**Title**

CARL: Activity-Aware Automation for Energy Efficiency

**Author**

Brian L. Thomas, Washington State University ,bthomas@eecs.wsu.edu

Diane J. Cook, Washington State University, cook@eecs.wsu.edu

**Abstract**

Electrical device usage distributions are estimated for each activity, and any devices not associated with the current activities may be turned off by CARL to reduce energy consumption. The utility of CARL is demonstrated in one of the smart home testbeds available as part of the CASAS (Center for Advanced Study of Adaptive Systems) smart home project at Washington State University. An evaluation of CARL is based on activity recognition accuracy, effectiveness at identifying devices to turn off, and energy consumption with, and without, activity-aware automation.

**Keywords**

smart homes, activity recognition, home automation, energy eﬃciency

**Introduction**

The impacts of lifestyle choices on energy usage and the environment are increasingly becoming more noticeable and discussed in society. As a result, research resources are being directed toward green technology, environmentally-friendly building designs, and active demand response within the smart grid. In this paper, we look more closely at the user side of sustainability and ways ubiquitous computing may aid in reducing energy consumption. In particular, we design a machine learning-based intervention to promote energy-efficient, sustainable behavior through home automation.

In 2010, the United States consumed 97.722 quadrillion btu of energy, a 300% increase from 1949 [12]. The growth of energy usage is not entirely due to manufacturing plants and automobiles. In fact, the residential sector is responsible for 16-50% of energy consumed worldwide [7]. A utility bill provides insights about monthly whole-building consumption, which leaves homeowners to guess at the reasons for an unusually high or low bill. Earlier studies reveal that home residents reduce consumption by as much as 15% in response to simply viewing raw usage data [4] and indicate that widely-varying residential behavior can influence usage by as much as 100% in a single house [10].

This paper hypothesizes that activity recognition techniques can be used to provide energy-efficient automation in a smart home environment. This type of automation makes use of behavior analysis and ubiquitous computing to reduce energy consumption, while still supporting a resident’s everyday activities. To validate this hypothesis, CARL (CASAS Activity-based Resource Limitation), a smart home automation technology was designed and implemented to control devices in the home. CARL utilizes a real-time activity recognition algorithm [8] to identify current activities being performed by the resident from sensor data in an instrumented smart home.

Electrical device usage distributions are estimated for each activity, and any devices not associated with the current activities may be turned off by CARL to reduce energy consumption. The utility of CARL is demonstrated in one of the smart home testbeds available as part of the CASAS (Center for Advanced Study of Adaptive Systems) smart home project at Washington State University. An evaluation of CARL is based on activity recognition accuracy, effectiveness at identifying devices to turn off, and energy consumption with, and without, activity-aware automation.

**Related Work**

Until recently, occupant behavior has been difficult to accurately capture. Adherence to self-reports of behavior and energy consumption is error prone for some populations [11] and whole-home meter monitoring does not capture the behaviors in the home that influence consumption.

Approaches have been utilized to explore the gap between the minimum amount of consumption that is needed for daily activities and the consumption that is actually observed [13]. Some early work has focused on linking resident activity with energy consumption. The hypothesis that providing users with knowledge about the relationship between their activities and energy consumption and automation support for energy reduction will result in substantial decreases in overall consumption is supported by an increasing body of work that links awareness of energy consumption and its impact on behavioral routines and behavioral change [1, 5, 9]. Until recently, validating this hypothesis was not possible. However, with the convergence of technologies in ubiquitous computing and machine learning, gathering data on human behavior is now automatable. Data can be collected from sensor-filled smart homes [2] and smart phones [6] in an unobtrusive manner while individuals perform their normal daily routines. Because these sensor modalities operate in a continuous mode, feedback and interventions repeat ad infinitum, thereby maximizing the persistence effect.

**Smart Home Monitoring**

CARL utilizes the sensing and automation techeologies available in the CASAS smart home architecture. The CASAS smart home project at Washington State University [3] deﬁnes a smart home environment as one that acquires and applies knowledge about its residents and their physical surroundings in order to improve their experience in that setting [1]. Such home environments, equipped with sensors for detecting features such as motion, light level, temperature, and energy and water consumption, are ideal testbeds for investigating the relationship between resident behavior and energy consumption and for providing activity-aware energy-eﬃcient home automation.

