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ENRICHME Integration of Ambient Intelligence and Robotics for AAL

Nicola Bellotto, Manuel Fernandez-Carmona, Serhan Cosar
Lincoln Centre for Autonomous Systems (L-CAS)
School of Computer Science, University of Lincoln
Lincoln LN6 7TS, United Kingdom

Abstract

Technological advances and affordability of recent smart sensors, as well as the consolidation of common software platforms for the integration of the latter and robotic sensors, are enabling the creation of complex active and assisted living environments for improving the quality of life of the elderly and the less able people. One such example is the integrated system developed by the European project ENRICHME, the aim of which is to monitor and prolong the independent living of old people affected by mild cognitive impairments with a combination of smart-home, robotics and web technologies. This paper presents in particular the design and technological solutions adopted to integrate, process and store the information provided by a set of fixed smart sensors and mobile robot sensors in a domestic scenario, including presence and contact detectors, environmental sensors, and RFID-tagged objects, for long-term user monitoring and adaptation.

1 Introduction

Ageing and increased life-expectancy of the population worldwide are bringing new challenges that soon many countries will have to face with. One of these is the well-being of the older citizens, including their quality of life and independent living at home. In order to address the latter, the European project ENRICHME[1] is developing new technologies to enable health monitoring, complementary care and social support for elderly people with Mild Cognitive Impairments (MCI), helping them to remain active and independent for longer. In particular, the project integrates a mobile robot within a smart-home environment to provide new Active and Assisted Living (AAL) services for the older person (see Fig. 1).

The key research questions of ENRICHME are three:

- Which are the best robotics and smart-home solutions for AAL services enabling older people with MCI to remain independent and safe?
- How to provide experimental long-term evidence demonstrating that such services are effective to prolong the independent living of the elderly at home?

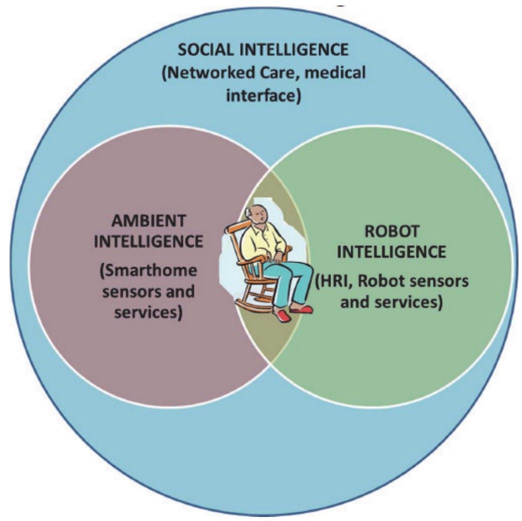


Figure 1: Three levels of ENRICHME intelligence provided by the robot, smart-home and networked care platform.

- What is the acceptability of the proposed robotics and smart-home solutions for the elderly and their caregivers?

To answer these questions, the integrated system in ENRICHME is designed to facilitate cognitive capability preservation, long-term social interaction and leisure activities, implementing new solutions for discrete monitoring of relevant motion activities, physiological parameters, and behavioural changes, which are indicative of the person state. This information is exploited by individualized AAL services delivered through an interactive mobile robot and a remote platform for tele-care assistance.

This paper describes some of the technological solutions adopted in the ENRICHME system and its architecture, with particular focus on the integration of smart-home and robot sensors for human and object localisation, activity monitoring, and detection of abnormal behaviours. Four main aspects of the project are here considered:

1. Distributed architecture for AAL services based on ROS[2];
2. Probabilistic solution for object localisation with a mobile

[1]ENabling Robot and assisted living environment for the Independent Care and Monitoring of the Elderly – http://www.enrichme.eu

[2]Robot Operating System – http://www.ros.org

robot based on RFID technology;

3. Vision-based approach for estimating the level of activity of a person;
4. Entropy-based system for detecting anomalous motion patterns at home.

The remainder of the paper is as follows: Sec. 2 reviews the state of the art on AAL, with particular focus on ambient intelligence and RFID technology; Sec. 3 explains the general architecture of the ENRICHME system; the practical steps for the integration of its components are described by the following Sec. 4; Sec. 5 summarises some of the key services provided by the system; Sec. 6 then describes their implementation, in particular for object localisation, activity monitoring and anomaly detection, with some preliminary results; finally, Sec. 7 concludes the paper summarising the achievements so far and highlighting directions for future research.

