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RESEARCH ARTICLE

Activity Recognition In Smart Home Using Ontology

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ABSTRACT

Activity recognition has gained a lot of importance in the computing era, making the system intelligent so that it automatically recognizes human tasks is attracting a number of application domains. It can be applied to real-time scenarios and human-centric tasks such as health care. Activity recognition in smart homes helps the elderly to live their life independently. A knowledge-driven approach that uses rich domain knowledge is used where ontology is used to represent the knowledge including the representation of the sensor inputs as the individuals of the ontology. The activities are considered to happen in specific locations, i.e., spatial knowledge and under specific circumstances of time, i.e., temporal knowledge. Using ontology makes the system reusable and also does not need a large amount of the data as required in data-driven approaches. Once the ontology is created as the knowledge base, the activities can be inferred with the help rules using an appropriate inference engine. In this thesis, a goal ontology and a belief ontology are proposed to identify activities of daily living within a smart home. The recognition of ADLs can be used to provide activity guidance for elderly and also those suffering from cognitive deficiencies.

Key words: Activity recognition, ontology, rule parse, smart home

INTRODUCTION

A smart home is one that provides its user's comfort, security, energy efficiency, and convenience at all times, regardless of whether anyone is home. "Smart Home" is the term commonly used to define a residence that has appliances, systems that are capable of communicating with one another and can be controlled remotely by a time schedule. Smart homes equipped with sensors, actuators, and devices, which are augmented residential environments inhabited by the elderly or disables, operated by professionals, and health services. They infer the current activity for application-level functions by supporting reasoning based on real-time streaming sensor data. Some of the examples of the activities of daily living (ADL) are washing, preparing a meal, etc.

Elderly people will be able to live an independent life with the help of activity recognition in smart homes. The elderly population has the need for assistance as the aging population is increasing. It is probable that in coming years the number of people who comprise working age will decrease in comparison with the elderly, this, in turn, will reduce the support that can be provided. The research groups have suggested ambient assisted living (AAL) to solve the problem associated with providing the assistance to the aging population. The AAL, in turn, makes use of the smart homes as a technology to provide assistance for the aged population and also for the ones who are suffering from cognitive diseases such as Alzheimer's.

Activity recognition aims to recognize the actions and goals of one or more agents from a series of observations on the agents' actions and the environmental conditions. Focuses on accurate detection of the human activities based on a predefined activity model. Monitoring peoples to recognize their physical activities either if they are with or without disabilities to help them in carrying out their daily tasks or prevent emergencies are included under the core building block called human activity recognition.

A good representation scheme is a compromise among many competing objectives. A representation is rich enough to express the knowledge needed to solve the problem.

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As close to the problem as possible; it should be compact, natural, and maintainable. It should be easy to see the relationship between the representation and the domain being represented so that it is easy to determine whether the knowledge represented is correct. A small change in the problem should result in small change in the representation of the problem.
Amenable to efficient computation, which usually means that it is able to express features of the problem that can be exploited for computational gain and able to trade off accuracy and computation time.
Able to be acquired from people, data, and past experiences.

