A Model for Activity Recognition and Emergency Detection in Smart Environments

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***Abstract*—Activity recognition has become an important feature in smart environments designed for helping old people living alone and independently in their homes. This paper presents a model for detecting emergencies in case of human activity recognition in such a smart environment. The emergencies detection is performed using a stochastic context-free grammar with attributes together with a domain activity ontology for modeling the daily programme of the supervised person.**

Keywords-activity recognition; smart environments; context-free grammar with attributes; emergency detection.

I. INTRODUCTION

The percentage of elderly people in today’s societies keeps on growing. As a consequence we are faced with the problem of supporting older adults in loss of cognitive autonomy who wish to continue living independently in their home as opposed to being forced to live in a hospital. Smart environments have been developed in order to provide support to the elderly people or people with risk factors who wish to continue living independently in their homes, as opposed to live in an institutional care.

In order to be a smart environment, the house should be able to detect what the occupant is doing in terms of one’s daily activities. It should also be able to detect possible emergency situations. Furthermore, once such a system is completed and fully operational, it should be able to detect anomalies or deviations in the occupant’s routine, which could indicate a decline in his abilities.

Our goal is to develop an integrated ambient intelligent system for elderly people or people with risk factors, called AmIHomCare, which includes several modalities of surveillance and assistance of people with special needs. One component of the system is the human activity recognition module, which is dedicated to recognizing human activities as part of daily living. Identification of daily activities is done using ontologies [1], vision-based models [2], sensor-based models [3] or different algorithms such as Hidden Markov Models [4]. Also the module is responsible with the detection of emergency situations during the daily activities. The paper presents a model for emergency detection for a set of human activities known to take place in the living room. The rules used for activities recognition are modeled with a stochastic context-free grammar. Different types of emergencies are detected during the activity parsing using a set of data: (i) an attribute for modeling the duration of activity added in the activity grammar and (ii) a domain ontology for represented activities’ properties (e.g., normal duration, usual place of performing an activity, time of the day or usual sequence of some activities).

The rest of the paper is organized as follows: Section II presents existing methods for activity recognition and Section III describes the general structure of the AmIHomCare system in which the component responsible for activity recognition will be integrated. Section IV introduces the model for emergencies detection in activity recognition. Experimental results are presented in Section V and the paper is concluded in Section VI.

II. RELATED WORK

Activity recognition became an important research issue related to the successful realization of intelligent pervasive environments. It is the process by which an actor’s behavior and his or her environment are monitored and analyzed to infer the activities. Activity recognition consists of: (a) activity modeling, (b) behavior and environment monitoring, (c) data processing and (d) pattern recognition. There are several approaches for activity recognition as described in [1]:

- Vision-based activity recognition which uses visual sensing facilities: camera-based surveillance systems to monitor an actor’s behavior and the changes in its environment. It is composed of four steps: human detection, behavior tracking, activity recognition and high-level activity evaluation. Various other research approaches used different methods such as: single camera or stereo and infra red to capture activity context. For example, in [2], a system for recognizing activities in three steps is presented: (i) track pedestrians across a scene and recognize a set of human activities; (ii) use multiple cameras to observe the scene and (iii) use an active dual camera for task recognition at multiple resolutions.
- Sensor-based activity recognition uses sensor network technologies to monitor an actor’s behavior along with its environment. In this case there are sensors attached to humans. Data from the sensors are collected and analyzed using data mining or machine learning algorithms to build activity models and perform activity recognition. In this case, there recognized activities included human physical

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movements: walking, running, sitting down/up as in [3]. Most of wearable sensors are not very suitable for real applications due to their size or battery life.