2 Related Work

Modern AAL frameworks aim to provide an adaptable, lightweight and expandable infrastructures for real user scenarios. For example, the AAL architecture of CASAS (Cook et al. 2013) comprises three conceptual levels using a simple and stable API. The lowest level is the sensor layer, based on Zigbee technology. Above this, the middleware layer uses a subscription/publication paradigm, acting as memory of the system. Finally, an application layer lies on the top.

In Europe, one of the most successful frameworks is UniversAAL (Ferro et al. 2015), an open platform focusing on the standardization of AAL solutions. UniversAAL offers a semantic and distributed software platform designed to ease the development of integrated AAL applications. Being specifically focused on solutions for ambient intelligence, it makes use of a complementary middleware, called openHAB[3], to control various domotic sensors. However, a full solution integrating smart-home and robotics technologies for advanced AAL service is still an open area of research and potential innovation.

One of the technologies embedded in recent AAL systems is Radio Frequency Identification (RFID), often used for human or object localisation within indoor environments. The only constraint is that the person or the object must carry a small, inexpensive tag. RFID localization is an interesting technology that uses classical techniques such as Time Of Arrival, Time Difference Of Arrival, Received Signal Phase or Trilateration (Bouchard et al. 2014) based on radio-frequency propagation models, including physical aspects of RFID communication (Saab and Nakad 2011). Other approaches rely on statistical models of the tag detection event itself, for example applying k-nearest neighbour (Huiting et al. 2013) or proximity-based methods (Soltani 2013). Bayesian models have also been proposed to include some physical properties of RFID radio propagation, described and exploited by dedicated RFID sensor models (Joho, Plagemann, and Burgard 2009). Recent improvements on the accuracy of the latter have also been made by using alternative likelihood functions (Koch and Zell 2016). In most of the cases though, object localisation relies on several fixed, often expensive, RFID antennas sparse in the environment, rather than a single mobile solution as the robot provided by ENRICHME.

RFID technology, however, is more suitable for localising objects than humans, in particular when also the activity of the latter needs to be monitored. Accelerometers have been widely considered as practical sensors for wearable devices to measure and assess physical activity of people (Yang and Hsu 2010; Atallah et al. 2009; Ravi et al. 2005). In the work of Ravi et al. (2005), a triaxial accelerometer is used to recognize basic activities such as sitting, walking, and running. Mean, standard deviation, energy, and correlation features are extracted and used by various classifiers (e.g., decision tree, SVM) for this task. Atallah et al. (2009) used a lightweight ear-worn accelerometer to categorize the daily activities of people into four levels: i) very low (e.g., sitting), ii) low (e.g., reading), iii) medium (e.g., preparing food), and iv) high (e.g., sports). However, although wearable accelerometers provide enough information to measure the activity level of a person, they are obtrusive and often forgotten and not worn by elderly people. Video-based approaches offers less intrusive and efficient solutions to analyse human activity. Pal and Abhayaratne (2015) grouped daily activities of elderly people in three activity levels: i) no activity, ii) low activity, and iii) high activity. Optical flow vectors are used to detect regions on the image that represents a motion. Then, histograms of oriented gradients (HOG) features are extracted in these regions. Finally, a neural network is trained to classify the level of activity. However, considering the noise of optical flow, extracting HOG features can be computationally expensive. Thus, the solution in ENRICHME follows a different approach, detecting the activity level of the person by analysing the global and local motion of the whole body and of some body parts, respectively.

Besides localised and short-terms activity levels, though, it is important to asses also the overall motion behaviour of the person over extended period of times, for example to detect anomalous situations indicative of some health condition. Abnormal activity events are common among patients with dementia or cognitive impairments. States of confusion and agitation usually take place around sunset, and they are symptoms of the *sundowning syndrome* (Ter Haar 1977). Studies described its tight relationship with abnormal motor activity levels and circadian rhythms (Bedrosian and Nelson 2013). Despite the importance of the problem, there are few examples of syndrome monitoring on real patients. Solutions based on motion trackers have been proposed to characterise these events (Godfrey et al. 2010). However, a more general approach is usually taken, modelling user patterns and studying their changes over time. Anomalies arise then when the models are unable to predict the current user behaviour. A recent approach adopted cross-entropy metrics to evaluate the capability of a model of predicting behavioural changes (Aran et al. 2016). The latter partly inspired also the solution adopted in ENRICHME for anomaly detection.

