Interoperable Services based on Activity Monitoring in Ambient Assisted Living Environments

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***Abstract*—Ambient Assisted Living (AAL) is considered as the main technological solution that will enable the aged and people in recovery to maintain their independence and a consequent high quality of life for a longer period of time than would otherwise be the case. This goal is achieved by monitoring human's activities and deploying the appropriate collection of services to set environmental features and satisfy user preferences in a given context. However, both human monitoring and services deployment are particularly hard to accomplish due to the uncertainty and ambiguity characterising human actions, and heterogeneity of hardware devices composed in an AAL system. This research addresses both the aforementioned challenges by introducing 1) an innovative system, based on Self Organising Feature Map (SOFM), for automatically classifying the resting location of a moving object in an indoor environment and 2) a strategy able to generate context-aware based Fuzzy Markup Language (FML) services in order to maximize the users' comfort and hardware interoperability level. The overall system runs on a distributed embedded platform with a specialised ceiling-mounted video sensor for intelligent activity monitoring. The system has the ability to learn resting locations, to measure overall activity levels, to detect specific events such as potential falls and to deploy the right sequence of fuzzy services modelled through FML for supporting people in that particular context. Experimental results show less than 20% classification error in monitoring human activities and providing the right set of services, showing the robustness of our approach over others in literature with minimal power consumption.**

I. INTRODUCTION

In recent years, we have witnessed a rapid development in assisted living technologies due to fast ageing of the world population and the miniaturisation of hardware devices that are becoming more and more ubiquitous and smart. Thanks to the enhanced functionalities provided by these supportive technologies, aged people or persons in recovery can maintain their independence and, as a consequence, improve the quality of their life with technology-driven healthcare[1]. In order to achieve this goal, AAL is aimed at monitoring human actions and deploying the right collection of services to support people in with their Activities of Daily Living (ADL).

Currently, AAL systems designed as a proof-of-concept for technology-driven healthcare has also lead to the new paradigm of Smart-Homes(SH): a residential home with Information Technology-based services [2]. However, in spite of the large number of AAL enabled SH systems presented in literature, the design of these systems are strongly centred on spatial and temporal base reminders. Thus using sensors to monitor the behaviour and providing assistance or alert the inhabitant of the SH to perform an intended activity in real-time [3], [4]. A major gap currently exist between sensor data generation and assistive provision based on context-aware personalised ADL with SH presented in literature. Generally, activity recognition in SH presents three major challenges [2]:

- The order or sequence of activities within an ADL has a high degree of freedom. Thus ADLs that follows the same kind of pattern are no necessarily constraints on the sequence and duration of the actions.
- SH may generally have a number of sensors data fused together to establish the context of the ongoing ADL. Thus, only when all sensors data are available can the ADL be recognisable, this increases the uncertainty of sensor data as well as the reliability of recognition.
- Most ADLs are composed of a sequence of temporal actions. Hence, activity recognition should be carried out at discrete time points in real time in a progressive manner.

Some authors have used context-aware service [5] rather than probabilistic or statistical analysis methods [6] to recognize activities in SH. In this paper we used a knowledge-driven approach to process multiple sources of sensor data to determine activity or resting location and deploy suitable environmental actions with fuzzy logic. The purpose of our approach is to combine the level of activity with learned location-based activity to deployed required service. Thus, effectively eliminating the over reliance on sensor data which is a major challenge with context-aware personalized systems of assistive technology. The approach is motivated by the resting locations and, the associated sensor and environmental activities. Example maintaining the sitting room condition to a fixed temperature whiles the inhabitant is in a particular location watching a movie. Again, the blinds can be adjust depending on the inhabitant's resting location. Also pattern of activity for any specific inhabitant is used to build a personalised user profile reflecting their ADL, and thus creating a model that avoids the need for a large dataset from training and testing.

The ultimate purpose of the presented approach is the deployment of interoperable and personalized services related to environmental actions to support people's needs and comfort. In order to achieve this goal, the proposed system uses 1) the Fuzzy Markup Language (FML) [7] for modelling, in an hardware independent way, the inference engine used to take user-oriented decisions which determine the services to be deployed starting from identified resting locations; 2) a learning strategy exploited to provide an adaptive personalization of services by facing environmental or user's needs changes. The choice to provide fuzzy services modeled through FML is motivated by the awareness that the imprecise phenomena are typically and largely present in AmI context where the measurable entities are described by a large set of highly dynamic values (i.e. temperature, luminosity, etc.).

