Prediction of humans’ activity for learning the behaviors of electrical appliances in an intelligent ambient environment

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Abstract—In this paper we propose a mechanism of prediction of domestic human activity in a smart home context. We use those predictions to adapt the behavior of home appliances whose impact on the environment is delayed (for example the heating). The behaviors of appliances are built by a reinforcement learning mechanism. We compare the behavior built by the learning approach with both a merely reactive behavior and a state-remanent behavior.

Keywords—Human activity prediction ; Reinforcement Learning ; Multi-agent simulation; Ambient intelligence

I. INTRODUCTION

Home power consumption represents 29% of the global power consumption [3]. Reductions of power consumption can thus have a critical impact on global consumption, but simple reduction without taking into account the comfort of inhabitants is not sustainable. An adapted strategy of use of power must to carry both reductions of consumption and the improvement of the comfort of humans. Such strategy of use of power must be based on accurate prediction of human activities. That prediction is particularly crucial to adapt the behavior of home appliances whose impact on the environment is delayed (for example the heating). The prediction of humans’ activities has been addressed in different works [2], [4], [6], [7], [5], [1]. Those works base the prediction of future actions on the pattern recognition of sequences of past actions. The main pitfall of those different works is that they only consider a single human in their environment. The problem of prediction of activities of several humans that inter-influence each other is not solved. That problem is difficult because, when considering several humans the combinatory of mutual interactions, that can influence the choice of future actions, is huge. In this paper we propose a statistics based method of prediction of people location. We consider several humans, the members of a family, at the same time. The predicted displacements are then used to determine when a room will be empty or occupied so as to adapt the behaviors of the appliances.

Before predicting the humans’ displacements, it is necessary to have a representation of human’s activity. In order to meet that challenge, in SMACH we propose to decompose humans’ activity into sequences of intertwined tasks (see section II). Each task must be done in a given room, in that way a sequence of tasks corresponds to a sequence of humans’ displacements. Given that description the second challenge is thus to accurately predict the humans’ activity to anticipate displacements in order to fix the behavior of the appliances. The appliances will be then able to prepare rooms to “receive” people in the more comfortable conditions. In order to meet this second challenge, we propose in section III both a human activities prediction mechanism and a reinforcement learning based mechanism to build the behaviors of appliances. The activities predicted by the first mechanism are used to build the space of states that will be explored by the reinforcement based mechanism.

II. MODELING THE SCENARIOS

SMACH is a platform that allows a non-specialist to simulate the everyday life’s behavior of a family. The model concentrates on tasks description for agents representing humans and reaction to user presence for agents representing appliances. In this paper, we will consider different strategies for appliances-agents, from reactive ones to cognitive (machine learning) approaches.

Definitions

Let \( \mathcal{A} \) be the set of agents representing appliances, \( \mathcal{H} \) the set of agents representing humans, \( \mathcal{T} \) the set of possible tasks for human-agents and \( \mathcal{R} \) the set of rooms in the house (locations for the agents in the house).

Let \( \prec \) be a precedence relation on tasks \( \mathcal{T} \), \( \forall (\tau_i, \tau_j) \in \mathcal{T}^2, \tau_i \prec \tau_j \) means that \( \tau_j \) can not be performed before \( \tau_i \) is finished. Let \( \text{poss} : \mathcal{H} \rightarrow 2^\mathcal{T} \) be the function that determines the set of possible tasks for a given human. \( \tau \in \text{poss}(h) \) means that \( \forall \tau' < \tau, \tau' \text{ is finished} \). Let \( \text{pref} : \mathcal{H} \times \mathcal{T} \rightarrow \mathbb{R} \) be the function that defines the preference of a human for executing a given task. Let \( \text{loc} : \mathcal{R} \rightarrow 2^\mathcal{T} \) be the function that defines the localization of a task. \( \tau \in \text{loc}(r) \) means that \( \tau \) can be performed in the room \( r \).

For each room \( r \in \mathcal{R} \) we note \( \mathcal{EV}_r \), the set of variables associated with \( r \) (e.g. "temperature", "light", etc). For each appliance \( a \in \mathcal{A} \), we note \( \text{room}(a) \in \mathcal{R} \) the room in which \( a \) is located and \( V_a \in \mathcal{EV}_{\text{room}(a)} \) the environmental variable
that is modified by $a$ in its room (for instance, a heater acts upon the room’s temperature). We note $\mathcal{VAL}^t_a$ the values’ space of $V_a$ and $V_a^t \in \mathcal{VAL}^t_a$ its value at the time $t$. We note $\mathcal{ST}_a$ the states’ space of $a$ and $st_a^t \in \mathcal{ST}_a$ the state of $a$ at the time $t$.

