. Performance summary and problems.

generation of new individuals e.g. for problematic situations.

8. CLINICIAN FEEDBACK

At the application level, Dem@Lab provides a multitude of user interfaces to assist clinical staff, summarizing an individual's performance and highlighting abnormal situations. Fig. 6 depicts the Assessment screen, prior to the initialization of a protocol, where users can check the status and activate/deactivate sensors, according to the current protocol step, as described in Section 5.2. An example of the Results page for 4 IADLs is shown in Fig. 7 where both complete and incomplete activities are visualized (highlighted in green and red respectively). Various additional details for each activity are provided, such as their relative order, total duration and number of repetitions. Meanwhile, the bottom of the screen shows a line-chart of the person's moving intensity, indicative of the time he has been walking (beginning and end of the session), as measured by the DTI-2 sensor.

The Dem@Lab framework deployment in Greece has already been successfully carried out for more than a hundred participants, achieving a mean accuracy of clinical assessment close to 83% among healthy and MCI participants [7], based on direct observation annotation and neuropsychological assessment scores. According to Dem@Lab results, activity frequency differed significantly between MCI and healthy participants. In addition, differences in execution time have been identified among the groups for all activities. Correlation analysis demonstrated that some parameters, such as the activity execution time, correlate significantly with neuropsychological test results, e.g. MMSE and FAB scores.

9. CONCLUSION AND FUTURE WORK

Dem@Lab enables complex task monitoring of individuals in a controlled pervasive environment. The framework is currently applied in the field of healthcare, providing the semantic models and detection of IADLs to assist in the clinical assessment of autonomy and cognitive decline.

The activity recognition capabilities of Dem@Lab present certain limitations, significant to consider as future research directions. First, it cannot handle missing information, since activity semantics are modelled using fixed TBox axioms that should be all satisfied. Second, it does not handle uncertainty and conflicts, as it assumes that all observations have the same confidence. Although these limitations do not significantly impact the current lab deployment (given the predefined activity zones that simplifies activity recognition and compensates for sensor errors), deployment in more realistic environments, e.g. in homes, imposes additional challenges to be met.

Future works for the expansion of the framework, e.g. for home usage, entail secure protocols for data exchange and interoperability beyond the system (e.g. with epSOS[10] national contact points). The lab sessions required a minimum delay of up to 10 seconds, which may differ in other settings. While scalability in the lab has been discussed in Section 6, more thorough studies are required for other settings, involving the number of sensors of possible cloud components.

10. ACKNOWLEDGEMENT

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