In order to evaluate the performance of the proposed system, some preliminary experiments have been carried out by considering four different office environments and the variation of the lighting intensity. The experimental results show less than 20% classification error in monitoring human activities and providing the most suitable set of FML fuzzy services with minimal power consumption. The remainder of the paper is organised as follows: Section II discusses existing and related literature, section III outlines the system architecture for the proposed FML service deployment, describing into details the activity level measure and the data-driven fuzzy logic architecture. In section IV we describe some of the experimental scenarios and conclude with future work in section V.

II. Related Work

Activity recognition can be classified in two main approaches [2]; the use of visual sensing facilities like cameras to monitor an actor's behaviour and the use of emerging sensor network technologies for activity monitoring. In [8] a wide angle camera was used to monitor movement of a single room occupant. The systems uses visual information to build an edge map of the room which is then used to extract new edges representing the new or moving object. They further estimate the resting location of the object and use that for possible fall detection. The head location systems presented has the capability of running on resource constrained hardware.

Cristani et. al [9] presents the automated video surveillance of human activities that brings in notions and principles from social, affective and psychological literature also referred to as social signal processing. The social signalling oriented approaches for human behavioural analysis in a surveillance context and how social signalling may improve the human behaviour analysis has also been addressed. Three major problems that can be addressed effectively with the social signal processing approach includes threatening behaviour, modelling of groups and modelling of interactions in outdoor situations. Chaaraoui et. al [10] focuses on visual techniques for human behaviour analysis applied in ambient assistive living. To avoid vision-based difficulties like occlusion, view-dependent features and lightning conditions, the video data is enhanced with RFID labels as well as other sensory data.

Zhou et. al [11] presented an automated activity analysis and summarization for the monitoring of the elderly. They used an adaptive learning method to estimate the physical location and moving speed of a person from a single camera view. Chan et. al [12] presented a multi-sensor home monitoring system to help elderly people by observing mobility changes indicative of abnormal events. The design assesses changes in occurrence, time and duration from a statistical perspective. People with dementia often have low physical activity and some sleep problems [13]. The daily life activities and sleeping conditions has been used by Suzuki et. al [13] for the early detection of dementia. Adami et. al [14] described a system for unobtrusive detection of movement in bed that uses load cells installed at the corners of a bed. The system focused on identifying when a movement occurs based on the forces sensed by the load cells.

A system that focuses on analysing human activities according to a known behaviourist scenario using wearable cameras is presented in [15]. Hidden Markov Model is used to define a structural model of video recordings, the video features are expressed as dynamic activities, localization in the home environment and image content. [16] demonstrates the use of multiple cameras for human activity monitoring by using a framework developed for the placement of multiple cameras in the scene. the systems uses a dual-camera to track subjects, measure position and velocity, and attempt to classify each individual's activity based on the tracking information.

In [17] Lee and Mase proposed a new method for detecting and classifying a person's activity using dead-reckoning-based location recognition and a set of inexpensive, wearable sensors. Using the measured acceleration and angular-velocity data, the method can recognise activities such as sitting, standing, and walking. It can also classify walking behaviours into three subcategories: walking on level ground, ascending a stairway, or descending a stairway. Based on this activity recognition, the authors propose a method for detecting transitions between preselected locations, which uses the integration of incremental user motions over time with heading measurements and a simple nearest-neighbourhood algorithm. The authors conducted experiments at five indoor locations.

Chen et. al [2] presents a knowledge-driven approach to real-time, continuous activity recognition based on multi-sensor data streams in a SH. The approach uses domain knowledge for activity recognition and ontologies for explicit context and activity modelling and representation. The system extends on existing data-mining methods to address complex activity scenarios like multi-occupancy and concurrent activities, to develop alternative activity recognition paradigm. In [6], Mulvenna et. al discusses visualization of data from the perspective of the needs of differing end user groups through contextualization and conveying information across location and time by providing night-time ADL services for people with dementia. The focus on night-time ADL services centres around lighting and guidance, motion monitoring, and intervention decision-support.