- Activity recognition algorithms can be divided in three categories: machine learning techniques, grammar based techniques and ontological reasoning. Many types of machine algorithms for activity recognition were developed, including Hidden Markov Models, Bayesian Networks or Support Vector Machine techniques. Among them Hidden Markov Models and Bayesian Networks are the most commonly used methods in activity recognition. Standard Hidden Markov Models (HMM) are employed for simple activity recognition as described in [4][5]. They are not suitable for modeling complex activities that have large state and observation spaces. Parallel HMM [6] are proposed for recognizing group activities by factorizing the state space into several temporal processes. Another approach for activity recognition based on HMM is semi-Markov models as described in [7]. Other models are represented by conditional random fields. Conditional random fields are discriminative models for labeling sequences [8]. They condition on the entire observation sequence, which avoids the need for the assumption of independence between observations. The Conditional Random fields method performs as well as or better than the HMM even when the model features do not violate the independence assumptions of the HMM as described in [8]. Other type of methods for human activity recognition is based on hierarchical Bayesian networks [9] or dynamic Bayesian networks [10], which can model the duration of an activity. Another method for activity recognition uses context-free grammar. A context-free grammar for the description of continued and recursive human activities is presented in [11]. Other types of grammars are used for activity recognition. An example is stochastic context-free grammars. Detection and recognition of temporally extended activities and interactions between multiple agents are modeled using a probabilistic syntactic approach (stochastic context- free grammar), as described in [12]. Stochastic context-free grammars are also used for recognizing kitchen-specific activities as in [13]. In [14], an attribute grammar which is capable of describing features that are not easily represented by finite symbols is proposed. This grammar is used for representing multiple concurrent events which involve multiple entities by associating unique object identification labels with multiple event threads. The ontological reasoning models activities in an ontology and the reasoning is realized based on the properties of the compound entities as described in [1].

III. ACTIVITY RECOGNITION IN AMIHOMCARE SYSTEM

The general structure of an ambient intelligent system (an intelligent house) for home medical assistance of elderly or disabled people, called AmIHomCare is presented in [15]. The paper describes the main components of the system, the purpose of each component and the links between them.

The main objective of this system is to develop an intelligent environment for ambient assisted living, which achieves home monitoring and assistance for elderly people or patients with risk factors, controls the environment, and detects medical emergencies.

The system has four main components:

- A component to monitor and control ambient factors such as light, temperature, humidity, as well as home security;
- A component to monitor patient health status by using non-intrusive and intrusive sensors, and send alerts in case of risk values;
- A component to achieve patient gesture recognition and gesture-based interaction with a “robot like” personal assistant;
- A component to achieve human activity monitoring (the supervising system), offers to the patient pervasive access and retrieval to medical products information (the retrieval system). Both the supervising system and the retrieval system work based on captured images and patient specific context.

AmIHomCare also includes a connection to a call center and a home assistance center. The AmIHomCare system proactively assists people in their daily activities or medical needs, detects medical emergencies, and sends information to a call center.

The supervising system analyses the images captured by the supervision cameras. For each image, the context of the detected person together with its pose are determined. The context together with the pose form a sub-activity. An activity is composed by a set of successive sub-activities. The process for human activity recognition is described in Figure 1 as it is presented in [16].

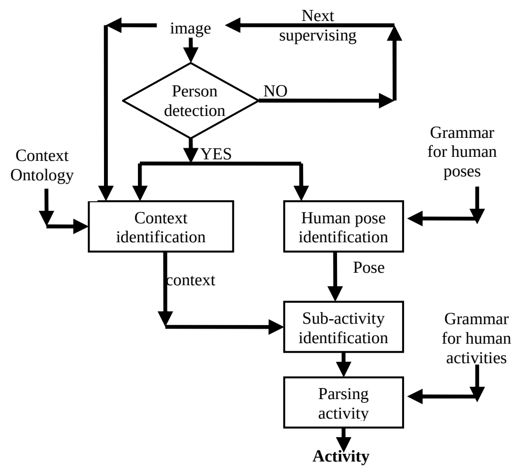

Figure 1. Human activity recognition

A supervising camera is installed in each room of the house. It takes snapshots at a predefined interval. Each image is analyzed in order to perform human activity recognition. The main steps of the human activity identification, as described in [16] are: (i) Person detection in the image; (ii) Identification of the detected person's context (iii) Person's pose identification in the recognized context and (iv) Sub-activity identification based on the obtained context and on the person's pose. The context of a person refers to the zone from the room in which the person was detected, together with the surrounding objects (furniture objects) from the room. Thus, each room is divided in zones of interest. For example, the living room from Figure 2 is divided in three zones: R1 (the resting zone), R2 (the reading zone) and R3 (the dining zone). For example, if we consider a person in the living room from Figure 2 in zone R2, near the armchair, his context will be (zone:R2, furniture object: armchair).