The CASAS “smart home in a box” software architecture components are shown in Figure 1. During perception, sensed information ﬂows up from the physical components through the middleware to the software applications. When taking an action, control moves down from the application layer to the physical components that automate the action. Each of the layers is lightweight, extensible and ready to use as is, without additional customization or training.

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| Figure 1: CASAS smart home components. |

The CASAS physical layer contains hardware components including sensors and actuators, utilizing a ZigBee wireless mesh to communicate directly with the hardware components. The middleware layer is governed by a publish/subscribe manager, providing named broadcast channels that allow component bridges to publish and receive messages. In addition, the middleware provides valuable services including adding time stamps to events, assigning UUIDs, and maintaining site-wide sensor state model. Every component of the CASAS architecture communicates via a customized bridge to this manager over XMPP. Examples of such bridges are the ZigBee bridge, the Scribe bridge, which archives messages in permanent storage, and bridges for each of the software components in the application layer. To date, CASAS has installed over 40 smart home testbeds.

**Activity Recognition**

CARL’s activity recognition software, called AR (ActivityRecognition) [8], provides real-time activity labeling as sensor events arrive in a stream. The problem of activity recognition is to map a sequence of sensor events, x =< e1e2...en >, onto a value from a set of predeﬁned activity labels, a ∈ A. Activity recognition can be viewed as a type of supervised machine learning problem. The sequential nature of the input data, the ambiguous partitioning of data into distinct data points, and the common overlapping of activity classes mean that additional data processing must be performed in order to accomplish the goal of recognizing activities. The Activity Recognition (AR) algorithm learns a function that maps a feature vector, X, describing a particular sensor event sequence onto an activity label, h : X → A. In this supervised machine learning problem the classes are the activity labels and the sensor events are represented by features combined into the input vector X of D dimensions. AR can use the learned function to recognize, or label, occurrences of the learned activity.

**Automated Smart Home Testbed**

To test our ideas for an activity-aware automated home, the Navan smart home testbed was constructed as part of the CASAS smart home project at Washington State University. The apartment houses a single resident and the ﬂoorplan and sensor layout for Navan are shown in Figure 2.

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| Figure 2: Navan automated home testbed. |

Navan utilizes the CASAS smart home architecture to sense and control the space. Passive infrared motion sensors with integrated luminosity sensors are placed throughout the residence to detect motion events and relative light levels at each location. Magnetic door closure sensors are placed on the doors and windows. Two magnetic door sensors adjacent to each other are used to identify when a sliding door or window is closed, cracked open up to 4”, or open more than 4”. Temperature sensors are placed throughout the smart home either as a single sensor or as a pair of temperature sensors (one sensor is placed 8” from the ceiling and one 12” from the ﬂoor to identify temperature gradients). Power data is collected using a Ted5000 power meter, providing instantaneous wattage every few seconds. Arduino-based Wi-Fi thermostats were designed in-house and installed to control and monitor use of the baseboard heaters and log temperature setpoints.

In the Navan testbed, ZigBee light switches were attached to lights and the bathroom fan, facilitating automated control of these devices. In addition, custom electrical boxes equipped with ZigBee light switches were designed to allow monitoring and control of additional devices such as reading lamps and speakers. Each light switch reports the current state of the device upon state changes, and also reports button taps and tap counts. These taps provide a mechanism for the resident to provide feedback to CARL. In Figure 2, the locations of devices that are controlled by the ZigBee light switches are indicated by the name of each device. All of the indicated devices are lights except for F001 (the bathroom fan) and LL014 (the television speakers). Figure 3 shows the energy consumption for each device over the monitored time period. Device voltages ranged from 30 watts (F001, bathroom fan) to 250 watts (LL003, bathroom heat lamp), while most lights were between 60 watts and 120 watts.

