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A distributed smart home artificial intelligence system

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A DISTRIBUTED SMART HOME ARTIFICIAL INTELLIGENCE SYSTEM

Introduction

Many researchers claim that the next revolution of the Internet will properly be the Internet of Things (IoT). This revolution moves commonly known devices and objects to the Internet in a distributed manner. Based on this future perspective it assumed that they will be available in our smart homes as smart objects. Smart homes will have a huge impact on our future life. They will be able to act "intelligently" and provide services according to our personal preferences. Because IoT and their communication network systems are distributed, it is assumed that smart home systems could benefit from using a distributed architecture. Such a design strategy means distributing the smart home event and action processing between different parallel smart home systems. In addition the processing and network load can be placed on specialized hardware which is able to support this.

A distributed smart home system is also an enabler for a variety of different smart object types that offer different processing ability, different network resources[1] and the possibility to use the concept of embedded cloud computing[2].

A high degree of home automation has disadvantages in form of reduced usability. Users lose control and are overloaded with information from all the smart

[1] S. Bhardwaj, T. Ozcelebi, J. Lukkien, C. Uysal: *Resource and Service Management Architecture of a Low Capacity Network for Smart Spaces*, IEEE Transactions on Consumer Electronics 2012, Vol. 58, No. 2, p. 389-396.

[2] X. Ye, J. Huang: *A Framework for Cloud-based Smart Home*, International Conference on Computer Science and Network Technology 2011.

objects contained in a smart home[3]. An efficient way to deal with these problems is by employing an artificial intelligence framework that pre-processes, combines and sorts the huge amount of events that arrive from the smart objects. This concept ensures that only filtered events at a high level are brought to the user's attention.

This paper presents a distributed smart home architecture that is divided into a layered model. These layers offer a different complexity level of the embedded distributed artificial intelligence. At the lowest layer smart objects exists, they are small cheap embedded microcontroller based smart devices that are powered by batteries. At the next layer more complex systems exist. These systems offer the needed processing capability to support and run more complex artificial intelligence algorithms. In the presented system only two ayers exits, but in theory more layers could be used.

From a more detailed viewpoint this paper presents a distributed smart home system that contains two layers. These are named: Smart Home System part I (SHS-I) and Smart Home System part II (SHS-II). The SHS-I system is a distributed artificial intelligence system that is embedded into the smart home devices. It offers a simple system that is able to learn and predict stateless user actions as e.g. making breakfast, taking a shower, etc. SHS-II is basically a system that is able to learn an activity from a sequence of user initiated actions and propose a correlated smart home activity to the user.

The primary limitation of this work is that it only supports single user scenarios. However, this choice is justified by assuming that each user is identified by a human-recognition-based system, for example, based on a smart phone location system or a camera system[4].

1. Related work

Most work on smart home systems uses a centralized approach where the smart home sensors interact with a centralized server positioned in the smart home or offered as a cloud based service [5]. Some researchers look into using a distributed concept. Reinisch et al. discuss an Smart Object (SO) i.e. agent, based smart home

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[3] Bernheim, A.J. Brush: *Home Automation in the Wild: Challenges and Opportunities*, ACM Conference on Computer-Human Interaction 2011.

[4] T. Gill, J.M. Keller, D.T. Anderson, R.H. Luke: *A system for change detection and human recognition in voxel space using the Microsoft Kinect sensor*, in IEEE, Applied Imagery Pattern Recognition Workshop (AIPR) 2011, p. 1-8; L. Xia, Chia-Chih Chen, J.K. Aggarwal: *Human Detection Using Depth Information by Kinect*, IEEE Computer Society Conference on Computer Vision and Pattern Recognition Workshops (CVPRW) 2011, p. 15-22.

[5] D. Cook, A. Crandall, B. Thomas, A. Krishnan: *A Smart Home in a Box*, IEEE NCASAS 2012; X. Ye, J. Huang: *A Framework for Cloud-based Smart Home*, International Conference on Computer Science and Network Technology 2011.

named ThinkHome[6]. They introduce a concept where an ontology based knowledge database processes and store learning. This learning is supplied from a set of highly specialized agents in a multi-agent system. Each agent has its own scope as e.g. an AI based agent, user preference agent, context inference agent, etc. On top of the multi-agent system is the user interface where preferences and control can be applied to the system. Their approach use a high level allocation strategy for the agents which is the opposite of this work which assumes that agents are atomic.