[3]http://www.openhab.org

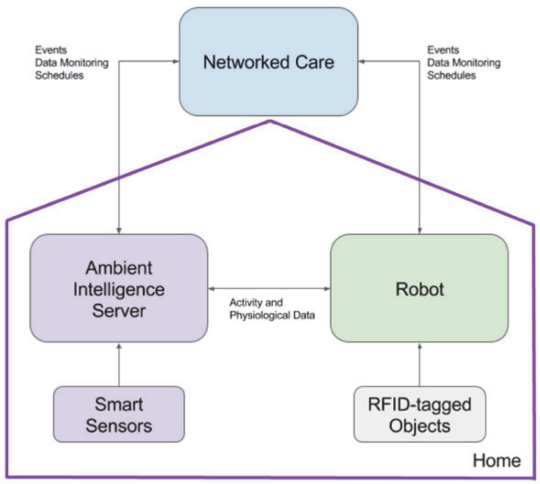


Figure 2: ENRICHME general architecture.

3 System Architecture

The general architecture of the ENRICHME system is based on three main interconnected components: the Robot, the Ambient Intelligence Server (AIS), and the platform for Networked Care (see Fig. 2). Together, they provide the three levels of intelligence introduced in Fig. 1. The first two components mostly exchange data about human activity and physiological measurements; they both communicate with the Networked Care regarding monitored data and new or scheduled events. The AIS and the Robot's intelligence are complemented, respectively, by the smart sensors and the RFID sub-system.

The Robot is a mobile platform, equipped with sensors and other devices, which navigates in the house, monitors the user (including physiological parameters) and interacts with the latter to offer various services, such as reminding appointments, suggesting physical and cognitive exercises, or finding lost objects. It is a Kompaï[4] model enhanced with advanced sensing and interactive capabilities. Besides cameras and laser sensors for human monitoring, it carries a long-range RFID system to detect and localise tagged objects, as well as an embedded environmental sensor for monitoring room temperature, lighting, humidity and particles (i.e. dust) in the air. The robot shares with the AIS real-time information about the current activity and the physiological data of the user, as well as other details for scheduled events and remote connection with the professional staff of the Networked Care.

The AIS runs on an independent computer at home, which collects the information shared by the robot and other smart sensors in the environments. It exploits the long-term user and environment monitoring to provide high level information, non-necessarily in real-time, to the other components of the ENRICHME system. In particular, the AIS consists of a small high-specs PC connected via wireless to a set of domotic sensors, including motion, contact, and energy consumption sensors. The fact of being physically located in the domestic environment facilitates the communication of the AIS with the robot and the smart sensors, avoiding potential problems due to internet bandwidth or poor quality-of-service. It provides also the opportunity to extend the system with further optional wired sensors (e.g. fixed RGB-D camera) directly connected to the AIS computer.

[4]Kompaï Robotics – http://www.kompai.com

Finally, the Networked Care is a software platform for remote users, i.e professional and medical staff, to interface to the domestic environment and access relevant information provided the other components. It is also the part of ENRICHME through which it is possible to schedule and deal with particular events relevant for the elderly user. However, since the Robot and the AIS are the only two components physically present in the domestic environment, they are also the only ones considered in this paper.

4 Smart-Home and Robot Integration

In order to facilitate interoperability across different sensors and software/hardware platforms, the ROS middleware was chosen, since already broadly acknowledged as the de-facto standard in the robotics community. ROS is a flexible framework for writing robot software. It is a collection of tools, libraries, and conventions that aim to simplify the task of creating complex and robust behaviours across a wide variety of robotic platforms. The availability of ROS interfaces to other popular home-automation middlewares, discussed in the following sections, reinforced the rationale behind this choice.

In ENRICHME, there are two ROS instances running at the same time, both installed on top of a Linux distribution (Ubuntu 14.04). One runs on the robots PC to implement the perception modules for human tracking/identification, physiological monitoring, environmental monitoring and RFID object localisation. It communicates with the navigation software, already embedded in the Kompaï platform, through HTTP/JSON interfaces. This ROS includes also the modules to orchestrate the various behaviours of the robot platform, with a hybrid behaviour-based architecture acting as a bridge between the internal and external data signals and the lower level control system of the robot (Ferland, Cruz-Maya, and Tapus 2015).

The other ROS instance runs on the AIS computer to gather information from the smart-home sensors, store it together with the robot's information, and process it for inference and events notifications. The AIS is key to the implementation of AAL services in ENRICHME, including those considered in this paper, and it is discussed more detail in the next section.