RELATED WORK

Nowadays, progress of smart environments in remote monitoring, elderly assistance, and telemedicine has gained importance. The smart home organization is depicted and is studied across USA, Europe, Asia, Australia, and New Zealand. A brief review on what objects are used in smart homes, along with the equipment used, technologies and the applications have been illustrated by Chan *et al*.[1] He has presented a survey on the smart home environments, also including the challenges involved. Few of the many applications in which a smart environment can be deployed using the desired equipment are the computer vision applications, artificial intelligence applications, intelligent agents, and context modeling to name a few. Bao and Intille[2] have developed algorithms to detect the physical activities carried out by a person such as running, walking, and jumping. These activities are recognized using a wearable sensor which is worn by the person whose activities are to be monitored. Five small biaxial accelerometer sensors are worn simultaneously in different parts of the body. This approach is dependent on the generative methodology which makes use of the classifiers such as decision table, naïve Bayes, C4.5, and IBL. For each of these ways, accuracy in recognition of activities was calculated with respect to the training data available. Some of the activities such as watching TV, and riding an elevator could be recognized by adding the temporal information.
Ravi *et al*.[3] uses the triaxial accelerometer to detect the activities performed by an individual. The triaxial accelerometer sensor measures the data in all x, y, and z dimensions. The activities are performed using the discriminative approach using the classifiers. The values from the sensor are read by a Bluetooth device and are converted into ASCII values using python script. The ASCII data are then annotated from which the features are extracted, and the activities are recognized by labeling them according to the dataset. The features that were extracted are mean, standard deviation, energy, and correlation. The rate at which the activities were performed was also valued by the means of temperature, heartbeat information. Gayathri *et al*.[4] proposed system performs activity modeling through Markov Logic Network, a machine learning strategy that combines probabilistic reasoning and logical reasoning with a single framework. Activities in a smart home are categorized as simple and composite activities; wherein composite activities are defined as related simple activities within a given time interval. The proposed system models both simple and composite activity using soft and hard rules of MLN. Experiments carried over the proposed system shows the effectiveness of the proposed work for recognizing simple and composite activity.
Hao *et al*.[5] have introduced a new knowledge-driven approach based on the formal concept analysis to predict and recognize ADLs in ubiquitous computing environments, to duly provide continuous assistance for residents. The proposed approach constructs an incremental inference engine and achieves progressive deductive reasoning to recognize an unfinished ongoing ADL in real-time. For the purpose of finding out the most probable ongoing activity among possible candidates, we propose an assessment based on the root-mean-square deviation to evaluate the relevance of each intermediate prediction. Besides the on-the-fly recognition mode, our approach also possesses high discrimination in differentiating derived and similar activities. The recognition results show the accuracy of 70% for different set of activities.
Accuracies (more than 70%) are obtained in the experiments. George *et al*.[6] presented a hybrid approach to composite activity modeling by combining ontological and temporal knowledge modeling formalisms. Ontological modeling constructors, i.e., concepts and properties for describing composite activities have been developed

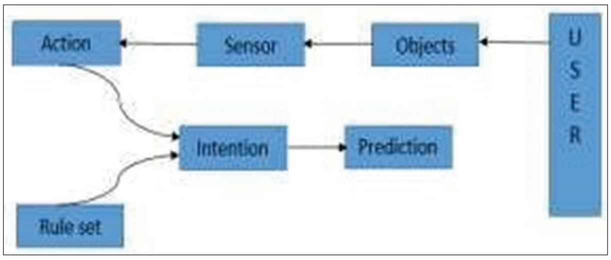

Figure 1: System overview

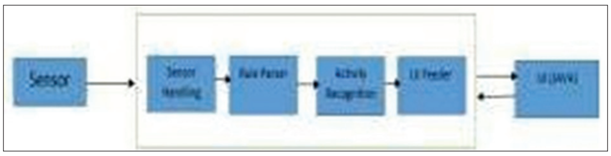

Figure 2: Block diagram of the system

and temporal modeling operators have been introduced. As such, the resulting approach is able to model both static and dynamic characteristics of activities. Several composite activity models have been created based on the proposed approach. In addition, a set of inference rules has been provided for use in composite activity recognition. A concurrent meal preparation scenario is used to illustrate both the proposed approach and associated reasoning mechanisms for composite activity recognition. Safyan *et al*.[7] have presented an approach for completing the personalized model specific to each inhabitant at smart homes using generic model (incomplete) is presented that can recognize the sequential, parallel, and interleaved activities dynamically while removing the spurious activities semantically. A comprehensive set of experiments and results based on a number of correct (true positivity) or incorrect (false negativity) recognition of activities assert the effectiveness of the presented approach within a smart home.

FRAMEWORK DESIGN

The proposed system works on the knowledge driven approach. SH domain knowledge is the common sense knowledge of the ADLs being performed. It provides rich links between actions, activities, and the environment a shown in Figure 1. An inhabitant ADL preferences and the sequence in which the ADL is performed provides a priori knowledge about the ADL. Such domain and prior knowledge are very useful in creating ADL models avoiding the need of large dataset collection and training. The block diagram of the system is shown in Figure 2.

VONTOLOGY

The field of ontology deals with the questions concerning what entities exists. In general, it can be defined as knowledge about how the world is conceptualized. It includes machine interpretable definitions of basic concepts in the domain along with the relations with each other. Ontologies represent a key aspect for the integrating the information coming from different sources, to improve the information retrieval; in general, important for reasoning on the available knowledge. It typically contains representation and description of the different objects in the domain, their attributes, and values, relationships with the other objects along with axioms.