A paper by Alam et al. published in 2012 support the concept of using distributed artificial intelligence agents. In their paper they review smart homes in the past, present and the future where they conclude: *It seems that home intelligence will be employed in a distributed manner. This distributed intelligence may be applied in the form of smart devices. The system will also use different user interfaces to acquire user feedback, most of which will be based on auditory, visual, and hap tic perceptions.*

This statement is in good agreement with the presented work. The same point of view is stated by Shoraby et al. in their book about sensor networks[7].

2. Centralized vs. distributed approach

As stated in the introduction, IoT devices (named SO) and their communication systems have a distributed nature and it is reasonable to assume that using a similar approach in smart homes will be beneficial. Thus, these SO are designed to use distributed networks like most Wireless Sensor Networks (WSN) do. This means that they use a WSN topology that is mesh-based, star-based or a mix between these. In a smart home the mixed variant will properly be the dominant one because it will consist of a collection of network hybrids defined by the different standards as e.g. IEEE 802.11a /b/g (WiFi), IEEE 802.15.1 (PAN/Bluetooth), IEEE 802.15.3 (ultrawideband) and IEEE 802.15.4 (ZigBee). Added to this will be the existing standards for simple home control systems as e.g. Insteon, UPB, X10, Z-Wave and CEBus. Using a mixed WSN topology means that there will be a collection of islands linked together by a clustering node that in turn links to the overall network. In such a framework the SO network load will be high because each SO node will need to emit the high level of sensor events normally found in a smart home. E.g. in the CASAS data set[8] it was found that the average number of sensor events on a daily basis is large, i.e. 1795. For battery powered nodes that need to

[6] C. Reinisch, M. Kofler, W. Kastner, ThinkHome: A Smart Home as Digital Ecosystem, IEEE International Conference on Digital Ecosystems and Technologies (IEEE DEST) 2010.

[7] K. Sohraby, D. Minoli, T. Znati: *Wireless Sensor Networks*, Wiley interscience 2007.

[8] D.J. Cook: *Learning Setting-Generalized Activity Models for Smart Spaces*, IEEE Intelligent Systems 2012, Vol. 27, No. 1, p. 32-38.

use a wireless transmitter this amount of events will fast wear out the batteries. A second factor that adds to the WSN load is the routing of messages that takes place in single and multi-hop networks.

An alternative to the mixed WSN topology could be to distribute the artificial intelligence processing so each SO cluster performs part of the needed processing locally. This approach exchanges the battery power needed for wireless transmitting with the much less power needed to run part of the artificial intelligence system. However, because these nodes have a very restricted processing capability and limited battery resources they are not capable of doing all the processing needed for running a full-blown artificial intelligence system. So, conclusively it is beneficial to divide the processing of the artificial intelligence system into layers where the different layers take care of an appropriate part of the calculation burden.

A comparison of the distributed smart home system from the previous discussion with a more centralized system reveals that distributing the reasoning layer into some SO also distribute the network load. This means that the heterogeneous network elements and its transmission channels connecting them to the distributed SOs are able to work in parallel. This lowers network load in the bottlenecks that e.g. a centralized server would create. Distributed SOs also provide some of the benefit given by a lumped network meaning shorter distances, i.e. less noise sensitivity, lower power consumption and the possibility to use different routing and bridging technologies, i.e. an average lower network load. Regarding single point of failure and power savings the SO approach also benefits from its distributed nature. SOs not in use can be powered down and if some of them fail the other will still be able to work, but with a reduced performance. However, looking into the downside and the non-effected parameters distributing SOs does not solve the problem when a specialized SOs fails, if e.g. the heating SO fails the complete heating system will also fail. Adding more wireless SOs that communicates in parallel adds a new radio disturbance problem in form co-channel and adjacent channel interference. Furthermore, the user interface part does not provide a clear coupling between the smart home device and the portable interface device. So, dividing a smart home into some functional units does not solve all the problems.

3. The smart home system architecture model

An abstract model over the presented smart home system architecture is illustrated in

Fig.