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| Figure 3: Time (in minutes) and energy consumption (in watt hours), listed for each device,  with (CARL) and without(baseline) activity-aware home automation. |

As a ﬁrst step, AR was trained to learn a model of 17 routine activities based on the captured data. Ground truth activity labels were provided by an external annotator based on observing a playback of the sensor data events, the ﬂoorplan with sensor layout, and a summary of typical activity locations and times provided by the resident. The learned activities include Sleep, Watch TV, Toilet, Relax, Work on computer, Bathe, Water plants, Leave home, Enter home, Wash dishes, Eat, Drink, Cook, Bed toilet transition, Dress, Entertain guests, and Other.

We recognize the robustness of an activity-aware automated home depends on the accuracy of the activity prediction algorithm itself. Therefore AR is ﬁrst tested using 10-fold cross validation on the collected data. AR classiﬁes the set of 17 activities in this case with 97.27% accuracy.

**CARL Automation Algorithm**

CARL’s initial automation strategy is to turn oﬀ devices that are not needed in support of the current set of activities. To do this, ﬁrst identify all of the current activities then determine the devices that are used by these activities.

Determining the set of current activities presents a particular challenge when processing data in real time. Segmentation algorithms can be used to mark the begin point and end point for any particular activity. However, these typically process historic data in oﬄine mode. For real-time processing, a delay value is maintained for each activity class and device. The delay value DelayAi represents the amount of time that has elapsed since a sensor event was observed that was labeled with activity label Ai. If the delay value for a particular activity is within a threshold number of time units then the activity is considered current. The delay value represents the amount of time that has elapsed since device Dj was observed changing state to ON. Each device Dj has an associated DeviceThresholdj that is used to prevent the device from being turned oﬀ seconds after the resident turned the device on, allowing new activities to be initiated before the device is evaluated by CARL. Additionally, turning the device on with a double tap of the light switch informs CARL that the automatic decision to turn it oﬀ was incorrect and DeviceThresholdj should be set to LongThreshold.

CARL Automation(A,D):

// A is the set of known activity classes

// D is the set of available devices

LongThreshold = DelayThreshold ∗ 4

for j = 1 to |D| : // set threshold for each device

DeviceT hresholdj = DelayThreshold

t =1

while observe new sensor event et :

CurrentActivities = ∅

CurrentDevices = ∅

// get activity label for sensor event

At = AR(et, A)

for i = 1 to |A| : // update times for each activity

expidite if Ai = At :

DelayAi = 0

else:

DelayAi = DelayAi + 1

for j = 1 to |D| : // update times for each device

if et == Dj and State(Dj,ON) :

DelayDj = 0

if et == DoubleT apOn :

DeviceT hresholdj = LongThreshold

else:

DeviceT hresholdj = DelayThreshold

else:

DelayDj = DelayDj = δt

for i = 1 to |A| : // get set of current activities

if DelayAi < DelayThreshold :

Append(CurrentActivities, Ai)

for j = 1 to |D| : // get set of current devices

if Dj ∈ Devices(CurrentActivities) :

Append(CurrentDevices, Dj)

for j = 1 to |D| : // turn off not-needed devices

if State(Dj,ON) and Dj ∈ CurrentDevices :

if DelayDj > DeviceT hresholdj :

ChangeState(Dj,OFF)

t+ = 1

Algorithm 1: Activity-aware device control algorithm.

Next, for each activity Ai, the algorithm maintains a probability distribution over devices whose status is ON. Devices with a suﬃciently great probability of being associated with Ai are left untouched when activity Ai is current. On the other hand, any device Dj whose status is not typically ON for any of the current activities is a candidate for CARL to turn oﬀ if is greater than DeviceThresholdj. The activity-aware automation algorithm is summarized in Algorithm 1.

A modiﬁcation to the algorithm was made after a brief pilot test with the resident. A guard statement was added to prevent CARL from turning oﬀ lights in the bathroom while the bathroom door was closed. There are no windows in the bathroom so unexpectedly turning oﬀ the light could present an unsafe situation.