Brdiczka et. al [5] addresses the problem of learning situation models for providing context-aware service in a smart home. The system is based on a 3D video tracking system capable of detecting and tracking people in the scene with multiple cameras. The approach addresses the problem of acquiring context models that reflect user behaviour and needs in a SH by providing an intelligible framework for acquiring and evolving an intuitive comprehensible context model of the scene. With the use of visual and audio data the system is able to detect and track targets in an environment. The tracked targets are then used to detect individual roles which is further feed into an unsupervised situation extractor to supervise situation learning. The learned situation model is then used to integrate the user preferences. The approach has been tested in a laboratory mock-up of a living room environment in a smart home.

This paper proposes, mainly, a methodology for learning activity levels and resting locations. The objective is to use FML to build and evolve a data-driven approach for providing location-aware services in a smart environment. The proposed framework consists of two major movement detection sensors with extracted data fed into different machine learning methods to determine the current location of objects and deploy the location-based fuzzy services acquired by a learning approach. The approach has been implemented in a mockup smart home environment to actuate designated sensors using FML.

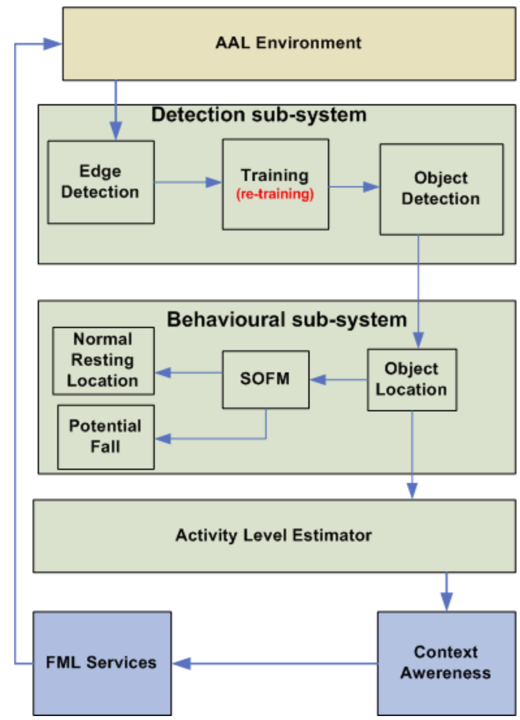

Fig. 1. An overview of the Human-Centric Services deployment system.

III. AAL Architecture

Ambient Assisted Living, a new paradigm in social computing referring to the convergence of assisted living and ambient intelligence are implemented to either replace or complement a care provider [6]. Various AAL services like activity, cognitive and sensory support, may provide alarms to detect dangerous situations, monitor the well-being of the user or even enable users to keep in touch with family members. In this article, we demonstrate how artificial intelligence and automated reasoning techniques can be used to activate and deploy the right set of services when the user is located in a given semantic area. Our aim is use artificial intelligence techniques to model user behaviour by their level of activity and deploy the required services with minimal user intervention. The system presented in this article has four sub-systems; the detection, behavioral, activity level and the context awareness sub-systems. Fig. 1, is a pictorial representation of the various sub-systems in our design.

Human behaviour evolves over time, as inhabitants in a smart home usually perform routine daily activities specific the circumstances. Activities and scenarios may emerge and disappear in a smart environment. For example using the remote to turn on the television set may involve sitting comfortably in a sofa, leaning for the remote control and later adjusting the window blinds depending on the lighting intensity. This is generally referred to as the context for the corresponding activity [2]. As humans have different lifestyles, habits and special requirements, an individual's ADL may vary from one person to the other and hence a fixed context model or approach for a smart home is not sufficient. Again, an individual's action may vary from one room to the other and even in the same room from one location to the other. The proposed approach addresses activity at a level applicable to all (generic) and at a level with individual subtleties (personalised) by providing a framework for acquiring and evolving an intuitive comprehensible fuzzy model of the needed service at a location, thus the *location fuzzy service*.

