Poster Abstract: A Practical Model for Human-Smart Appliances Interaction

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ABSTRACT

Buildings are increasingly equipped with smart appliances that allow a fine grained adaption to personal comfort requirements. Such comfort adaption should be based on a human-feedback loop and not on a centralized comfort model. We argue that this feedback-loop should be achieved through local interaction with smart appliances. Two issues stand out: (1) How to impose logical locality when interacting with a smart appliance? (2) How to mediate conflicts between several persons in a room, or between building-wide policies and user preferences? We approach both problems by defining a general model for human-smart appliance interaction. We present a prototype implementation with an off-the-shelf smart lighting and heating system in a shared office space. Our approach minimizes the need for location metadata. It relies on a human-feedback loop (both sensor based and manual) to identify the optimal setpoints for lights and heating. These setpoints are determined by considering individual comfort preferences, current user location and a global goal of minimizing energy consumption.

1. INTRODUCTION

Buildings are increasingly equipped with smart appliances that allow a fine grained adaption to personal comfort requirements. Compared to BMS, smart appliances enable direct and fine grained forms of user interaction. However, the current interface abstractions of smart appliances are not well designed. They build on appliance metadata (e.g., a light is tagged with building, floor no., room no. and location: `ITU/4/4D21/Ceiling1`) and possibly on localization. Dynamic and logical human-appliance relations are difficult to represent in metadata and with traditional localization: Metadata requires that users know where they are located (e.g., I am in `4D21`) and where appliances are located inside. Added localization still requires that users know the impact of appliances on them (e.g., which light affects me). Further, most appliances affect more than one user. Individual preferences are different. This makes it necessary to mediate potential conflicts. Such mediation needs be based on user comfort preferences, the current location of users and the impact of appliances on them. Our requirements for improved smart appliance interaction are thus:

(1) **Logical Locality.** Appliance identification should be based on the impact (logical relation) on the single user.

(2) **Conflict Mediation.** Conflicts must be mediated locally between users (considering their preferences), or between individual preferences and global infrastructure-use policies.

We approach these requirements by (1) defining a model for human-smart appliance interaction and (2) by implementing a prototype with a smart lighting and heating system in a shared office. Our approach minimizes the need for location metadata. It relies on personal sensors (e.g., smartphones, wearables) and human-in-the-loop feedback to identify the optimal setpoints for lighting and heating. These setpoints are determined by taking comfort preferences, current physical and logical location and a minimal energy consumption into account. Our prototype achieved 94% energy efficiency for lighting using a probabilistic method of identification, while adhering to the occupants' comfort ranges. For heating, we achieved an improvement of 80% in comfort while keeping a 3.3 °C lower overall heating setpoint.

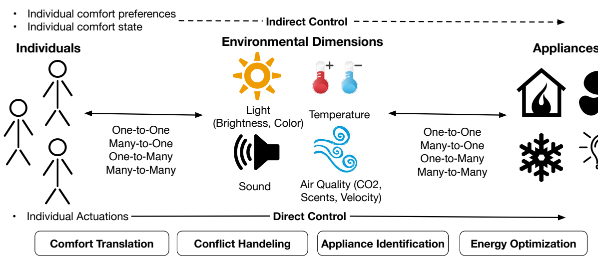

Figure 1: Human-Smart Appliance Interaction

2. INTERACTION MODEL

We adapt the smart environment to comfort needs of current occupants by matching different environmental dimensions like light, temperature, sound or air quality (see Figure 1). This matching is achieved by altering the output of appliances according to their logical relation (e.g., the user's light state is too low → increase brightness of affecting smart light). The bottom of Figure 1 shows the four building blocks of our model. We now discuss each of them.

BuildSys '16 November 16-17, 2016, Palo Alto, CA, USA

ACM ISBN 978-1-4503-4264-3/16/11.
DOI: http://dx.doi.org/10.1145/2993422.2996404

Comfort Translation. We translate comfort preferences between human and appliances using relative intents (e.g., "I am too cold/hot"). This decision is based on data collection among 50 people at our campus on measured and perceived temperature (the result shows a mean estimation error of 2.1 °C, single estimates are off by 8.6 °C).

Appliance Identification. We map appliances to their environmental dimensions and then to individual occupants by their logical relation. Some appliances influence more than one dimension (e.g., heating influences temperature and air quality; window shades influence light and temperature). Multiple occupants are often influenced by a single appliance (e.g., a ceiling light, room heating).