**Experimental Results**

Data collection on a single resident for the baseline method occurred over 14 days in February 2014, shortly followed by 14 days of data collection with CARL running in February and March 2014. The resident was instructed on disabling CARL if the system started malfunctioning or there would be guests in the apartment, and did so for a 6 hour window when entertaining guests one evening. Data from the window was removed to ensure comparison of single resident behavior only between the baseline method and CARL. Ultimately, the primary goal is to determine how much energy savings can be achieved by using CARL. However, human factors need to be considered as well. As a result, CARL is evaluated on a number of different performance measures. These measures include: total time, watt hours, RMSE, and NRMSE.

Total time measures the sum total time that devices are on. Watt hours measures the sum watt-hours of power that are used by a particular method (CARL or the baseline method of no automation) combined over all of the devices that could be controlled in the residence. Power data from other devices, refrigerator, stove, heater, etc. were not included in the calculations. The RMSE (Root Mean Square Error) is computed to indicate the error in CARL’s automation due to being too aggressive (turning off devices when the resident needed them) or too conservative (not turning off devices when they were not needed). The too-conservative case occurred twice. In both situations, this was due to the smart home infrastructure not detecting the request to turn off a device. The too-aggressive situation was more common and was typically due to errors in recognizing the current activity. The errors were indicated by button taps by the resident and are therefore measured using this feedback, as shown in Equation 1. In this equation, D represents the number of devices, CARL\_Off(i) represents the number of times that CARL turned off device i, and DoubleTap(i) represents the number of times that the resident indicated an automation error via a double tap.

 (1)

The NRMSE (Normalized RMSE) is computed in order to better interpret the RMSE values. This is obtained by dividing the RMSE result by the maximum possible error. The resulting value ranges between 0.0 (no error) and 1.0 (maximum possible error).

 (2)

The results comparing total time and watt hours for CARL-based automation and no automation are summarized in Figure 3 and Table 1. As the figures indicate, there is consistent reduction in energy consumption and unnecessary device utilization through activity-aware automation. Most of the energy reduction is due to turning off lamps when they are not needed (e.g., when the resident is not at home) and turning off speakers when the resident is not in the living room listening to music or watching television.

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|  | Baseline | CARL |
| Total Time (minutes) | 19, 826.04 | 13, 867.64 |
| Consumption (watt hours) | 25, 297.85 | 18, 352.27 |
| RMSE | 0.00 | 11.15 |
| NRMSE | 0.00 | 0.15 |

Table 1: Reduction and accuracy results for CARL.

Table 1 summarizes the reduction and accuracy results. There is a significant (p < 0.01) reduction in both energy consumption and total time using activity aware automation. This automation does come at the expense of occasional overly-aggressive device control. This is reflective of the almost 3% error reported earlier for recognizing the targeted 17 activities in real time. Error is also influenced by the rate at which the resident switches between different activities, a resident with a stronger, deliberate routine will have less activity recognition errors than a resident who switches between several activities quickly and often. As activity recognition becomes more robust this error will be further reduced.

**Conclusion**

In this paper, a novel method for automating energy-efficient smart homes based on activity awareness was introduced. Initial experimental results indicate that real-time activity recognition and device usage profiling can provide effective mechanisms for turning off unneeded devices and thereby reducing energy consumption. This work is just a first step in utilizing activity awareness for home automation. Reliable home automation depends heavily on reliable activity recognition, which is continuing to be refined. As this capability becomes more robust, more control may be given to CARL. This control will include turning devices on as well as off. Future work will also explore the creation of machine learning techniques to time various activities (i.e., washing clothes) for ideal conditions (e.g., when renewable or low-cost energy is available) and to automate alternative activity supporting mechanisms (e.g., open the blinds instead of turn on a light to provide sufficient light for reading).