A. Monitoring

The first part of our system has the ability to determine the presence of a subject (the AAL user) and estimate the location in the room with minimal power consumption with an ultra-low cost small form factor, high performance embedded device like leopardboard [18]. Apart from the constraints (in terms of memory and processing power) of the embedded development platform chosen for this implementation, the design is also constrained by a low-power budget. This is to enable the system run for longer period when battery-powered. To satisfy these requirements, a novel edge-based differencing algorithm has been developed and implemented on the embedded ARM9 processor, rather than the standard background differencing algorithm [8], which requires the camera and the leopardboard to run continuously to update the background model. The system described in this article uses edge-based differencing, as edges are less sensitive to illumination changes. A low power motion detector is used to trigger the camera only when activity occurs. For unobtrusiveness, a high-mounted fish-eye lens with viewing angle of 105 degrees has been used. This effectively reduces the number of cameras needed in any single living environment to one. Fig. 2 is sample output of the fish-eye lens used in this development when mounted high up in the ceiling of an office. A powerful 5-Channel Power Management IC with two step down converters and 3 low input voltage LDOs chip TPS65053 is provided on the leopardboard 365. The board is powered by +5VDC power supply and consumes less than 2W, which includes the 5 Mega-pixel camera board running at 30fps.

The detection and behavioural sub-systems are activated every time the camera switches to RUN mode when there is enough activity in the scene. The detection sub-system has three major phases: edge detection, training (re-training) and object detection. The edge detection phase uses the Sobel edge [19], which calculates the gradient of the image intensity at each point. The training phase is activated when the system is powered on for the first time. Retraining of the system becomes necessary when the camera drifts slightly or when too many objects appear in the scene. Compared to [8], the proposed system is capable of identifying multiple objects and keeping track of the unique trajectory of those objects. This is then used for the personalised activity association. The learned trajectory information includes the *(x,y)* location of the object and the velocity (represented as the first differential movement information – $(\delta x, \delta y)$) .

To extract the edges of moving object, a simple edge-based differencing algorithm is used. The edge-map extracted from the current frame **E** is compared with the background model **M** to extract any new edges that appears in the scene. Fig. 2 is a sample output of the object detection phase. The edges of the input image are compared with the background model to extract the new edges, which forms the outline of any moving object. The images in Fig. 2 are actual processed images on the embedded device.

The central location of moving objects in the scene are estimated in the object location phase of the behavioural sub-system. To estimate the area where most edges are concentrated, a tiling operation is adopted. Similar to a compression operation, the entire image is divided into blocks each of size 16×16 pixels. Thus for a VGA sized image there are 40×30 blocks. The number of edge pixels in each block is compared with a threshold value to determine if the resulting block is set or cleared. A block-based horizontal and vertical histogram is generated to estimate the areas with edge blocks above an empirical set threshold. The intersection block is the block (or area) with the recognisable number of edges. This is then used to establish the central locations of all moving object in the scene. The position of the subjects are estimated using the threshold vertical and horizontal block-histogram peaks. To compute the level of activity **T** between two frames, a distance measure (Manhattan distance) given as $\mathbf{T} = |x_t - x_{t-1}| + |y_t - y_{t-1}|$ is used. This is accumulated over a period of time to measure the overall activity level.

The central location (x_t, y_t) of an object is collected over a period of time and used in the SOFM clustering phase to

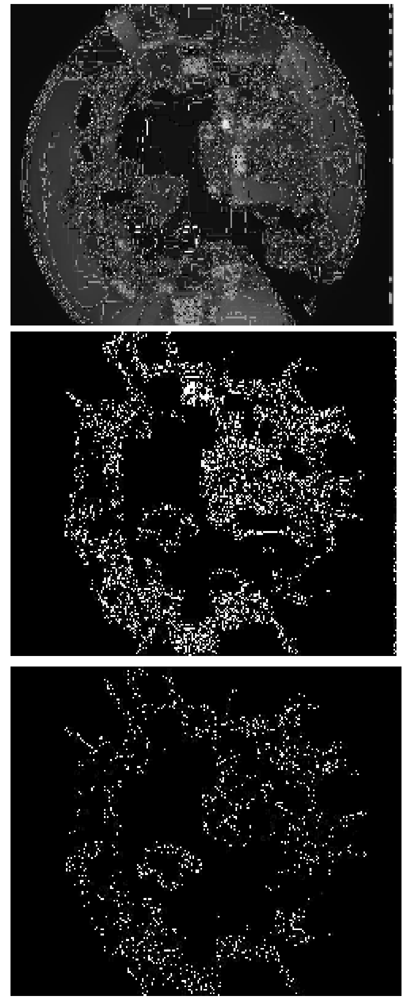

Fig. 2. Processed output from the fish-eye camera setup. The background edge-model image is shown on the top with the processed edge difference to the bottom.