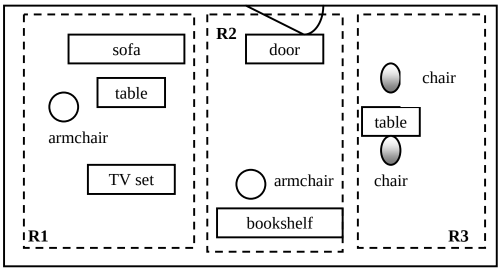

Figure 2. Areas from the living room.

The image from the supervising camera is analyzed in two steps in order to detect the person's context. First the image is annotated so that image objects will get associated keywords. Image annotation is performed with a parallel genetic algorithm, described in [17], which determines the best match between each image region and the corresponding objects in the room. Secondly, the image is analyzed for person detection. The bounding boxes of the objects from the image (the detected person and the furniture objects) are compared. Thus the objects close to the supervised person will be identified. Then these objects will be used to determine the zone of the room in which the person is located. This assumes a model of the house is available. The house model is a domain ontology – the context ontology, which consists of the rooms in the house, the zones inside each room and the furniture objects. Each room has its component zones and each zone consists of the component furniture objects. For a better person's context identification, each furniture object from the house and the supervising person have associated a depth using a distance sensor (sonar). Thus each furniture object from the ontology will have an associated list of one or more depth values. Each depth value in the list will be measured considering a known angle of the distance sensor. Next the ontology is queried with the objects close to the supervised person. The query result is zone R which contains the majority of objects close to the detected person (under a predefined threshold). The zone R together with the nearest furniture object(s) from R forms the person's context.

The position of the detected person is obtained using its depth (from the distance sensor) combined with a movement sensor. In case of movement detection, the human pose is identified. The human pose identification is described in [16]. The human body is modeled by its body components. A list of known poses stored in an and-or graph is used for this purpose. The pose is obtained using a set of rules modeled as a stochastic context-free grammar, which is transformed into the equivalent and-or graph. The human pose identification is performed probabilistically, by bottom-up constructing a list of parse trees in the grammar. The parse tree with the biggest probability is chosen from the result list.

Each activity is decomposed into a sequence of sub-activities. Each sub-activity consists of the human pose and its context. For the human activities, in [16] there are considered three possible activities:

- Watch TV: walk through the living room and sit down on the armchair (from R1) or on the sofa;
- Have a snack: walk through the living room and sit down on a chair near the dining table;
- Read a book: walk through the room, go to the bookshelf and sit down on the armchair (from R2).

A set of successive sub-activities are assembled in an activity using a stochastic context-free grammar.

IV. EMERGENCIES DETECTION IN HUMAN ACTIVITY RECOGNITION

Activities of Daily Living (ADL) have some general characteristics: (i) they are composed of component sub-activities (for example for preparing a meal somebody takes the ingredients and then will cook it); (ii) they are performed in specific circumstances (in a specific environment with specific objects for specific purposes) (for example people go to bed in a bedroom at a specific time or meals are made in a kitchen with a cooker) and (iii) people have different lifestyles. Thus activity recognition must be used together with an emergency detection technique. For this purpose the activity recognition technique must be used together with the daily programme of the supervised person which will be inferred with an emergency detection mechanism.

Emergencies detection in activity recognition implies (i) activity recognition based on a model for activities and second (ii) emergency detection inferring the detected activity together with the general daily programme of the supervised person. Thus it is necessary to have a model for activities such that it can be easy to detect some abnormalities in the daily programme of the supervised person.

In this paper, four types of daily activities abnormalities are considered:

- Activities with a longer duration than usual, which will generate a duration emergency;
- Activities which are performed in a wrong place, which will generate a context emergency;
- Activities which are performed at an unusual time of the day, which will generate an unusual time emergency.