Ambient Intelligence Server

The AIS collects and processes information coming from both the robot (including the embedded RFID system) and the available ambient sensors (e.g. motion and contact detectors) in the domestic environment. It is implemented as an independent server on a small PC unit (Intel NUC Core i7) and connected to the other components of the ENRICHME system (i.e. Robot and Networked Care) via wireless connections. Fig. 3 shows a diagram representing the software architecture of the AIS.

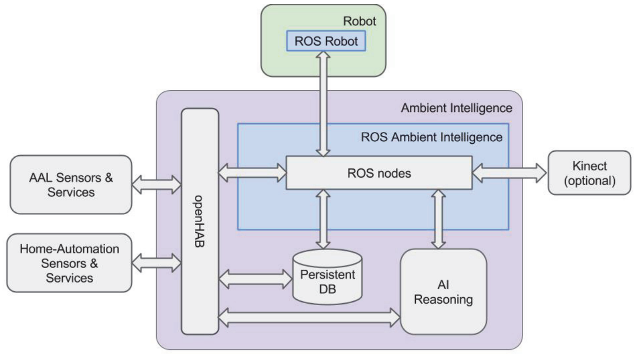


Figure 3: Software architecture of the Ambient Intelligence Server (AIS) linked to the Robot.

As already mentioned, the software implementation of the AIS is based on the same open-source ROS middleware of the robot. The ROS instance running on the AIS computer communicates with, but is independent from, the ROS instance running on the robot. This distinction guarantees a more efficient and robust handling of local sensors, either robot or smart-home related, yet keeping the communication easily manageable between the two ROS instances, thanks to dedicated packages (i.e. `multimaster_fkie`, see Fig. 4). In the AIS, ROS is used as an efficient server to handle asynchronous events and messages between different components (smart sensors, DataBase, Robot and Networked Care). In addition, a full home-automation software, called openHAB[5], complements this part.

OpenHAB allows for an easy integration of additional smart sensors and technologies from different standards, including the popular KNX[6]. It is also designed to enable the integration of further middlewares, such as the European AAL platform universAAL[7]. The latter offers an open framework for developing AAL services that are easy to install and configure in multiple execution platforms. It is important to notice that openHAB is mainly designed for home-automation and does not provide access to many AAL sensors/services available instead with universAAL. On the other side, the latter lacks several functionalities for home-automation, not necessarily AAL related, which are present instead in openHAB. Although there is a partial overlap between the two platforms, in terms of functionalities, future extensions of ENRICHME will include both and will use them in a complementary way.

As illustrated in Fig. 3, the ROS instance on the AIS resides on the latter together with openHAB, a persistent DataBase and a Reasoning modules. In particular, openHAB gives access to several functionalities, including presence detection, opening/closing of doors and cupboards, use of electrical appliances, which are all available in the ENRICHME system. Through ROS "nodes" (i.e. special software interfaces), this middleware maintains an asynchronous communication among all the internal and external modules, the latter being robotic and smart-home sensors.

[5]http://www.openhab.org

[6]http://www.knx.org

[7]http://www.universaal.org

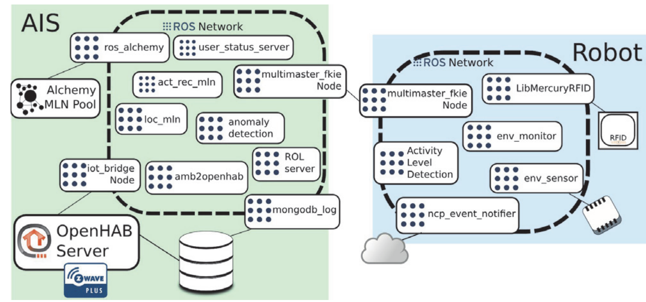


Figure 4: ROS-based implementation of the ENRICHME's distributed architecture, shared between AIS and Robot.

Smart-Home Sensing

Many of the AIS' functionalities rely on the available ambient sensors, accessible through openHAB. This is a software platform for integrating different home automation systems and technologies into a single solution that allows high-level automation rules and offers uniform user interfaces. It is an open source system that provides access to many smart devices, such as motion detectors, temperature sensors, security systems, TV/audio, lighting, Bluetooth, Z-Wave, and much more. Most importantly, it can easily interface to KNX home-automation devices, which is a common standard also adopted by some of the testing sites in ENRICHME. Furthermore, openHAB can connect to web services such as Twitter, Weather, etc. It is designed to be vendor-neutral, as well as hardware/protocol-agnostic, and can run on any device that is capable of running a Java Virtual Machine (Linux, Mac, Windows). It includes a powerful rule engine to fulfil many home-automation needs, and it comes with native user interfaces for iOS and Android. Dedicated APIs facilitate extensions and the integration with new systems and devices.