determine resting positions. The SOFM algorithm presented in [20] is based on a competitive learning algorithm, the winner-take-all (WTA) network, where an input vector is represented by the closest neuron prototype vector, which is assigned during training to a data cluster centre. The prototype vectors are stored in the "weights" of the neural network. The architecture consists of topologically organized array of neurons, each with $N-$dimensional weight vector, where N is also the dimensionality of the input vector. The basic principle of the SOFM is to adjust the weight vectors until the neurons represent the input data, while using a topological neighbourhood update rule to ensure that similar prototype occupy nearby positions on the topological map.

The collected central positions are used as input to train the SOFM. To efficiently implement a *resting location* discriminator on the embedded device using Self Organising Feature Map and Gaussian distribution, we analyse the minimal dimension that can be used to represent the point-to-point location data $(x_t, y_t, \delta x, \delta y)$ without losing any behavioural information.

Secondly, we analyse the most efficient way to represent the location data in the SOFM and yet able to identify outline location data. By reducing the dimension of the location data we are able to implement the SOFM on the embedded device using minimal resource. During training, we first count a group of input vectors that are associated with each neuron, and then calculate mean value μ and standard deviation σ of the group of distances, alongside the minimum and maximum distances (D_{min} and D_{max}).

Activities of Daily Living (ADL) such as making tea, using the telephone and turning on/off lights are collected periodically using FML to deploy the required actions when the user is in the specified semantic area. The following section provides detail on the action centric interoperable service deployment.

B. Smart Services Design Deployment

When the proposed system works, it runs a set of fuzzy services in order to automatically manage the active space by taking into account user's preferences and the learned resting locations. *Fuzzy services* are defined as a mapping process from the current fuzzy context to a set of suitable policies, where each one is the most suitable for a given service. In detail, a *fuzzy context* includes environmental conditions and location information, whereas, a *policy* is a rule which determines which service level to be delivered based on the context in a given time, referred as *context situation*. By taking into account a fuzzy view, a policy set can be simply modeled through a collection of fuzzy sets, whereas, the context can be represented by exploiting the antecedent part of a fuzzy rule. Therefore, the mapping process, a fuzzy service, can be viewed as an inference method that uses the fuzzy inference operators (Mamdani or TSK) to establish the most suitable policies for the current fuzzy context situation. In this view, the implementation of fuzzy services strongly depends on the hardware characteristics related to the device realizing them. Consequently, in hardware heterogeneous contexts, as can be considered AmI environment, the services development time can be sensibly affected. For this reason, the proposed system exploits the Fuzzy Markup Language [21], an XML-based language for fuzzy modeling, in order to minimize software development time thanks to higher fuzzy service abstraction. FML syntax is realized by using a set of tags representing the different components of a fuzzy controller [22]. It is based on (1) XML in order to create a new markup language for fuzzy modeling; (2) XML Schema in order to define the legal building blocks of a fuzzy document. In particular, XMLSchema of FML defines a set of datatypes composing a fuzzy controller model as an n-ary tree called Fuzzy Objects Model (FOM) [23] shown in Fig. 3. Therefore, it is possible to state that each FML program can be associated to an instance of a FOM tree.