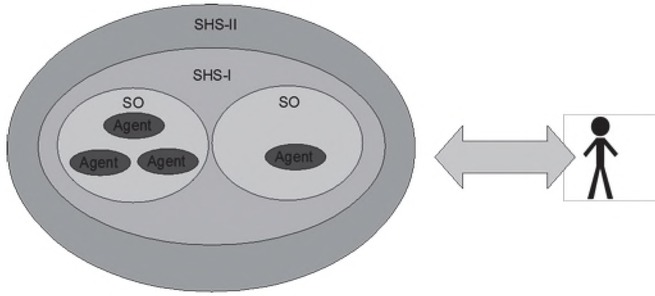

Fig. 1. An architecture model for a distributed smart home

Source: own elaboration.

Rightmost in Fig. 1. is a smart home user who carries out scenarios in the form of a normal living pattern in a smart home. This way the user interacts indirectly with the smart home by triggering sensors and receives feedback in the form of actions. These actions are carried out by the smart home system actuators. In the presented smart home system these sensors and actuators are collected into groups named Smart Objects (SO). An SO node also contains processing power in form of an embedded micro processor or micro controller. This allows the SO to implement artificial intelligence and thereby enables it to act intelligently. The artificial intelligence part in a SO is named an agent. So, one particular agent handles one particular action like e.g. turning the kitchen table light on when the agent detects that the user would like to dine.

A collection of SO (that contain a collection of agents) are assigned the conceptual name SHS-I. Such a system is minimalistic in many ways. I.e. it is limited by the low amount of processing power available in the small embedded microcontrollers and the available battery power source, etc. To overcome these limitations an advanced and extended smart home system is added in form of a more sophisticated artificial framework. This framework is named Smart Home System two (SHS-II) to indicate that it is an add-on to SHS-I. Actually, the SHS-II system is also a distributed system, i.e. it consists of many devices that contain communication capability and processing power like e.g. a TV or a radio.

The SHS-II cannot be used as a standalone system because it require the predicted actions from the SHS-I system or from some other compliant systems, as input. Thus, is uses the actions from SHS-I that is suggested to the user or carried out by the system to make its own prediction.

4. The smart home system behaviour model

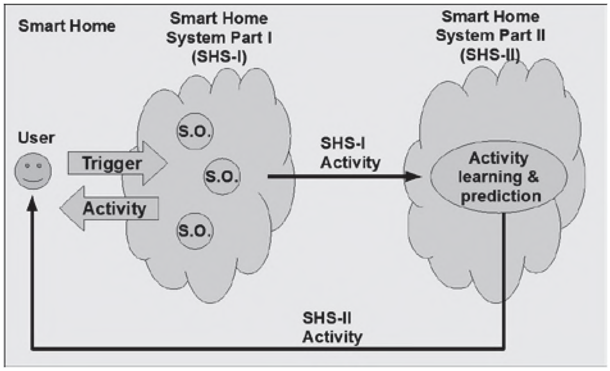

Fig. 2. Context model for the smart home system

Source: own elaboration.

The presented smart home system offer services to its user based on artificial intelligence. One of its main goals is to learn from the user's habits when a user related activity is performed. Based on this learning, the system offer related actions in the form of scheduled services to the user. These services are recommended to the user, for example by using a smart phone interface or put into a smart home calendar.

The presented smart home system is illustrated in Fig. It consists of two blocks and some communication links. These blocks are named: *smart home system part I* (SHS-I) and *smart home system part II* (SHS-II). As illustrated in Fig, the user (green smiley) carries out scenarios in a smart home. These scenarios triggers strategically placed sensors that are connected to the smart objects (SOs) contained in the SHS-I context. Such an activation of the SOs causes an action sequence to be emitted that needs to be processed by the smart home systems SHS-II. Some of the events are from smart objects that can schedule services to the user (e.g., turn on TV). These events are action-events that are named "actions" to distinguish them from the simpler sensor events (e.g., a door open/close switch) that are named "events". However, the term actions are twofold because they contain both an action and an event part. The action part enables the user and the smart home system to manipulate embedded actions, such as, turning on the kitchen light. Whereas the event part is only informative, that is, it emits events to the smart home system (e.g. information on the kitchen light status). Based on these emitted events, the smart home system predicts and suggests actions to the user. Thus, from a more technical perspective, the actions are used to learn from the user's actions and thereby train the smart home's artificial intelligence in handling that particular action. Based on this trained behaviour, the smart home system processes incoming events and if the correlation is high enough, it suggests activities to the user or performs them autonomous.