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- Activities which are performed in an unnatural order, which will generate an unnatural order emergency.

In all the above cases, we can have a high or a low emergency.

The majority of the methods for human activity recognition are based on a set of rules for discovering activities. These rules are modeled as Bayesian networks or stochastic context-free grammars, as described in Section II. In these cases the time of the day, the place or the order of the activities are ignored. In [10], the duration of an activity is also taken into account, leading to an activity model based on dynamic Bayesian networks. In this case, the modeling of the four abnormalities described above: (duration, place, time of the day and order of activities) is done with a stochastic context-free grammar with an attribute for activity recognition, plus an activity ontology. The attribute from the grammar will keep the duration for the recognized sub-activity/activity. The normal duration, the time of the day, place and activity order are modeled by the activity ontology (the daily programme ontology).

The use cases described in [18] are used for abnormalities modeling. Mary is an old woman who is living alone in the smart environment. The following examples are considered:

a) Reading a book: Mary is going to the bookshelf. She is taking a book, then she is walking to the armchair. But after that she will be walking through the room for a long time. This situation is a low emergency and the smart environment will alert Mary that she wants to read a book and she will go to the armchair which is near the bookshelf and sit down.

b) Resting on the sofa: Mary is resting on a sofa for a period which is longer than usual. In this situation for the beginning it is a low emergency and the smart environment will alert Mary to stand up. If Mary doesn't stand up, the emergency will become a high emergency and the smart environment will send a message to the call center to intervene.

c) Lying down on the floor: Mary is lying down on the floor in the middle of R2 zone. In this situation it is a low emergency and the smart environment will alert Mary that she must wake up. If she will remain lying down on the floor the emergency will became high and the smart environment will send a message to the call center.

d) Having a nap after the breakfast in the morning: Mary just finished her breakfast and she went to the bedroom and fell asleep. This is unusual, because after she finished her breakfast she made a phone call with her friend. In this situation, initially a low emergency is triggered and the smart environment will alert Mary that she must wake up. If she will remain falling asleep the emergency will became high and the smart environment will send a message to the call center.

For doing this it is necessary to modify the model for activity recognition so that the duration of a sub-activity/an activity can be determined. Thus the stochastic context-free grammar used for activity recognition in [16] will be modified in a stochastic context-free grammar with an attribute. The attribute associated with the grammar will model the duration of each sub-activity / activity. The normal duration of a sub-activity, the place in which an activity is performed, time of the day at which each activity is realized and the acceptable sequence of activities form the daily programme of the supervised person. The daily programme of each supervised person is modeled in a domain activity ontology. A domain activity ontology for some activities of daily living was created. The daily programme of each supervised person will be an instance from this ontology. The conceptual activity model of the ontology is described in Figure 3.

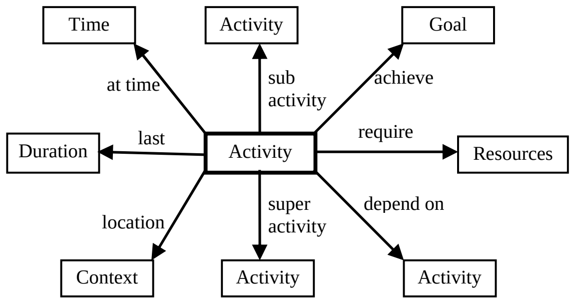

Figure 3. The conceptual activity model from the daily programme ontology

Each activity is described by a number of properties: (a) *Sub-activity*: some activities are composed of a set of component sub-activities (for example the reading activity is composed of: walking – going to the bookshelf, taking the book and then walking again – to sit on the armchair); (b) *Super-activity*: each activity may be part of other activity (for example walking is part of the reading activity or of the resting activity)*;* (c) *Context*: each activity is performed at a specific location (context) (for example the resting activity is performed on the sofa in the living room or on the bed in the bedroom); (d) *Duration*: each activity has a normal duration; (e) *Time*: each activity is performed at a specific time of the day; (f) *Goal*: each activity has a specific goal; (g) *Resources*: some activities need a set of resources (for example the reading activity requires a book taken from the bookshelf); (h) *Dependence*: each activity is made after another activity or after a set of activities (for example resting takes place after lunch).