Listing 1 gives a sample of FML code implementing a fuzzy service. As shown in the listing, FML grammar defines a tag for modelling fuzzy concepts, fuzzy rules and fuzzy inference engines. For example, the FML tag <FuzzyController> is used to open any FML program, whereas, the tags <KnowledgeBase> and <Rulebase> are used, respectively, to model the set of fuzzy concepts and the set of fuzzy rules. Each tag is characterized by some attributes. For example, the tag <Rulebase> has five attributes: *name* which uniquely identifies the rule base; *type* which permits to specify the kind of fuzzy controller (Mamdani or TSK); *activationMethod* which defines the method used to implication process; the *andMethod* and *orMethod* which define, respectively, the and and or algorithm to use by default. In particular, the tag <FuzzyController> is characterized by the attribute *ip* which assumes as values TCP/IP addresses. In our proposal, the ip attribute is used to define the endpoint of web service computing the FML controller.

```
<?xml version="1.0" encoding="UTF-8" standalone="no"?>
<FuzzyController ip="127.0.0.1" name="HomeSystem">
  <KnowledgeBase ip = "127.0.0.1">
    <FuzzyVariable
         domainleft = "0" domainright = "1"
         ip = "127.0.0.1" name = "Luminosity"
         scale = "Lux" type = "input">
      <FuzzyTerm name="low">
        <PIShape
              param1 = "0.0"
              param2 = "0.45"/>
      </FuzzyTerm>
      <FuzzyTerm name="medium">
        <PIShape
              param1 = "0.5"
              param2 = "0.45"/>
      </FuzzyTerm>
      <FuzzyTerm name="high">
        <PIShape
              param1 = "0.55"
              param2 = "1"/>
      </FuzzyTerm>
    </FuzzyVariable>
    ...
  </KnowledgeBase>
  <RuleBase ip="127.0.0.1"
         name="RuleBase1" activationMethod="MIN"
         andMethod="MIN" orMethod="MAX" type="mamdani">
     <Rule connector = "and" ip = "127.0.0.1"
                                                weight = "1">
       <Antecedent>
         <Clause>
           <Variable> input_Luminosity </Variable>
           <Term> high </Term>
         </Clause>
         <Clause>
           <Variable> location </Variable>
           <Term> living room </Term>
         </Clause>
          <Clause>
           <Variable> hour </Variable>
           <Term> evening </Term>
         </Clause>
       </Antecedent>
       <Consequent>
          <Clause>
           <Variable> output_Luminosity </Variable>
           <Term> low </Term>
         </Clause>
       </Consequent>
     </Rule>
   ...
  </RuleBase>
</FuzzyController>
```

Listing 1. FML sample program

As aforementioned, human behaviour evolves over time and scenarios may emerge and disappear in a smart environment. Therefore, the proposed system periodically performs a learn-

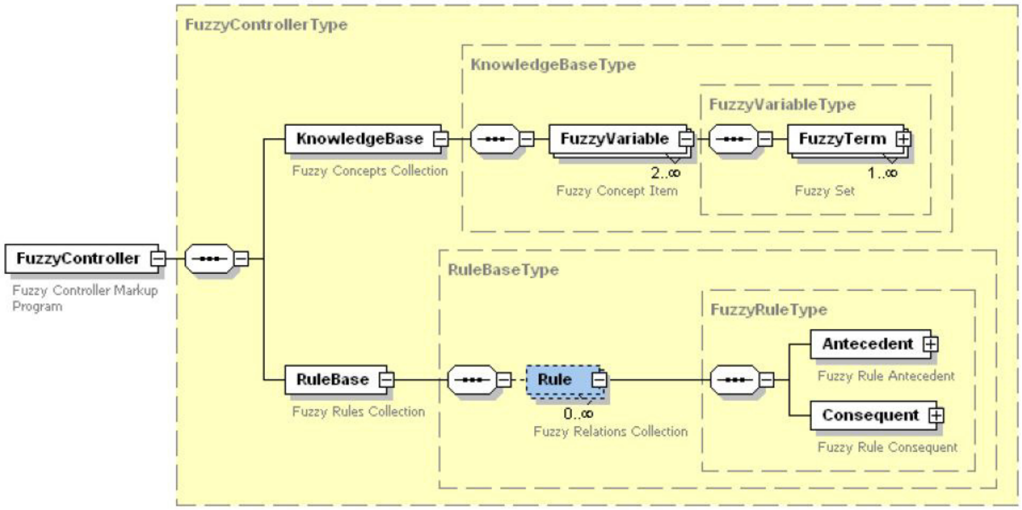

Fig. 3. Fuzzy Objects Model.

ing phase to capture the users' preferences and give the most suitable services. During the learning phase, the proposed system generates fuzzy services that will be exploited to support people in their ADLs. This phase consists in two steps: 1) generation of a contextual data set and 2) applying of a learning strategy to define fuzzy services. Formally, the contextual data set is composed by two parts, as shown in Fig. 4, (1) AmI environment status matrix; (2) user's environmental actions vector. Once the contextual data set is collected, it exploits these data to build the related fuzzy services. This task is accomplished in two sequential steps:

1) To cluster and fuzzify the *user's environmental action vector;*
2) To construct an optimized rulebase mapping the fuzzy service's behavior.