It is noted that the SOs contained in the SHS-I system is agent based; i.e. only one instance (agent) is trained for each particular user action. So, when an event is triggered, all the connected SO agents receive it and each of them calculate a posterior probability that is compared to a threshold limit. If the probability exceeds the threshold limit an action is scheduled. The SHS-II system Fig receives the preprocessed actions from SHS-I system and uses it to make more advanced predictions.

5. Smart home system I and II object models

An object process methodology model for the SHS-I and SHS-II systems are presented in the following section.

The SHS-I system is a framework that contain SOs. Each of these SOs contains a collection of highly specialized agents where each agent takes care of one particular action. So, the presentation covers the object model for one of these agents.

As shown leftmost model in Fig, the user (*SH-user* object) carries out scenarios by performing normal living pattern in a smart home (leftmost process).

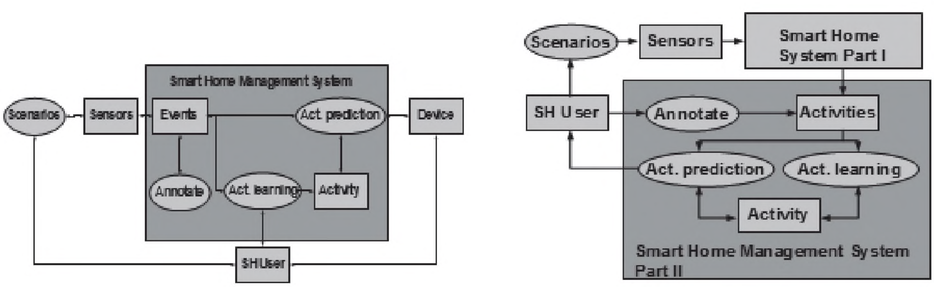

Fig. 3. Object model of the agents containing the SHS-I and SHS-II systems

Source: own elaboration.

When the user interacts with the smart home system through these scenarios, the SOs contained sensors are triggered and activated (*Sensor* object). Each sensor emits events that are received by the agents contained in the SO. On arrival, these events are annotated with a time stamp (*Annotate* process). At this point, the annotated events are divided into two streams: one for actions that are fed to the activity learning process (*Act. learning*) and the other for simple events that are fed to the activity prediction process (*Act. prediction*). Thus, the activity learning process only uses actions for training the artificial intelligence model positioned in the agent activity object (*Activity* object) and simply ignores the other event types. Based on the trained artificial network, the activity prediction process processes the annotated events and thereby predicts an upcoming user activity. If an acceptable activity posterior probability level is found, the activity prediction process schedules the activity on the addressed smart object (*Device* object) and thereby offers the predicted service to the user or schedule it autonomously.

The SHS-II system it is illustrated in Fig rightmost part. The user interacts with the SHS-I system as described earlier. The agents in the SHS-I system send predicted actions to the SHS-II system. As discussed earlier the SHS-II system is distributed, i.e. it consists of a collection of dissimilar systems where each one has different processing and communications capabilities. I.e. an instance has been dedicated to capture one specific predefined high level user activity, for example, set the home light, heating and ventilation system to “nobody home state”. So, in a smart home context, many of these instances must be expected to coexist.

The last part of the SHS-II system behaviour is very similar to the one described for the SHS-I system why it will not be presented further.

6. Smart Home system example usage scenario

A scenario is presented to illustrate the use of the smart home system. The smart home user Bob performs the following scenario: *Bob enter the kitchen to get something to eat so he takes a plate from the cupboard and sits down at the dinner table. When he makes this change dinner table kitchen light automatically is switched on and set to a coloured that visualises the food in a nice way. Some nice relaxing music also plays in the background. The wall mounted monitor shows all the last mails and face-book new. It also remembers him that the football match starts at 19.00.*

Even though this scenario seems simple a lot of complex processing and communication is going on behind the scene. First, the scenario needs to be learned by the artificial intelligence system where it adapts and tracks the user behaviour. Next, the artificial system needs to be able to predict the user activity pattern and suggest actions based on this.