Agent behaviors

The behaviors of humans depend on the global goals of the family (e.g. to respect deadlines - to leave home on-time-, to reduce the cost of consumption - to use the wash-machine in the cheaper periods-, to perform some social tasks -to eat together- and to perform mandatory tasks -to get dressed before leaving home-). The next task $t_n$ that a human $h$ performs is chosen from the $poss(h)$ set. $t_n$ is the task that maximizes the priority. That priority depends on the value of $pref(h, t_n)$ and on the global goals of the family. The duration of $t_n$ depends on its priority and on a random factor.

The objective of an appliance-agent $a$ is twofold: to maximize the comfort of humans and to minimize the consumption of electricity. The comfort of humans depends on the value $V_a^t$. In this paper, we are interested in appliances whose effect on their related $V_a$ variable takes a relative important time (e.g. a heater). We call that period of time the transition period ($Tr.P.$). We note $V_a^t = map(st_a, \Delta t)$ the fact that the value of the variable $V_a$ changes after keeping the appliance $a$ in the state $st_a$ for a given $\Delta t$ time. For instance, $cold_{heater} = map(\text{OFF}_{heater}, 30)$ (the room gets cold when the heater is off for 30 minutes). To maximize the humans comfort in a given room $r$, the value of $\Delta t$ has to be taken into account to determine the behavior of the appliance $a$.

- If $r$ is empty, $a$ has to make that $V_a$ reaches the comfort value before the arrival of the first person.
- $a$ has to keep the comfort conditions while the room is occupied.

To minimize the electricity consumption, when the room gets empty, $a$ has to pass to a less energy-consuming state. $a$ should only perform that action if there is enough time to make that the room reaches the comfortable state before the arrival of new people (see figure 1).

Example: In this paper, we consider heaters with 3 states ($Off$, which consumes nothing; $Standby$, which consumes 3 units; and $Max$ which consumes 5 units) associated to 3 states for rooms ($Frozen$, $Cold$, $Comfortable$) with a transition period $Tr.P. = 5$. The ideal behavior of heaters is to ensure that the room is $Comfortable$ when there is somebody, $Cold$ when there is nobody and $Frozen$ when the whole house is empty.

In the former version of SMACH, the behavior of appliances is merely reactive: an appliance changes of state depending on the presence of people. This kind of behavior is not well suited for appliances that have a delayed effect on the environment because of the transition period (people are unsatisfied for the duration of that period). In the next section we propose several strategies to overcome that pitfall.

III. IMPROVING ELECTRICAL APPLIANCES’ BEHAVIORS

A. A simple remaining strategy

To improve the merely reactive behavior a first proposition is to introduce a remanence factor. It is to keep the room in a comfortable state for $X$ units of time after it gets empty. This remaining time is used to prevent the arrival of another human. Depending on the value of $X$, the satisfaction level can be improved significantly. Sadden this strategy has two main pitfalls : 1) there is a potential waste of energy if nobody comes into the room in the remanence period, 2) if nobody arrives in the remanence period, the behavior of the appliances goes back to its merely reactive form.

B. Predicting humans displacements to learn appliances’ behaviors

To overcome the pitfalls of the two first strategies, we propose a reinforcement learning based strategy coupled to the prediction of the displacements of humans in order to adapt more accurately the behavior of appliances. The prediction of displacements is based on the observation of the human activity through simulations (see section III-B1). We use the classical Q-Learning algorithm [8] to build the appliances behaviors (see section III-B2).

1) Prediction of humans’ displacements: The mechanism of prediction of the humans’ displacements is based on the statistical observation of human activities and the calculation of the more probable times to leave and to reach a given room. This calculations are used to determine a reduced number of occupancy states of the rooms. The learning mechanism explores then those states in order to build the appliances behaviors.

