**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.

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。

|  |
| --- |
|  |
| 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.

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。

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.

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。

|  |
| --- |
|  |
| 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.

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。

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.

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%。