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**题目**

CARL：基于活动感知的家庭能源自动化管理系统

**作者**

Brian L. Thomas, 华盛顿州立大学, bthomas@eecs.wsu.edu

Diane J. Cook, 华盛顿州立大学, cook@eecs.wsu.edu

**摘要**

在当今社会，人们生活方式的选择对于能源、环境的利用发挥着越来越重要的作用。本论文持有以下观点：基于普适计算技术，进行居民活动感知，实现的家庭能源自动化控制可以帮助居民减少能耗。具体地讲，我们引入了一种基于人活动和关联设备感知的，家庭能源自动化管理的方法；该方法可以使得家庭能源经济运行。本文描述了CARL，这个促使能源经济运行的智能家庭原型系统；并且，本文评估了利用历史和实时传感器数据，感知居民活动，进而驱动家庭自动化控制算法的性能。

**关键词**

智能家庭，活动感知，家庭自动化，能源效率

**简介**

当今社会，人们生活方式的选择对于能源、环境的利用发挥着越来越重要的作用。因此，当今研究的关注点集中于绿化技术，环境友好的建筑设计，以及智能电网中的需求侧响应。本文着眼点在于：用户侧可持续能源利用以及普适计算方法的应用，能帮助居民节能。值得指出的是，本文设计了基于学习的家庭自动化能源管理系统。该系统旨在实现家庭能源的经济运行与可持续使用。

在2010年，美国消耗了97.722千兆英热的能源；较之1949年，增长了3倍[12]。能耗的增长并不是完全由大规模发电站和汽车造成；实际上，居民能耗占世界总能耗的16-50%[7]。月账单提供给用户整个建筑内的能耗。用户通过月账单，可以推测造成账单账目高低的原因。早期的研究揭示：居民可以通过简单浏览粗略的能源使用数据，调整家庭能源的使用，节省能耗大概15%[4]；并且，多变的居民行为变化可以极大影响单个家庭中的能源使用[10]。

本文假定活动识别技术，可以在智能家庭的环境中提供能源经济自动化运行。这种类型的自动化在支持用户的日常活动的同时，利用了行为分析和普适计算的方法来减少能耗。为了验证假定，本文设计并实现了一项智能家庭自动化技术（CARL，即基于活动的资源限制技术），来控制家庭中的设备。CARL利用了实时活动识别的算法[8]，结合智能家庭中部署的传感器的数据，来识别当前居民的活动。

对于不同的活动，电器设备的使用分布被进行了预估。为了达到节能的目的，任何与当前活动不相关的设备都会被CARL系统关闭。CARL系统的功效性在一个智能家庭的实验平台上体现。该实验平台是华盛顿州立大学一个智能家庭项目，CASAS（自适应系统高级研究中心）的一部分。CARL系统的评估主要基于以下几点：1）活动识别的准确度，2）识别关闭设备的准确性，3）与未使用该系统的能耗对比。

**相关工作**

至今，居民行为仍然难以精确捕获。行为和能耗的自报告，针对某些人群，错误率较高[11]；并且，全家的电表测量并不能抓取影响能源使用的行为。

相关学者已经使用许多方法，来研究维持居民生活所需的最小能耗与实际观测到的能耗的差[13]。一些早期工作关注点在于：找出居民活动与能耗的映射关系。 大量有关能耗感知以及其对居民日常行为的影响的研究支持一个假说，即：通过提供用户日常活动和能耗的关联知识，并给予用户节能的自动化支持，可以帮助用户极大地减少家庭总能耗[1, 5, 9]。到目前为止，验证该假说的正确性还不太可能。然而，随着普适计算方法和机器学习技术的结合，人行为数据的采集过程已经可以自动化。数据可以用一种不引人注意的方式，从部署有传感器的智能家庭[2]和智能手机[6]采集；采集过程不会对用户的日常生活造成干扰。因为这些传感程序工作在连续模式，并且反馈和设备控制可以持久重复，所以可以达到持久的效果。

**智能家庭监控**

CARL系统利用了在CASAS智能家居架构中使用的传感和自动化技术。华盛顿州立大学的CASAS智能家居项目[3]定义了一个智能家居环境。该环境可以获取用户活动和住宅环境的知识，并运用获取到知识来提高用户体验[1]。该家庭环境部署有多种传感器，可以检测多种特征，例如：运动，光照等级，温度，能耗，水耗；因此，该环境是研究居民行为和能耗关系的理想实验平台。此外，该平台还可以为用户提供，基于活动感知的家庭能源经济运行自动化系统。