In the AIS, there is a dedicated ROS package, called `openhab_bridge`, which provides a bridge between ROS and the openHAB platform. With this package, virtually any home automation device can be easily setup to publish new data on the `openhab_updates` ROS topic, and therefore new information for the AIS and relative web services. ROS can also publish on the openhab_set topic to set new values on specific openHAB devices. This allows the creation of new domotic devices in openHAB from ROS-based sensors. For example, the data from the environmental sensor (Uniscan UiEM01), mounted on the robot, is redirected to openHAB as any another domotic device.

Finally, ROS can publish instructions on a dedicated `openhab_command` topic in order for the selected openHAB device to act upon such commands (e.g. switch-on a light). This solutions facilitates the easy integration of ENRICHME with existing home-automation systems and future extensions to provide extra AAL functionalities.

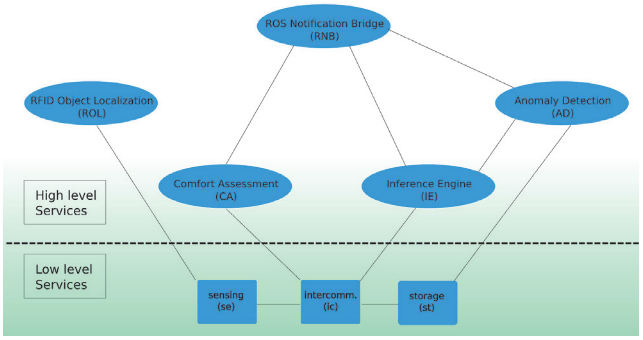


Figure 5: Organisation of low- and high-level technical services, and relations among them.

5 AAL and Technical Services

There are many potential services that an integrated system such as ENRICHME could deliver. It is therefore important to make an informed choice based on actual user requirements, focusing in particular on the elderly with MCI and their formal/informal caregivers. In recent studies (Salatino et al. 2016) it was found that many user expectations were high but still technologically feasible, given the appropriate resources and commitment. From a robotic and ambient intelligence point of you, among the numerous services identified in these studies, the most interesting ones are those related to the capability of the system to 1) locate lost objects in the domestic environment, 2) monitor the activity of the elderly, and 3) detecting abnormal situations possibly related to health problems.

In order to transform these AAL requirements into actual system components capable of implementing them, a hierarchical structure of low-level and high-level (technical) services has been created, as illustrated in Fig. 5. These services are grouped as follows:

- Low-Level
  - sensing (se): provides raw or partially processed measurements from the ambient and robot sensors
  - intercommunication (ic): links and enables the asynchronous communication among different modules
  - storage (st): stores relevant data (e.g. sensor readings, anomaly detections, etc.) necessary to other modules
- High-Level
  - RFID object localisation (ROL): detects and maps the location of RFID-tagged objects
  - comfort assessment (CA): monitors the optimality of the environmental settings
  - inference engine (IE); estimates the current location and activity of the user
  - anomaly detection (AD): detect anomalous situations in the user's behaviour
  - ROS notification bridge (RNB): receive instructions by and notifies professional staff in case of interesting events.

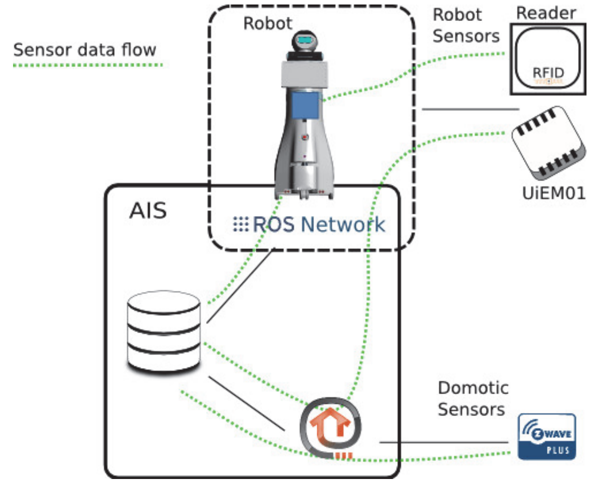


Figure 6: ENRICHME sensor dataflow.