Many methods and tools have been proposed for the design, edition, maintenance, alignment, or the evaluation of ontologies.

Construction of a basic ontology is as follows: Collect all the related terms, concepts, and determine the relationship between the concepts. Start the Portege and choose the engineering format. Select OWL classes tab, properties tab, and individual tab, and add various concepts, various characteristics, individuals, respectively. Continuously modify and complete the ontology editor.

ACTIVITY MONITORING IN SMART HOMES USING SENSORS

Smart homes today work on the concept of ubiquitous sensing where sensors are integrated with processing devices to yield a multi-modal stream of data. The data are then analyzed to recognize and monitor basic ADL performed by the elderly people, Alzheimer patients or any other inhabitant such as bathing, preparing a meal, and taking proper medication. The sensors can either be wearable sensors worn on the person’s body or sensors attached to the objects with which the inhabitant interacts while performing the ADL. Thus, the sensors are activated when an action is performed by the inhabitant. The sensors later use radio-frequency identification (RFID) to recognize the activity. The RFID uses electromagnetic fields to automatically identify and track tags attached to objects. The tags contain electronically-stored information.

ACTIVITY RECOGNITION

Rules

Rule-based approach is one method which determines the ongoing events by modeling activity using rules or sets of attributes that describe an event. Rules are basically the universally quantified statement. Each activity of the event is considered as a set of primitive rules/attributes, which helps in the construction of a descriptive model for the activity recognition.

They are commonly based on first-order logic and possible extensions. The most popular formalism for rules is the SWRL which expresses rules in the form of if-then. For the sake of decision-making ontologies are not considered to be expressive whereas rules are enough expressive to provide reasoning support. The rules are built on the ontology classes or instances.

Inference engine

Inference engine is a major component of an expert system which applies logical rules to the knowledge base to deduce the required new information. That is, the system iterates as every piece of data in the knowledge base trigger additional information in the inference engine. Various methods can be used to implement the inference engine and perform reasoning, such as fuzzy logic and Bayesian logic the two primary modes of inference used are forward chaining and backward chaining. Forward chaining starts with the known facts and asserts new facts. Backward chaining starts with goals and works backward to determine what facts must be asserted so that the goals can be achieved.[8] The inference module consists of two sub-modules rule parser and activity recognizer.

Rule parser

The rule parser creates an event action graph of all the atomic actions and the end events which are used by the activity recognizer to transverse across the different states of the graph and reaches the end goal.

The inference mechanism is used to infer the goals from the actions detected by the sensors. It fetches new facts from the knowledge base. The conclusions can be drawn through forward chaining which uses the rules or backward chaining inference method that works backward from the goals. Thus, the sensors are deployed to monitor the activities. Furthermore, activity models are created with knowledge representation formalisms. We then select appropriate reasoning algorithms to infer the activities from the sensor data. The sensor data are read using ARDUINO which transmits the corresponding action to the UI. The UI then updates the action to the database using the data updating module. These actions are further passed to the activity models.

Detailed implementation

The atomic actions and goals are modeled using ontology with sensors, atomic actions, and end goal as the classes. Using the classes of the ontology, rules are constructed which include the sequence of ADL. RFID sensors are attached to the objects involved in the activities. The sensors are activated when an inhabitant lifts the container. The RFID receiver detects the sensor activation and sends it to the Arduino. Arduino then determines the atomic action being performed in the smart home environment and transmits it to a smart device. Device receives the corresponding action and updates the database. Furthermore, ontology is updated with the instance of a particular sensor type along with the timestamp of sensor activation. Inference module parses the rules such that it returns a tuple with an event list and the corresponding goals. An action event graph is built that is used to reach the end goal if the set of actions are carried out in order. The inference is carried out by a state machine which traverses through the action event graph to reach the goal.