Firgure1描述了CASAS软件架构的组件。在感知阶段，传感信息从物理组件流出，经过中间件，传输到软件应用。在发起动作阶段，控制指令从软件应用层流到自动执行控制序列的物理组件。每一层都是轻量级，可扩展，并且易用的（不需要额外的定制或训练）。

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| Figure 1: CASAS smart home components. |

CASAS物理层，主要含有利用ZigBee无线网，进行短距离通信的传感器和制动器。中间件层，主要含有一个发布/订阅管理器；该管理器可以提供允许组件桥接模块发布和接收消息的命名广播通道。此外，中间件还可以提供如下有价值的服务：1）加上事件对应的时间戳，2）分配通用唯一识别码，3）维护站点范围内的传感器状态模型。每个CASAS架构中的组件，通过一个定制化的桥接模块，利用XMPP协议（可扩展通讯和表示协议）与中间件层中的管理器进行通讯。CASAS架构中的桥接模块主要有：1）ZigBee桥接模块，2）用来压缩消息并持久化存储的Scribe桥接模块，3）应用层软件组件之间的桥接模块。至今，CASAS已经部署在超过40个智能家庭实验平台。

**活动识别**

CARL系统的活动识别软件AR（活动识别）[8]可以实现当传感器事件流到达时，进行实时活动标记的功能。活动识别的问题是，映射一个传感器事件序列，x =< e1e2...en >，到一个包含在预定义活动标签集合中的值a，a ∈ A。活动识别可以看成是一种带监督的机器学习问题。输入数据的顺序特性，数据分治到不同数据点的含糊性，以及活动类的重叠意味着，需要有额外的数据处理才能达到识别活动的目的。活动识别算法，学习了将一个描述传感器事件序列的特征向量X映射到一个活动标签的函数h : X → A。在这个有监督的机器学习问题中，类别是活动标签，输入向量X是D维的传感器特征数据。AR可以利用学习到的函数来识别或标记已经学习过的活动的出现。

**自动化的智能家庭实验平台**

为了测试本文提出的基于活动感知的自动化控制家庭，Navan智能家庭实验平台被搭建。该公寓居住有单个居民，公寓的楼层平面图和传感器布局如Figure2所示。

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| Figure 2: Navan automated home testbed. |

Navan利用了CASAS智能家庭的架构来感知环境，并控制能源设备。被动红外运动传感器和光亮度传感器被部署在居民住宅的各个房间，用来检测运动事件和不同位置的光亮度。磁门关闭传感器被部署在门上和窗户上。两个毗邻的磁门关闭传感器被部署在同一位置，以此来识别何时滑门或窗户被关闭，并且通过该传感器来判断滑门或窗户的开启距离。温度传感器被单个部署或者成对部署在智能家庭中；若温度传感器被成对部署，其中一个被放置在离天花板8分位置处，另一个放置在离地12分位置处，由此来计算出温度梯度。功率数据由Ted500测量功率的电表采集，该电表采样频率大约为几秒一次。基于Arduino开发平台的Wi-Fi自动调温器被安装在家中，被用来控制并监测墙式烘炉的使用，并记录设定温度。

在Navan实验平台中，基于ZigBee通讯的开关与灯及浴室的风扇相关联，通过该开关，CARL系统可以自动控制这些设备。此外，定制有ZigBee开关的电箱可以来监控一些额外的设备，例如台灯和喇叭。当设备状态发生改变时，每个开关可以报告当前的设备状态，并且可以报告开关按钮被轻敲的事件以及轻敲的次数。这些开关轻敲提供了一种供用户给CARL系统提供反馈的机制。在Figure2，由ZigBee开关控制的设备位置，通过每个设备名称来标示。除了F001是浴室的风扇，LL014是电视机的喇叭，其他设备都是灯。Figure3展示了在所观测时间段内每个设备的能耗。设备的功率范围从30瓦特（F001，浴室风扇）到250瓦特（LL003，浴室加热灯）；大多数设备的功率在60瓦特到120瓦特之间。