The activity recognition and emergency detection can be described as in Figure 4. As described in Section III, first the context of the supervised person has been identified using the context domain ontology; then the human pose is estimated using a stochastic context-free grammar (SCFG) combined with an and-or graph which describes a set of known human poses. The identified context and the human pose form a sub-activity. Successive sub-activities will be assembled in a known activity by parsing in a stochastic context-free-grammar with an attribute (ASCFG). The ASCFG is obtained from the stochastic context-free grammar used in [16] for activity recognition in which is added an attribute for the duration for each sub-activity.

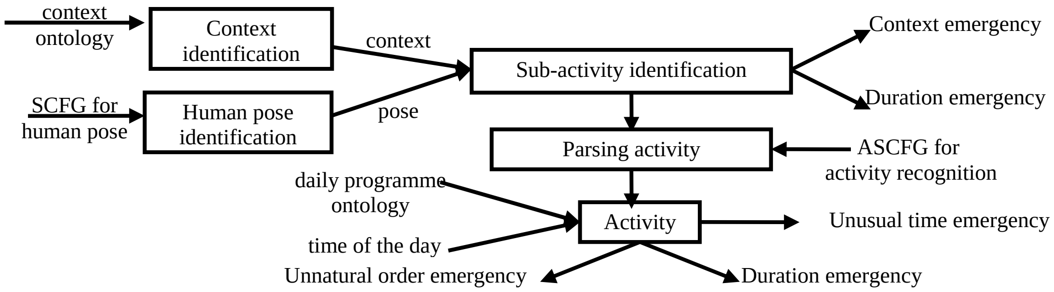

Figure 4. The general structure of the proposed model for the activity recognition- emergency detection

A part of the productions of the stochastic context-free grammar with attributes for the reading activity from the R2 zone is described in Figure 5:

- The rule (1) of the grammar consists of the three analyzed activities: reading, having a snack and watching TV. The duration of the activity is the duration of one of the possible activities.
- The rest of the rules (2) – (7) represents the rules for the reading activity.

(1) Start → Reading$^{0.333}$ | HaveSnack$^{0.333}$ | WatchTV$^{0.333}$
(2) Reading → Walking R2_Standing_Bookshelf $^{1.0}$

(3) Walking →
R2_Standing Walking $^{0.5}$ | R2 Standing $^{0.5}$
(4) R2_Standing_BookShelf →
R2 Standing Bookshelf Walking$^{0.5}$ |
R2 Standing Bookshelf R2_Sitting$^{0.5}$
(5) R2_Walking → R2_Standing R2_Walking $^{0.5}$ |
R2 _Sitting $^{0.5}$
(6) R2_Sitting → R2 Sitting Armchair $^{1.0}$
(7) R2 Standing → R2 Standing $^{1.0}$

Start.duration = Reading.duration
Reading.duration =
Walking.duration + R2_Standing_Bookshelf.duration
Walking.duration =
R2_Standing.duration + Walking.duration | 1
R2_Standing_BookShelf.duration =
R2_Walking.duration | R2_Sitting.duration

R2_Walking.duration =
R2_Walking.duration + 1 | R2_Sitting.duration
R2_Sitting.duration = 1
R2 Standing.duration = 1

Figure 5. The stochastic context-free grammar with attributes for emergency detection in human activity recognition