Both steps are performed by using ANFIS as described in [7]. In detail, ANFIS exploits the contextual data set to learn and adapt the parameters of a TSK fuzzy inference system [24] representing a fuzzy service. However, the user could change its preferences by acting on the environment with actions contradicting the rules inferred in learning mode. This situation is simply managed by the system by replacing some entries of the contextual data set with the novel users actions. In this way, the proposed system works by always considering the most recent users preferences.

IV. Experimental Results

To test the performance of the monitoring system implemented on the DM365 leopardboard, four different office environment have been used as mock-up SH. The first two of the four mock-up SH are office areas with single occupant; Figs. 5 and 6. The image shows locations with associated activities as shown in red and the area with the highest activity in the room is shown in green. Semantic activities learned and associated with each location have a FML fuzzy service that can be deployed at the known location.

$$\begin{bmatrix} temp_1 & temp_2 & \dots & \dots & \dots & temp_{\#data-1} & temp_{\#data} \\ lux_1 & lux_2 & \dots & \dots & \dots & lux_{\#data-1} & lux_{\#data} \\ \dots & \dots & \dots & \dots & \dots & \dots & \dots \\ \dots & \dots & \dots & \dots & \dots & \dots & \dots \\ presence_1 & presence_2 & \dots & \dots & \dots & presence_{\#data-1} & presence_{\#data} \\ extTemp_1 & extTemp_2 & \dots & \dots & \dots & extTemp_{\#data-1} & extTemp_{\#data} \end{bmatrix}$$

$$\left(userAction_1 \quad userAction_2 \quad \dots \quad \dots \quad \dots \quad userAction_{\#data-1} \quad userAction_{\#data-1} \right)$$

Fig. 4. The contextual data set template

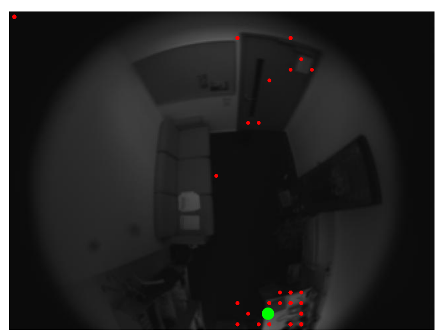

Fig. 5. The first mock-up SH with a single occupant.

The third of the four mock-up SH (see Fig. 8) is a multiple occupancy office environment with glass windows overlooking a very busy street. Most of the activities recorded were activities from the street including cars and pedestrians in the outdoor environment. Again, even though the level of activity around the window is high, because the FML has no specific activity those regions can be ignored. The final of the four

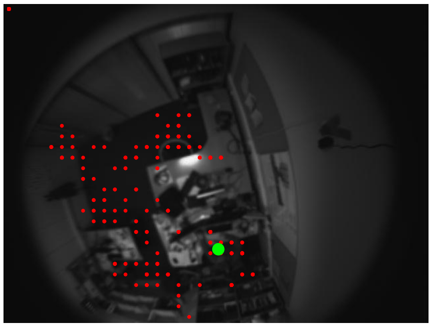

Fig. 6. The second mock-up SH with a single occupant.

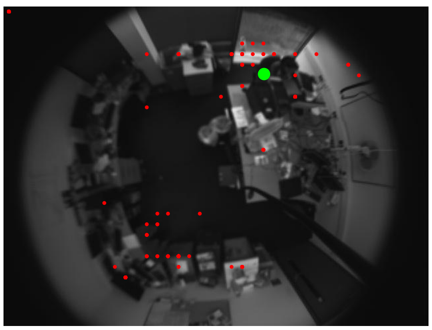

Fig. 7. The second mock-up SH with a single occupant.

mock-up rooms is also an office with multiple occupancy, see Fig. 7. Again, the figure shows locations with activities. The the location marked green has a kettle which is heavily used by all four occupants of the office. The associated FML activity in this instance will to warm the water in the kettle to a specified temperature when there is movement in that area.