OBSERVATION

Comprehensive design is transformed into functioning code. The proposed approach has been implemented in a feature-rich context-aware assistive system. The main components of the system are inhabitant, sensor, domain knowledge, ontology, rules, and activity recognition. Seven typical ADLs were selected for the purposes of experimentation they are brush teeth, wash hands, take medicine, make meal, watch TV, make coffee, and eating. For each activity, the required objects for performing the activity were identified, and to each of them, an appropriate sensor was attached [Table 1]. Activity classes in ADL ontologies are structured in a hierarchical tree with subclasses inheriting all properties from their super classes. For each activity, we specify how it is performed based on domain knowledge. It is specified as a sequence of user-object interactions. The interaction is detected by sensors when a user uses the objects to perform the activity. To help illustrate our approach, we use the Brush Teeth ADL class hierarchy, as an example for discussion. The activity "Brush Teeth" is specified as the sequence. "Pick toothbrush, pick toothpaste, pick mouthwash, and pick water container." These activities and all the sensors are modeled in ontologies and represented in OWL, which is uploaded into the system during system startup.

Approximately 13 sensors were deployed in the experiment. Each sensor was attached to one of the objects involved in these activities. On average, three objects (sensors) were used for each activity. The recognition operation is set to be performed each time a sensor is activated, i.e., a user interacts with an object.

When the system is in operation, it obtains real-time sensor activations from a designated communication port.

To test not only functionalities but also scalability and robustness, each activity was designed to be performed in three different ways, leading to three types of activity specification. Table 2 shows two selected activities, each with four types of specification.

Four actors took part in the experiments [Table 3]. Each of the participants performed 4 (times) × 8 (activity) = 28 activities in terms of the activity specification. This produced a total of 28 (activity scenarios) × 4 (actors) = 112 activities being performed in the experiment.

For each activity, the experiment was carried out as follows: An actor starts performing an activity by following the object sequence of the specified activity scenario. The evaluator observed and recorded the actor's action and the recognition results of the system, i.e., how many times the activity was identified correctly and how many times the system failed to identify the activity. This data were recorded in an experiment data sheet. The interval between two consecutive actions was set to approximately 40 seconds. Table 4 gives the recognition results of the 122 activities, 7 ADLs and number of times they were correctly identified and incorrectly identified are, respectively, shown. The sum in each column denotes the number of success and failure of activity recognition.

Table 1: Recognition results of four inhabitants

Actor	Correctly identified	Incorrectly identified
P1	20	8
P2	18	10
P3	23	5
P4	21	7
Total	82	30

Table 2: Action sequence for make meal

Make meal	Set of atomic actions
Type 4	get Water container, get Mouthwash, get ToothPaste, get Toothbrush
Type 1	get RiceContainer, get Pan, get Water container
Type 2	get RiceContainer, get Water container, get Pan
Type 3	get Pan, get Water container, get RiceContainer
Type 4	get Water container , get RiceContainer, get Pan

Table 3: Action sequence for brush teeth

Activities	Sequence of actions
Brush teeth	
Type 1	get Toothbrush, get ToothPaste, get Water container, get MouthWash
Type 2	get ToothPaste, get Water container, get ToothBrush, get MouthWash
Type 3	Get ToothPaste, get Toothbrush, get MouthWash, get Water container

Table 4: Example of activity specification

Activities	Objects required
Make coffee	Sugar container, coffee container, water container
Brush teeth	Toothbrush, toothpaste, mouthwash, water container
Wash hands	Hand wash, water container
Take medicine	Medicine, water container
Make meal	Rice container, pan, water container
Eating	Plate, spoon, water container
Watch TV	Remote

RESULTS

The system performance is estimated using various factors to check whether the activities are recognized correctly. This chapter includes the results details of the project, providing

Table 5: Recognition results of different activities

Activities	Correctly identified	Incorrectly identified
Make coffee brush teeth Wash hands Take medicine	10	6
	11	5
	12	4
Make meal eating Watch TV	13	3
	15	1
	16	0
	12	4
Total	89	23

description of the performance of project. 7 ADLs and corresponding 13 actions are considered to measure the performance of the system. We have analyzed activity recognition accuracies for individualactors. The goal is to evaluate how much different actors affect the recognition performance of the system. In a real-world environment, the system will be used by different users, the consistency of the system performance is therefore important. The prediction percentage and the accuracy of activity recognition depend on the:

1. Sensor readings
2. Sensor range
3. The sequence in which actions are performed.

As can be seen from Table 5, the recognition accuracies for the four actors were 89.3, 82.1, 78.6, and 96.4%, respectively, with small variations. This suggests that the system performance is consistent and stable in real-world contexts.

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