- Rule (2) means that the reading activity is composed by two sub-activities: walking in the room in zone R2 (Walking) and standing in zone R2 near the bookshelf (R2_Standing_Bookshelf). The duration for the reading activity will be the sum of the duration of the two component sub-activities.
- The walking sub-activity (the rule (3)) is composed by a sequence of pairs (context: R2, human pose: standing). Also the duration of the walking sub-activity is the sum of the duration of the component sub-activities. The duration of a sub-activity composed by context R2 and human pose standing is 1 unit (the same in case of rule (7)).
- The rule (4) describes the standing near the bookshelf sub-activity, which means taking a book from the bookshelf (context: R2, near the bookshelf and the human pose: standing) followed by the one of the two sub-activities: walking (R2_Walking) or sitting in the armchair (R2_Sitting). The duration of this sub-activity is the duration of walking or sitting sub-activity.
- The walking sub-activity used for R2_Standing_Bookshelf (the rule (5)) is a little different of the walking sub-activity from rule (3). The rule R2_Walking is composed by a sequence of walking sub-activities, which must end with the sitting in the armchair (rule (6)). The duration for rule (6) is considered 1 unit as in case of the rule (7). Each production rule has associated a probability. The sum of the production probabilities for each non-terminal is one.

The context ontology together with the daily programme ontology is integrated in the same ontology, named Home Medical HealthCare Ontology. Figure 6 presents a part of the ontology: (i) The context ontology (describes the living room presented in Figure 2 with 3 zones and some furniture objects); (ii) The daily programme ontology (the properties for several activities: walking, reading, resting and having a snack for a daily programme of a supervised person).

For the moment all the emergency situations have the same level of alert. The model does not distinguish between a low and a high emergency situation.

The parsing process consists of the bottom-up construction of the parse tree. Each sub-activity (which represents an internal node in the parse tree) will be inferred with the daily programme ontology in order to detect emergencies. Also this ontology will be used together with each recognized activity for verifying if an emergency is produced. In the case of a recognized activity the daily programme ontology is used together with the time of the day for verifying if an emergency appears. The context is inferred with each human pose in order to detect a corresponding emergency, too. If a long duration for the activity/sub-activity, a wrong context, an unusual time of the day for the detected activity/sub-activity or activities conducted in unnatural model are detected, a corresponding message will be generated.

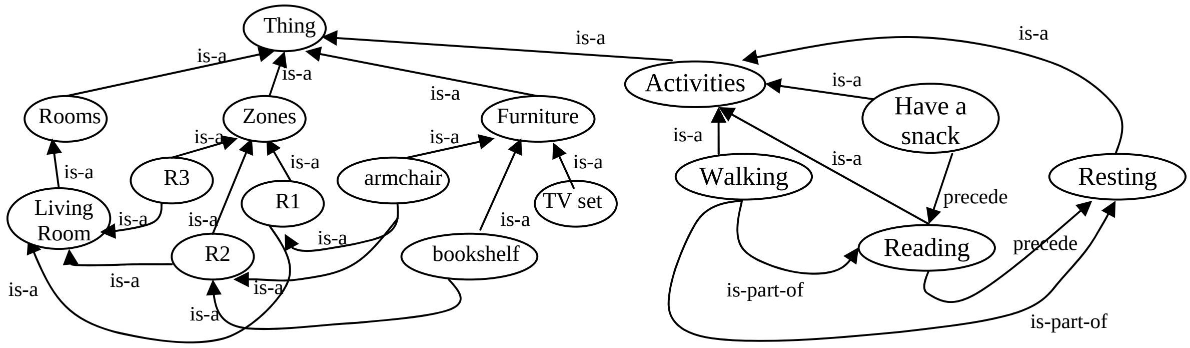

Figure 6. A part of the home medical HealthCare ontology

For example, we consider a set of observations: R2 Standing R2 Standing R2 Standing R2 Standing R2 Standing Bookshelf R2 Sitting Armchair. For this situation the bottom up parsing tree is represented in Figure 7.