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| Figure 3: Time (in minutes) and energy consumption (in watt hours), listed for each device,  with (CARL) and without(baseline) activity-aware home automation. |

首先，基于获取到的传感数据，AR被训练，来学习一个含有17个日常活动的模型。地面实况的活动标签由注释器产生；该注释器通过观察传感数据事件的回放，结合含有传感器布局的楼层平面外部布置图，并且利用由居民提供的典型活动位置和时间来产生活动标签。学习的活动包括：睡觉，看电视，上厕所，休闲，使用电脑，洗澡，养水生植物，离家，回家，洗餐盘，吃饭，喝水，烧饭，床与厕所过渡，化妆，招待客人和其他。

我们知道基于活动感知的自动化家庭的鲁棒性，依赖于活动预测算法本身。因此，我们首先利用已经采集数据对AR算法进行10层交叉验证。结果表明，AR对于17个活动的分类准确率高达91.27%。

**CARL自动化算法**

CARL系统最初的自动化策略是关闭所有支持当前活动集合不需要的设备。为了实现该策略，首先需要识别出所有的当前活动，然后决定支持当前活动中所需要的设备。

在实时处理数据时候，决定当前的活动集合是一个很大的挑战。分段算法可以被用来给特定的活动标记起始点和终结点。然而，这些算法都以离线模式处理历史数据。对于实时的处理，每个活动类和设备有一个时延值。时延值DelayAi代表了，从被标记活动Ai发生的传感器事件被观测开始，消逝的时间。如果该时延值在阈值DelayThreshold内，则认为该活动在当前活动集中。时延值DelayDj代表了，从观测到设备打开开始，消逝的时间。每个设备Dj有一个关联的阈值DeviceThresholdj，该阈值用来防止设备在居民打开设备数秒后就被关闭；从而，允许新的活动在设备被CARL系统评估之前被初始化。此外，双击轻敲开关打开设备的操作，告知CARL系统自动关闭设备的决策是不正确的。并且，设备时延阈值DeviceThresholdj应该被设定到较大的阈值LongThreshold。

CARL Automation(A,D):

// A is the set of known activity classes

// D is the set of available devices

LongThreshold = DelayThreshold ∗ 4

for j = 1 to |D| : // set threshold for each device

DeviceT hresholdj = DelayThreshold

t =1

while observe new sensor event et :

CurrentActivities = ∅

CurrentDevices = ∅

// get activity label for sensor event

At = AR(et, A)

for i = 1 to |A| : // update times for each activity

expidite if Ai = At :

DelayAi = 0

else:

DelayAi = DelayAi + 1

for j = 1 to |D| : // update times for each device

if et == Dj and State(Dj,ON) :

DelayDj = 0

if et == DoubleT apOn :

DeviceT hresholdj = LongThreshold

else:

DeviceT hresholdj = DelayThreshold

else:

DelayDj = DelayDj = δt

for i = 1 to |A| : // get set of current activities

if DelayAi < DelayThreshold :

Append(CurrentActivities, Ai)

for j = 1 to |D| : // get set of current devices

if Dj ∈ Devices(CurrentActivities) :

Append(CurrentDevices, Dj)

for j = 1 to |D| : // turn off not-needed devices

if State(Dj,ON) and Dj ∈ CurrentDevices :

if DelayDj > DeviceT hresholdj :

ChangeState(Dj,OFF)

t+ = 1

Algorithm 1: Activity-aware device control algorithm.