Module	Service provided	Description
`act_rec_mln`	AD	Performs inferences on user activity. Used in Anomaly Detection
`amb2openhab`	ic	Publishes ROS-based sensor information on OpenHAB
`env_monitor`	CA	Comfort Assessment module
`env_sensor`	se	ROS driver for UiEM01 environmental sensor
`LibMercuryRFID`	se, ROL	RFID modules (library, ROS driver, object localization module)
`ncp_event_notifier`	RNB	NCP notification service under ROS
`openhab`	se, st, ic	Open source domotic software installer, additional modules and configuration files
`ros_alchemy`	IE	MLN inference engine service under ROS
`user_status_server`	IE	Performs inferences on user location. Offers a probabilistic user location service.

Table 1: List of technical services.

As depicted in Fig. 6, the low level services manage the sensor dataflow for the high level services. The latter access and exchange information through a DataBase (MongoDB) and ROS, independently from the required data type.

The modularity of the approach adopted in ENRICHME facilitates the extension of the original services and the creation of new ones, depending both on the AAL requirements and the technological resources available to implement such services. The latter are provided by a set of ROS modules, which are listed in Table 1.

The full set of ROS modules, clustered by AIS and Robot's location, are illustrated in Fig. 4. An important remark is the fact that, given the distributed and modular architecture of the system, it is possible to move one or more ROS modules from one location to another without affecting the overall functionality of the system. This is useful in case a re-distribution of computing resources is needed, for example when the computational load of one of the two computers, either AIS or Robot, becomes unsustainable. Note also that the complete shut-down or failure of one of the two computers reduces but does not completely impede the functionality of the system.

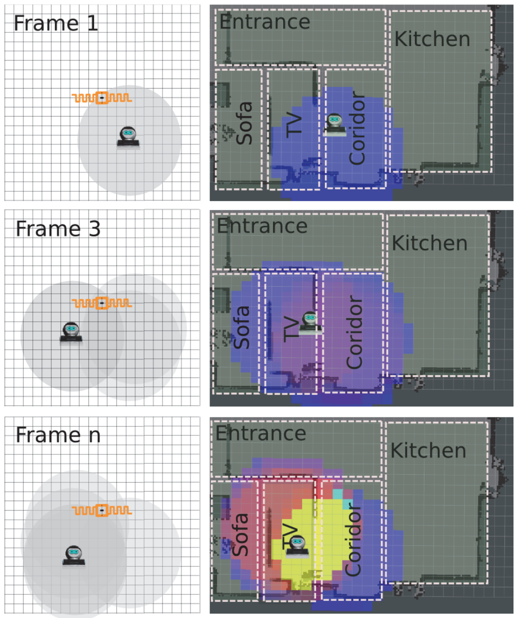


Figure 7: RFID object localisation. As the robot moves and detects a tagged object (on the left), a cumulative probability map is built by intersecting the detection areas (i.e. yellow = high probability; blue = low probability).

6 Service Implementation

Further details and some preliminary results are provided in the following sections regarding the implementation of modules for object localisation, human activity monitoring and anomaly detection, which are key to the provision of AAL services in ENRICHME.

RFID-based Object Localisation

The ENRICHME robot is provided with an RFID system (i.e. antenna and reader) to detect the presence of tagged objects in the environment, even when these are several meters away from the robot. The system, however, does not provide an exact direction and distance of the object, but just information about the strength of the signal received by its tag (plus some other low-level information). The solution adopted in ENRICHME, which is partly based on the work of Broughton et al. (2016), relies on a grid-map representation of the object location. When the robot detects a tagged object within its "confidence" range, it increases the weight assigned to the cells within that area, and decreases all the remaining ones. As the robot moves around the environment, the cells belonging to the intersection of the detection areas will receive higher weights than the others, effectively creating a probabilistic map of possible object's location(s). The process is illustrated by the sequence in Fig. 7 for a set of RFID detections of a single object recorded by the moving robot.

The layout of the environment, containing walls and other large indoor structures, is superimposed on the probability map to compute the probability of the object to be on a particular room or living area. Fig. 7 also shows the probabilistic map for a tagged object, according to which the most likely location of the object is in the TV area, where the cumulative probability is higher.