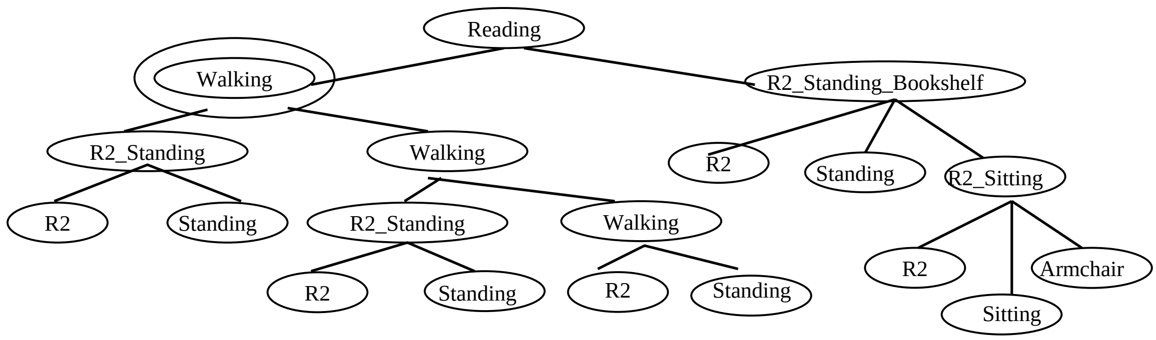

Figure 7. Example of a parsing tree for activity recognition

The emergency detection is checked in the obtained parsing tree:

- Internal nodes whose children are leaves in the tree are first checked by the relation between context and pose; this verification is made in the daily programme ontology based on the location of the sub-activity corresponding to the internal node; in case of a mismatch a context emergency is generated. For example we have a context emergency if there is a node with its children R2 Lying (lying on the floor in R2 zone). In the example from Figure 7 there is no context emergency.
- Internal nodes are checked for the duration of the corresponding sub-activity or activity. This is made using the daily programme ontology based on the duration of an activity. For example, the double circled node Walking from Figure 7 is verified by its corresponding duration. If its duration is longer than a normal value for the Walking sub-activity (the normal duration of the Walking activity is obtained from the daily programme ontology), a duration emergency will be generated.
- The root node is checked by the time of the day in the ontology. If an activity is identified at an unusual time an unusual emergency will be generated. Also the activity is checked by dependent activities. If an unusual order of the activities is detected, an unnatural order emergency will be generated.

V. TESTING THE MODEL

The proposed system was evaluated in a simulated environment. The room is modeled in 3D using 3D modeling software, OpenGL. The supervised human is also modeled using the same tools. Using a 3D modeling tool (the Blender 3D software in this case), we generated the camera and subject 3D models. Then, a few 3D key frames have been created, representing the person's key activities (e.g., walking in the room, standing by the table, sitting by the table, etc). Finally, the intermediate 3D positions have been generated using the interpolating functionality available in the tool. In this simulated environment there is no supervising camera or sensors (depth or movement sensors). In fact, the 3D scene is providing the very same essential information as the image annotation component. The viewing angle associated with the camera, the depth sensor or with the movement sensor is simulated by the field of view of the viewing frustum. The depth values obtained from the depth sensors are simulated by the distances between each object (furniture object or person) and the position of the camera from the scene. The daily programme ontology is developed in Protégé using OWL. Testing has been performed for the three activities described in Section III (reading, watching TV and having a snack) for which the three emergencies described above: context, duration and time of the day will be simulated. The results have been evaluated using the precision and recall metrics (precision indicates accuracy and recall indicates the robustness). The average values for precision and recall for emergencies detection are about 91.75%, respectively 95.65%, which indicates a good accuracy for the proposed model.

VI. CONCLUSION AND FUTURE WORK

The paper presented a model for daily activity recognition and emergency detection in a smart environment. The recognition process uses a context ontology (for the person’s context identification) together with a stochastic context-free grammar (for human pose recognition). A stochastic context- free grammar with an attribute is used for modeling emergencies detection in human activity recognition. The attribute grammar is used for modeling the duration of an activity. The duration of an activity together with the context in which the activity is performed and the time of the day when the activity is produced are used for inferring with the daily programme ontology for detecting emergencies. Based on the promising results obtained in case of this simulated environment, the system will be tested in a real smart environment, in which images from the supervising cameras and a set of collected data from a depth sensor and a movement sensor will be used. We also plan to extend the grammar used for activity recognition to represent a larger set of activities. Also the emergency detection model will be improved with a degree of emergency associated with each such situation. Another development will have as a purpose the recognition of interleaved human activities. In this case the parsing of an activity will be made by identifying a list of sub-trees in the parsing tree from the grammar. The obtained sub-trees will be connected in a single tree by common nodes.

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