The leopardboard has been used to collect data continuously over period of two weeks unobstructed. The robustness and retraining capabilities of the systems alongside its energy efficiency has also been evaluated. To test the ability to retrain, the system was deployed in a room with wide glass window exposed to external day light over a whole weekend. Over the period of three days, Friday to Monday, the system automatically retrained six times. It should be noted that because the room was not used over the weekend, the only cause of retraining was changes in external light and reflection in the room. Also the reflection in the room changes as the sun changes position during the day. Fig. 8 shows the six images taken by the system before each retrain occurred. However, the other three rooms used for testing have at least a single occupant for a minimum of nine hours everyday.

To test the activity levels and resting locations within the mock-up SH environment, trajectory data for all the test rooms are collected and fed into the SOFM to determine resting

Fig. 8. 6 images captured by the system before retraining.

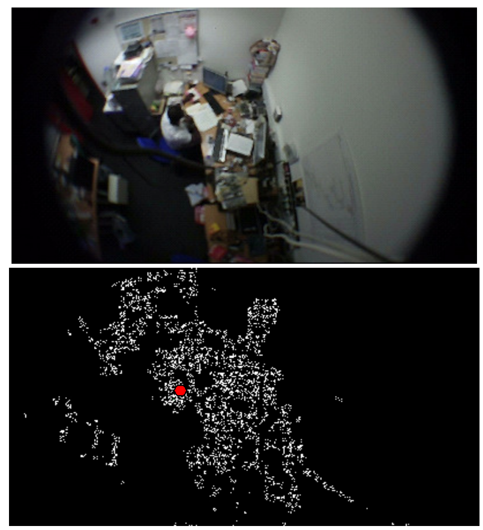

Fig. 9. Extracted central location of an object.

location or locations which may require a FML activity. The object detection and location capabilities of the system has also been tested and compared with a PC based implementation. As shown in Fig. 9, the moving object in the input image to the top is detected and its centre extracted as shown in the bottom image. The block-based vertical and horizontal histogram is used to estimate the centre of the moving objects, shown in red on Fig. 9. Object locations extracted from four test rooms have been examined to determine if the resting locations are correctly identified. Segments of the processed video streams on the leopardboard are visually compared with the PC based implementation to verify the object centre is correctly labelled.

A test has also been conducted on the number of trajectory points correctly classified with the implementation. For 520 trajectory points collected on a normal day, 421 were cor-

TABLE I
A TABLE SHOWING THE LEVEL OF ACTIVITY RECORDER OVER A PERIOD FOR ALL THE FOUR ROOMS.

Day	Traj. No.	Rest L.	Error Rate
Normal	520	421	4.4%
Vary Light	151	97	14.5%

rectly classified as resting location, 76 correctly classified as transient location and 23 were incorrectly classified as resting location, representing approximately 4.4% error. A similar test conducted on the same scene, with varying lighting intensity with a total of 151 trajectory points gave 97 correctly classified as resting location, 32 correctly classified as transient with 21 incorrectly classified as resting locations. This represents a total of 14.5% error. Table I is a summary of the total number of trajectories collected with associated error rates.

V. CONCLUSION

Over years, Ambient Assisted Living (AAL) is emerging as a suitable solution for enabling aged people to maintain their independence and, as a consequent, improving their quality of life. For this reason, several AAL systems have been proposed in literature. However, currently, a gap exist between sensor data generation and assistive provision based on context-aware personalized Activities of Daily Living (ADL). In order to face this gap, our approach uses a knowledge driven approach to process multiple sources of sensor data and to determine activity or resting location to deploy suitable environmental actions with fuzzy logic. By summarizing, the proposed system improves state of the art by giving the following main contributions:

1) The use of 2 dimensional camera data to infer location information to model movement and resting position;
2) The novel use of radar and other sensor information to support the camera data for activity level estimation;
3) The use of positional information to infer the ADL user in a smart environment;
4) The deployment of hardware-independent and personalized services through the use of FML together a learning strategy.

As shown by experiments, involving different environmental scenarios, the proposed system performs less than 20% classification error in monitoring human activities by providing the most suitable set of FML fuzzy services with minimal power consumption.

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