Activities	Feature	Status	Activity Level
Global	Instant speed of the person	stopped moving running	not active active highly active
Head	Instant speed of head point	stopped moving	not active active
Torso	Instant speed of shoulder points	stopped moving	not active active
Body	Standard dev. of volumes	stopped moving	not active active

Table 2: Features used to detect human activity levels.

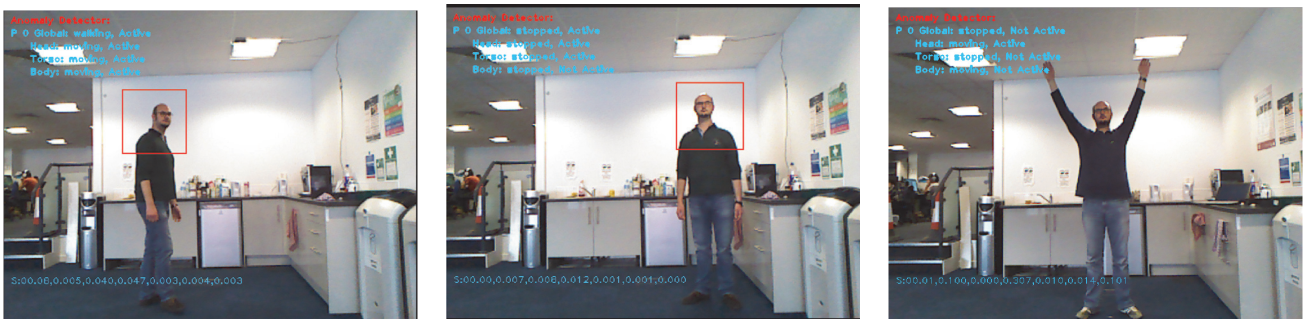
Activity Level Detection with RGB-D

In ENRICHME, the detection of activity levels is performed using the robot's RGB-D camera. It is based on four categories of activities: i) global activity of the person, ii) head activity, iii) torso activity, and iv) body activity. Global activity refers to global motion of the person such as standing still, or moving from one place to another. Head activity corresponds to the motion of the head, such as bending left/right. Similarly, torso activity corresponds to torso motion (bending, turning around) and body activity refers to limbs motion (e.g. scratching head, crossing arms).

The global activity is computed from the walking speed of the person in proximity of the robot. A real-time multisensor people tracker (Bellotto and Hu 2010; Dondrup et al. 2015) is used, based on 2D laser-based leg detections and RGB-D-based upper body detections. A Bayesian filter fuses the observations coming from both detectors and estimates human location and velocity. The latter is used then to categorized the motion activity of the person as still / moving / running by applying a two-levels thresholding. If the same motion state persists for more than 5 seconds, the person's activity level is categorized then as not active / active / highly active, respectively (see Table 2).

Head, torso and body activities are calculated based on a recent landmark point detection and body volume estimation approach (Cosar, Coppola, and Bellotto 2017). Head and shoulder points are detected, then volume of head, upper-torso, and lower-torso are calculated. As for the global activity, the instant speeds of head and shoulder points are calculated. The motion of the head and torso are categorized as stopped or moving by thresholding the instant speeds of the head and the shoulder points, respectively. Changes in volume of the body parts are used to categorize the body motion as stopped or moving by thresholding the standard deviation of such volume variations within a predefined time interval. As before, if the status of head, torso, or body remains the same for more than 5 seconds, the status of the person is described as not active or active, respectively.

The activity level detector was tested on data recorded by the ENRICHME robot. The sequence, partly shown in Fig. 8, includes a person walking in front of the robot, standing still for some time, and then moving his hands. The figure shows the correct estimation of the respective activity level detections for the global, head, torso and body motion.



(a) (b) (c)

Figure 8: Results of activity level detection when the person is (a) walking, (b) still, and (c) moving hands.

Entropy-based Anomaly Detection

Abnormal events are detected in ENRICHME using smart-home sensors. This approach minimizes invasiveness, and it is relatively easy to deploy in patient's homes. The main drawback is the limited amount of information provided by these sensors. However, it is more important to quantify the variations rather than the amount of information. The solution here presented relies on this concept.

Typically, a presence detector triggers an event whenever motion is produced within its detection field. It has two relevant parameters: triggering sensitivity and blind time. The first parameter is used to establish a motion threshold for triggering an event (i.e. the sensor is not triggered unless an object of significant volume is detected). The second parameter determines the minimum time between consecutive activations, useful to link the presence detector's output and a light or an automatic door. After this period of time, if no new events are triggered, the sensor reports an end-of-event.