对每个活动Ai，算法维护了一个开启设备的随机分布。在活动Ai为当前活动时，具有足够大概率与活动Ai关联的设备，会不关闭。而对于与当前活动关联不大的设备，CARL系统会把他们作为关闭的候选，当他们设备时延值超过阈值DeviceThresholdj时就会被关闭。基于活动感知的自动化算法在Algorithm 1中被概括。

算法在一个居民的试点测试后被修改。CARL系统添加了一个保护声明，来防止浴室的灯在浴室门关闭的时候关闭。因为浴室没有窗户，所有关闭浴室的灯会造成一种不安全的环境。

**实验结果**

数据的采集分为两个部分：1）基准方法的数据采集，从2014年2月开始持续14天；2）使用CARL系统后的数据采集，从2014年2月到3月之间持续14天。居民被告知关闭CARL系统的方法。当系统异常运行或者公寓中有其他客人时，居民会关闭CARL系统。但是，有其中一天晚上，居民忘记操作，留下了6个小时的招待客人时候的家庭数据；该数据被移除，以确保分析中仅仅比较单个居民在使用基准方法与CARL系统之间的差别。最终，目标是得出使用CARL可以节省多少能耗。并且，人机交互的因素也要考虑。因此，CARL在许多不同性能参数上被进行评估。设备整体使用时长，设备能耗，RMSE和NRMSE。

Total time表示设备开启的总时间。Watt hours表示总能耗，该能耗为在某数据采集阶段（使用CARL或未使用的14天）采集到的公寓中可以控制的设备的能耗总和；冰箱，火炉，加热器等设备的能耗不在能耗量测中。RMSE（均方根误差）被计算，用来指出CARL自动化控制中的错误。错误有两种类型：1）太积极造成的错误（在居民需要使用设备时候关闭设备）；2）太保守造成的错误（在居民不需要使用设备时候未关闭设备）。实验中，太保守的情况出现过两次。在这两种错误场景中都是由于智能家居基础设备没有检测到关闭设备的请求造成。太积极的错误出现得更寻常，并且，是由于当前活动的识别错误造成。错误可以通过用户对开关按钮的轻敲反馈获得，均方根误差计算公式如公式1所示。在公式中，D表示设备个数，CARL\_Off(i)表示CARL关闭设备i的次数，DoubleTap(i)表示居民通过双次轻敲按钮暗示自动化控制错误的次数。

 (1)

为了更好地解释RMSE（均方根误差）的值，NRMSE（归一化的RMSE）被计算。NRMSE通过RMSE的结果，除以最大可能的错误数得到。结果的范围在0.0（表示没有错误）到1.0（表示全是错误）。

 (2)

使用CARL方法前后的能耗、性能比较，在Figure3和Table1中呈现。从图表中可以看出，在使用基于活动感知的自动化系统后，通过关闭无用设备可以从一定程度上减少能耗。大多数的能耗减少都是因为：1）关闭不需要的灯（比如，当居民不在家的时候），2）关闭扬声器（在居民不在卧室听音乐或看电视的时候）。

|  |  |  |
| --- | --- | --- |
|  | Baseline | CARL |
| Total Time (minutes) | 19, 826.04 | 13, 867.64 |
| Consumption (watt hours) | 25, 297.85 | 18, 352.27 |
| RMSE | 0.00 | 11.15 |
| NRMSE | 0.00 | 0.15 |

Table 1: Reduction and accuracy results for CARL.

Table 1概括了能耗减少和控制精确度的结果。在使用基于活动感知的自动化控制系统后，能耗和设备使用时间有显著减少，尽管CARL会带来一些偶尔积极错关涉笔的控制。错误率还与人在不同活动的切换有关，一个拥有更规律的日常生活的人家中部署该系统将会有更少的活动识别错误。随着活动识别程序更加健壮，错误也会进一步减少。

**总结**

本文提出了一种基于活动识别的能源自动化经济运行的方法。最初的实验结果表明实时的活动识别和设备使用感知可以提供一种有效的机制，来关闭不需要使用的设备，从而达到节能目的。本文工作仅仅是，基于活动识别的家庭自动化中，进行的初步工作。可靠的智能家居自动化系统依赖于可靠的活动识别，这一方面需要进一步改进。随着活动识别算法的健壮性增强，更多的控制可以应用于CARL系统。未来，我们将会研究利用机器学习的技术，探索更多的设备使用场景（比如，可再生能源和低价能源可以获得时）；并且，我们会支持更多的自动化机制（比如，通过打开百叶窗来调节房间内的光强度）。

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