We base the dimensional mapping on metadata (e.g., a lamp has primary light and secondary heat output) and construct logical relations through a feedback loop that combines human-input ("I am too hot.") and sensor readings (personal temperature, brightness sensor). Our model abstracts these relations to a weighted property graph $G = (V, E)$. V and E have a set of key value pairs that represent properties (e.g., type, primary/secondary output, current state, edge cost). This graph of appliances, their output and affected occupants is incrementally constructed using the feedback-loop as input.

Comfort and Energy Optimization. We model comfort and energy optimization as constrained optimization, with individual comfort preferences as hard constraints of a building-wide energy optimization. When occupant preferences are divergent, our system provides strategies to mediate them: (1) By exploiting existing one-to-one mappings (users with different lighting preferences, but individual desk lights). (2) If the conflict cannot be solved in this way (only a single heating for a room), our system provides aggregation based strategies (median of all user preferences).

3. IMPLEMENTATION AND RESULTS

Our testbed consists of a shared office ($20\,\mathrm{m}^2$) with four smart lights (Philips Hue) and three smart thermostats (eQ-3 Homematic). Users access this setup from our Android app through Bluetooth (see [1] for more details). We use the phone's light sensor to measure brightness at user locations and store user comfort preferences for different rooms. We use a Raspberry Pi to coordinate requests between users and mediate conflicts. Users check-in to the room via our app and manually switch identified appliances or let our system decide on the best values based on comfort preferences.

Graph Exploration. To explore the graph, we put vertices into different groups according to their environmental dimension. In an unexplored graph (room), we assign each V a random probability and add it to a priority queue. Our algorithm then iterates through that queue and modifies each appliance state slightly, taking the sensor reading and human input as feedback. If a threshold is reached, the appliance setpoint is iteratively modified further. Both steps are repeated until the individual preference value has been reached (for lighting this takes <2 s). If the individual comfort level cannot be reached by these steps, we increase the modification level. This allows to identify also weakly connected appliances (e.g., a light with indirect radiation). The resulting incomplete graph is stored on the user phones. If a user visits the same room a second time, we use this information to speed up identification (we pick the most probable appliance first).

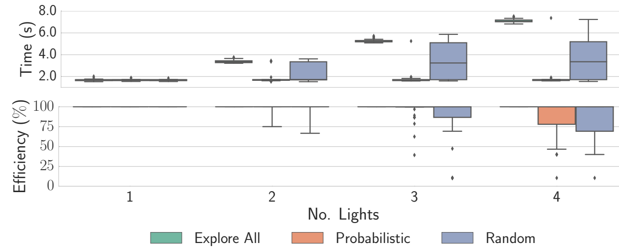

Figure 2: Latency/efficiency for different strategies.

3.1 Results

Identification Time and Energy Efficiency. We evaluate different identification strategies: (i) *Random* (we pick a random V), (ii) *Explore All* (we explore all V), (iii) *Probabilistic* (we pick V based on past results). We perform experiments at all three work desks of our office (see Figure 2). Exploration time grows linear with the number of appliances. Because we implemented state transitions with a delay of 1.5 s, it takes 7 s to identify all four lights. The random strategy results are widespread. We might initially pick a light with a strong logical relation, but in worst case, we iterate through all lights. The probabilistic strategy identifies lights mostly on first, and latest on second try.

Exploring the whole graph can improve energy efficiency. We define 100% energy efficiency when $\sum E.cost$ is minimal for the set of lights and setpoints. Exploring the whole graph ensures that the light(s) with the lowest cost are always chosen (100%). Random strategy results become more spread with the number of lights (mean value 78%). The probabilistic strategy achieves 94% mean.

Conflict Resolution. In our testbed, we are able to mediate lighting conflicts by exploiting one-to-one relations. However, room heating affects all occupants. To resolve conflicts, we set the heating setpoint to the median of the current users. This maximizes comfort for most people, while moderating outliers. Applied to our survey dataset, this results in a median of 21 °C, which is inside the comfort ranges of 36 out of 50 persons. The temperature is 3.3 °C lower than the mean measured temperature. We improve comfort from 20 to 36 persons (80%).

4. CONCLUSION

We presented a model for smart-appliance interaction that reduces the need for metadata and uses a logical human-appliance relation for identification. We have shown a first implementation of such a model using smart lighting and heating. Looking forward, a central building management might be partly substituted by such a decentralized model that combines local user preferences with global energy goals. Humans will be increasingly equipped with wearable sensors that enable an identification of logical relations in all relevant comfort dimensions. This also opens up a move from RF localization techniques to ambient techniques.

5. REFERENCES

[1] J. Fürst, K. Chen, M. Aljarrah, P. Bonnet, et al. Leveraging physical locality to integrate smart appliances in non-residential buildings with ultrasound and bluetooth low energy. In *IoTDI'16*. IEEE, 2016.