The ENRICHME's homes have R presence sensors, one for each room. Assuming a single resident, each sensor provides the amount of time $T(r_i)$ the person was active in a specific location. This information can be used to describe the following probability of being active in a room:

$$P(r_i) = \frac{T(r_i)}{\sum_j T(r_j)} \tag{1}$$

This probability relates to some user activity level, but it is not a good metric to determine when such level should be considered "abnormal". Instead, an approach based on the entropy H from information theory, to detect potentially abnormal situations, is proposed in ENRICHME:

$$H = -\Sigma_i P(r_i) log P(r_i) \tag{2}$$

The entropy defines the amount of information in a system. High entropy levels characterize also situations with a significant amount of activity. When the user is not very active and remains at the same location for most of the time, low entropy levels are expected. For a discrete uniform distribution, the maximum entropy is given by the number of possible outcomes. Therefore, the following relative entropy H_{rel} can be defined for a home environment with R presence detectors and used to classify normal vs. abnormal situations:

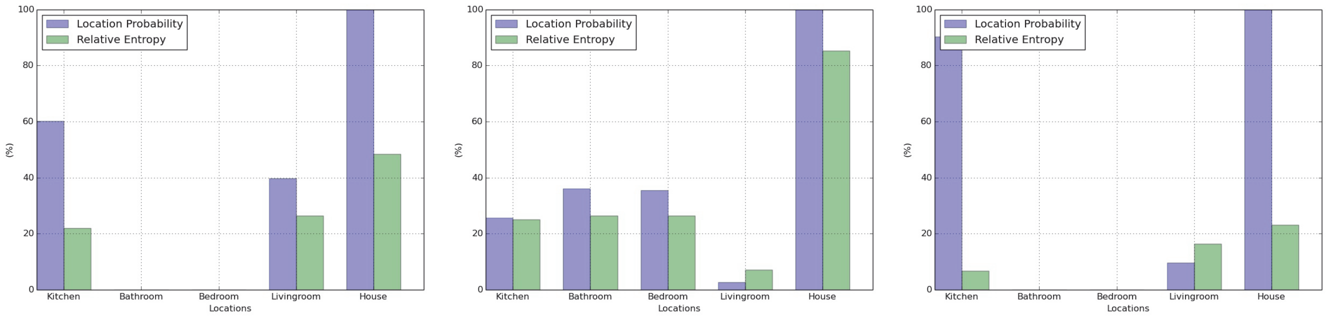
$$H_{rel} = -\frac{H}{log R} \tag{3}$$

Fig. 9 illustrates an example of entropy-based anomaly detection on real data collected from an installation in one of ENRICHME's living-lab testing sites. The graphs show the probability distribution of the user location across different rooms, accumulated over a pre-defined time interval of 30 minutes, as well as the total probability of being at home (always 1.0 in this case). They show also the relative entropy for each room, and the total one. The first graph (a) refers to the "normal" case, when the person spends most of the time between kitchen and living-room. In this case, the total home entropy is within a pre-set interval (between 25% and 85%) and therefore considered within the norm. The following graph (b) illustrates the case instead where the person moves frequently across different rooms, as it would happen in case of restlessness or temporary confusion, generating a very high total entropy and therefore triggering an "abnormal" situation. Similarly, in the last graph (c), such an event is triggered by the fact the user spends too much time in the kitchen only, which could be caused by an injury or temporary unconsciousness of the person.

7 Conclusions

This paper presents the architecture design and some key solutions adopted in the ENRICHME project to provide advanced AAL services for elderly people with MCI. Both general and practical aspects of the system implementation have been covered, with particular emphasis on the distributed ambient intelligence and the development of tools for object localisation, activity monitoring and anomaly detection, exploiting robotic and smart sensors in a domestic environment. These solutions could be applied to other user domains and environments for the provision of new and effective AAL services.

The project is currently under way and its technologies are being tested in living-labs with real users, to be then validated in several elderly homes across different European countries. Future research will include novel solutions to exploit precious data from the continuous long-term experience (i.e. several months) during the validation phase. It will also take into account new feedback from the actual users of the system to improve their quality of life, and therefore achieve the main goal of ENRICHME.



(a) (b) (c)

Figure 9: Entropy-based anomaly detection: (a) normal, (b) high and (c) low entropy situations.

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