Observation step: In this step, we build the activity graph $\mathcal{G}_h$ of every human $h$ from the statistical analysis of $h$’s activities on a set of simulations (see figure 2). The nodes of $\mathcal{G}_h$ represents the tasks that $h$ can execute. The edges represent sequences of execution between two tasks. Every edge has a probability of execution of its sequence. This probability is calculated as the ratio between the number of times that the sequence has been performed by $h$ and the number of times that $h$ has performed the starting task in the same edge. As every task is performed in a given room,
by using the activity graph, the next displacement of $h$ can be predicted from its current task.

We note $P(\tau_1|\tau_k)$ the probability that a given task $\tau_1$ is performed immediately after the task $\tau_k (P(\tau_1|\tau_k) = 0$ when there is no edge between the tasks). $\tau_k <_{GA} \tau_1$ represents that $\tau_k$ precedes $\tau_1$ in $GA$. We define $path_{GA}(A, B)$ as the set of paths where $A <_{GA} B$. Given the activity graph $GA_h$ of a human $h$, we can determine the probability that $h$ executes a task $\tau$ after finishing its current task $c_h^t$:

$$P(h, \tau|c_h^t) = \sum_{\forall p \in path_{GA}(c_h^t, r)} \prod_{\forall i = 1}^p P(\tau_i|\tau_{i-1})$$

We can also estimate the average time until $h$ starts $\tau$:

$$time_{to_start}(h, \tau|c_h^t) = time_{to_finish}(c_h^t) + time_{to_start}(mpp(GA_h, c_h^t, \tau))$$

with:

$$mpp(GA_h, c_h^t, \tau): \text{the most probable path}$$

$$time_{to_start}(path): \text{the average execution time of the path}$$

The probability that $h$ goes into the room $r$ is equal to the sum of the probability of every task that $h$ can perform in $r$ after its current task. Similarly, the probability that $h$ leaves its current room is equal to the sum of the probability of every task that $h$ can perform outside that room after its current task. Given those probabilities, we can estimate the times until emptying or occupying a given room. Given $H_{out}(r)$ and $H_{in}(r)$ the sets that represent respectively the humans outside and the humans inside the room $r$. $T_{out}(h, r)$ and $T_{in}(h, r)$ represent the sets of tasks that $h$ can perform after outside or inside $r$. Then:

$$T_{out}(h, r) = \{\tau|c_h^t <_{GA} \tau \land h \in H_{out}(r) \land r \in \text{room}\}$$

$T_{in}(h, r) = \{\tau|c_h^t <_{GA} \tau \land h \in H_{in}(r) \land r \notin \text{room}\}$$

**Estimation of the time until a room gets occupied:** For a given human and a given empty room ($H_{in}(r) = \emptyset$):

$$time_{to_arrive}(h, r) = \min_{\forall \tau, r \in T_{in}(h, r)} (time_{to_start}(h, \tau|c_h^t))$$

Then for a given empty room:

$$time_{in}(r) = \min_{h \in H_{out}(r)} (time_{to_arrive}(h, r))$$

**Estimation of the time until a given room gets empty:**

$\text{time}_{empty}$ is the time until an occupied room ($H_{in} \neq \emptyset$) gets empty.

$$\text{time}_{empty}(r) = \begin{cases} 0 & \text{if } H_{in}(r) = \phi \\ \infty & \text{if } \exists h \in H_{in}(r) \land T_{out}(h, r) = \phi \\ T_p(r) & \text{otherwise} \end{cases}$$

where: $T_p(r) = \sum_{h \in H_{in}(r)} \sum_{\tau \in T_{out}(h, r)} P(h, \tau|c_h^t) \times time_{to_start}(h, \tau|c_h^t)$

**Space of states:** Given an appliance $a$ placed in a given room $r$, we call the maximal time of transition ($MT_{r,a}$), the maximal time needed by $a$ to change the value of its associated environment variable ($V_a$) between two consecutive values. If we consider the $\text{time}_{empty}$ and the $time_{to_first_arrive}$ calculations we can define different states of occupancy of the room in function of the $MT_{r,a}$ value as presented in the table 1.

2) **Building the appliances behaviors by Q-Learning:** Given $r$ the room where the appliance $a$ is placed. The reward received by $a$ for moving to the state $s$ is:

$$\text{Reward}(a, s) = 1 - \frac{\text{Satisf}(H_{in}(r), \text{map}(s, Tr.P)))}{\text{consumption}(a, s)}$$

with:

$$\text{Satisf}(H_{in}(r), v) = \sum_{h \in H_{in}(r)} \frac{satisf(h, v)}{|H_{in}(r)|}$$

and $\text{consumption}(a, s)$: consumption of the appliance $a$ in the state $s$ (in percentage in respect to the max consumption value).