To illustrate these parts, i.e. the learning and prediction sequences a sequence diagram covering this scenario is shown on Figure 4.

This SO emits information about this activity in form of an action-event. This action-event is captured by the connected SO that uses this to update one of its contained agents by looking into the events that have arrived in the past - limited by a certain time window.

The prediction process works the other way around, i.e. the agent monitor the incoming events and if some degree of match relative to the learning events can be found the action that triggered the learning in the first place is suggested to the user. Flow 6 and 7 illustrates this. However, it should be noted that the actual learning and prediction processes are stochastic based, i.e. they are more complicated that presented in this high level introduction. This also means that these processes can change behaviour over time to track the user habits and changing behaviour. Like humans they also need time to learn, i.e. they have a poor performance in the beginning, but enhance performance over time up to a certain limit.

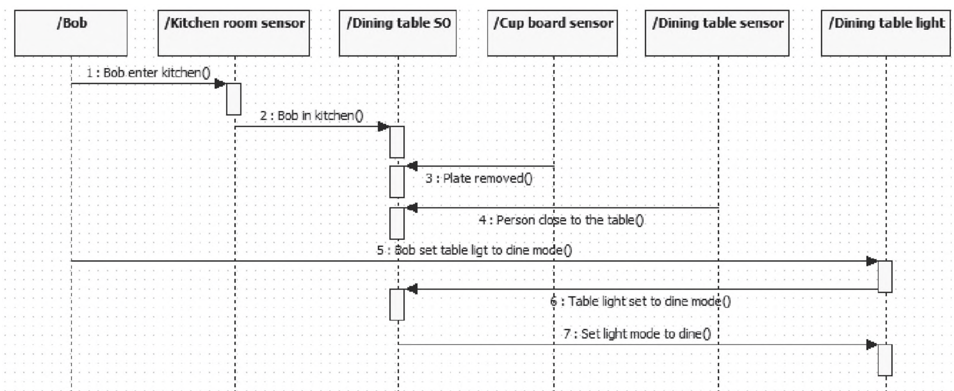

Fig. 4. The Bob scenario - sequence diagram for smart object learning and predicting

Source: own elaboration.

The flows for the learning and adaptation processes are:

1. Bob enter the kitchen;
2. Kitchen *room sensor* (could be a PIR based sensor) detect his presence and inform the *dining table SO*;
3. When Bob takes a plate and move it to the dining table the *cupboard sensor* inform the *dining table SO*;
4. Bob sits down at the dining table, this is informed to the *dining table SO* by the *dining table sensor*;
5. Bob uses his smart phone to remote control the *dining table light*;
6. This action is observed by the *dining table SO*, that learns from the past sensor events and this action;
7. When learned, the *dining table SO* will set the light to dine mode when it detect flow 2, 3 and 4.

Conclusions

This paper discusses using a distributed artificial intelligence approach as an alternative to the common centralized approach. It is found that a distributed concept has many advantages compared to a centralized concept. Some authors also claim that a distributed agent based approach will be the future of artificial intelligence in smart homes. In addition, using a distributed concept also seems as a logic consequence of the distributed area of internet of things. Because this area is still in its infant more research is needed to clarify its potential.

Literature

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Summary

A majority of the research performed today explore artificial intelligence in smart homes by using a centralized approach where a smart home server performs the necessary calculations. This approach has some disadvantages that can be overcome by shifting focus to a distributed approach where the artificial intelligence system is implemented as distributed as agents running parts of the artificial intelligence system. This paper presents a distributed smart home architecture that distributes artificial intelligence in smart homes and discusses the pros and cons of such a concept. The presented distributed model is a layered model. Each layer offers a different complexity level of the embedded distributed artificial intelligence. At the lowest layer smart objects exists, they are small cheap embedded microcontroller based smart devices that are powered by batteries. The next layer contains a more complex system that offer the needed processing capability to support and run more advanced artificial intelligence algorithms.

Translated by Per Lynggaard