**IV. Experiments**

To test the different strategies proposed in this paper, we have designed a scenario that represents the morning activity of a family of three humans (Dad, Mom, Child). We consider a home composed by three rooms (Sleeping, Bath and Social rooms) besides the outside of the house. We consider a heater in every room whose states are defined in the example in section II. The duration of one simulation is 120 u.t. (1 u.t. = 1 minute). We have built the activity graphs of every human from 100 executions of that scenario. As an example we present in figure 2 the activity graph of “Mom”.

**Table I:**

<table>
<thead>
<tr>
<th>Incoming time (I)</th>
<th>Emptying time (E)</th>
<th>Room’s state</th>
</tr>
</thead>
<tbody>
<tr>
<td>$I &gt; MT_{r,a}$</td>
<td>$E = 0$</td>
<td>Empty</td>
</tr>
<tr>
<td>$I \leq MT_{r,a}$</td>
<td>$E = 0$</td>
<td>Occupied</td>
</tr>
<tr>
<td>$I &gt; MT_{r,a}$</td>
<td>$0 &lt; E \leq MT_{r,a}$</td>
<td>Emptying</td>
</tr>
<tr>
<td>$I \leq MT_{r,a}$</td>
<td>$0 &lt; E \leq MT_{r,a}$</td>
<td>Occupied</td>
</tr>
<tr>
<td>$\forall I$</td>
<td>$E &gt; MT_{r,a}$</td>
<td>Occupied</td>
</tr>
</tbody>
</table>

![Figure 2: Activity graph of the human Mom. The probabilities of transition have been computed from the results of 100 simulations.](image)
the room is verified, for example, if the prediction is the Empty state for a given room, the room must remain empty from the moment of the prediction and for at least a duration equal to the transition time. In our tests, we have considered transition times between 5 to 45 minutes. For each value of transition time we have performed 100 simulations. Finally, for each set of simulations we have calculated the percentage of good predictions. The results are depicted in figure 3. Very good predictions (≈ 80% of success) are observed for small values of transition time (5 minutes). Reductions are observed as the transition time grows. That is a quite normal result, it is more difficult to predict the behavior of humans for longer periods of time. Nevertheless, even for important transition periods the accuracy of the results is still important (for 30 minutes we obtain almost 50% of success). For the given scenario, we can predict the displacements of people with an accuracy of more than 50% for periods until 20 minutes.

Validation of the learning mechanism: In order to validate the results of the learning process, we compare them to the results of the merely reactive and remanence based strategies (see table II). As we can observe the satisfaction values obtained by the different strategies are very close. In the opposite, from the point of view of the consumption, the learning strategy surpasses the two other strategies. If we compare the consumption of the learning strategy with that of the merely reactive strategy, a very important reduction is observed (37%). The remaining strategy compared to the other strategies performs slightly better as for the satisfaction value but increases the consumption of 9% compared to the merely reactive strategy. The improvements obtained with the remaining strategy are too small to be considered as a good result. From the point of view of the satisfaction, the learning strategy produces a slight reduction of the satisfaction compared with the other strategies.

V. Conclusion

We have proposed a very simple mechanism that allows very important reductions of consumption of power while keeping acceptable satisfaction levels. This mechanism is composed of two main steps: the prediction of the human’s displacements and the construction of appliances behaviors. The proposed prediction strategy is well suited to consider at the same time several humans that inter-influence each other. Moreover the displacements of people have been characterized by a very small set of states. Those states describe the occupancy of rooms. The small number of those states facilitates the subsequent learning process. For the while, those mechanisms have been only tested in simulation. The next step in perspective is to integrate the actions of users that interact with the system in participatory simulations. It will be certainly necessary to adapt our prediction mechanism to the variability of real humans’ activities. Moreover, we can ask a person to play its role in a participatory simulation only few times, then it will be necessary to consider alternative solutions to build the activity graphs. One simple way is to combine the observation of both automatic simulations and participatory simulations, by giving a more important weight to the latter.

REFERENCES


