Improving Energy Efficiency through Activity-Aware Control of Office Appliances using Proximity Sensing - A Real-Life Study

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***Abstract*—Energy efficiency is a key operational characteristic of today's office environments. In this paper, we present a system architecture to control desk appliances such as computer screens based on recognised desk and computer work activities. In a real-life intervention study at seven desks, we use screen-attached ultrasound sensors and explore a proximity-based activity recognition approach for saving energy by automatically turing computer screens off when not using them. We analyse online performance of our approach regarding recognition rate and screen resume delay. Furthermore, we present a comparative analysis of our proximity-controlled approach against the computer-controlled power management and a non-controlled baseline to quantify energy saving benefits. Our results show energy savings of up to 43% and 55% for proximity-controlled computer screens compared to computer-controlled and non-controlled scenarios respectively.**

***Keywords*-ultrasound rangers, energy conservation, activity recognition, office buildings.**

I. Introduction

Energy conservation is a key objective in operating today's smart office environments. While office buildings have been identified as large energy consumers, only few concepts aim to improve their efficiency [1]. User activities dynamically affect energy needs in an office space, such as a desk or room. To this end, current energy saving attempts often focus on overhead light control based on passive infrared (PIR) presence and movement detection. Further energy savings can be expected by controlling frequently used office appliances, such as computer screens. Additional ambient sensors could help in detecting relevant activities to perform the control.

Among the various desk appliances in office spaces, computer screens are omnipresent. Screens are typically stateless devices that could be power-controlled independently of model, type, or other properties. Due to their relevance for energy saving, various guidelines suggest to enable the computer-controlled power-saving of screens. For example, the energy saving guidelines of the US Department of Energy recommend that screens should be suspended to standby mode if input devices are unused for a timeout of $\sim$20 min. [1] Recently, Samsung introduced a proximity control feature into their monitors that could suspend the screen to standby, if no user movement is detected[2]. While typically computer screens are directly facing the user and thus provide ideal conditions for user activity sensing, their benefit for activity detection has not been fully investigated (see Sec. II). We expect that fine-grained activity information could provide energy saving gains over the classic computer-controlled approach. While various previous efforts considered simulations to investigate system performances and energy saving potential of activity-based control, actual intervention studies are rare.

In this work, we explore the energy saving benefits of a proximity-based control of computer screens in an intervention study to identify gains, robustness, and practical challenges in deploying energy-saving pervasive systems. In particular, this paper provides the following contributions:

1) We present a system to control computer screens according to desk activities and distinguish three basic activity states: using the computer screen, using the desk besides a screen, i.e., doing paper work or phone calls, and no presence. We utilise ultrasound range sensors (USR) attached to computer screens to measure user proximity and switch screens using plug-in power meters.
2) In a real-life intervention study, we used our proximity-based approach to control computer screens of seven desks. We analyse activity recognition performance and determine practical bounds for the system's screen resume delay, which has direct impact on detection performance and user acceptance.
3) Based on study data, we evaluate energy savings of our proximity-controlled approach in comparison to the computer-controlled scenario and a non-controlled baseline using simulations. With this comparative analysis we identified key advantages of the proposed proximity-controlled approach.

II. Related Work

Two recent surveys evaluate energy efficient applications: Nguyen et. al. [2] surveyed intelligent building research, considering user activity. Williams et. al. [3] described a

[1] http://energy.gov/energysaver/articles/energy-efficient-computer-use

[2] Proximity control in Samsung models of A550 and A850 series using a PIR sensor: http://www.samsung.com/uk/consumer/pc-peripherals/monitors/design/LS27A850DS/EN-features.

comprehensive meta-analysis on energy savings by means of different types of lighting controls and assessed user preferences. Several focused research studies addressed individual challenges related to office activity recognition and energy saving in office buildings.

1) Activity recognition in office environments: Computer vision techniques are commonly used to detect occupant behaviour in the built environment. Emphasis was give to recognising activities such as working with keyboard/mouse, making a phone call, doing paper work. [4], [5], [6]. In general, cameras are accurate, but computationally expensive and often involve user privacy concerns. Networks with multiple ambient sensing modalities have been evaluated, e.g. in [7]. The authors modelled rhythm patterns from data obtained through computer-mediated communication technologies, to share availability in remote working scenarios. Similarly, a soft sensing approach based on Wi-Fi access points, user calendar, system activity monitor, instant messaging clients and time-of-day was used, achieving recognition accuracies of 90% [8]. Conversely, commodity computer hardware, including computer microphones and speakers was used to recognise user activities from ultrasonic signals achieving a performance accuracy of up to 96% [9]. Authors of [10] employed several sensors to distinguish between heavy and light-use users and suggested that actuation policies may enable energy savings for the latter class. These results demonstrate how highly accurate context-aware applications can be supported in smart buildings. However, these works do not focus on the use of the activity retrieved information in order to further investigate adaptation and control of offices appliances for energy saving applications.

2) Energy saving potential in intelligent buildings: . Real-life deployments to estimate potential energy savings in buildings typically require dense sensor and actuator installations. In [11] a two day experiment in two rooms of an academic building was conducted. In this study, a TelosB network composed of PIRs, magnetic switches, ambient light sensors, and energy controllers (relays) was deployed to evaluate potential energy savings of various office devices using an on/off control strategy based on occupancy. The results of this approach revealed total energy savings up to 15%. Moreover, brightness control was implemented in home TVs, resulting in a reduction on energy consumption of $\sim$30% [12]. However, we found no studies that specifically focused on the saving opportunities of computer screens. Through behaviour simulation, savings of 30% compared to basic control strategies were found by creating dynamic schedules and connecting them to the building management energy systems [13]. Location awareness was considered in a long-term study to dynamically optimise the energy consumption in an office [14]. From the simulation results, it was suggested that around 140 Wh per computer (without accounting external peripherals) per day could have been saved, compared to a policy that had machines powered on for the entire working day.

In this present work, we illustrate how an online recognition system can be used for appliances control and we evaluate its performance regarding energy saving in a real-life study. Additionally, we assess user perception of our proposed system.

III. System Architecture

We developed an online activity recognition system based on proximity measurements of ultrasound range (USR) sensors and deployed it in an office environment to analyse potential energy conservation. Our approach is based on discriminating activity states according to estimated user distance from the screen. Based on two USRs, different activities at the desk can be discriminated.

A. Sensing and actuation approach

We use two USR sensors mounted at the top of a computer screen to recognise three basic desk activities: (1) working in front of the computer screen (*ScreenWork*), (2) working at the desk but not in front of the computer screen (*DeskWork*), and (3) being away from the desk (*Away*). Figure 1 illustrates the workplace configuration for the deployment of our recognition system.

An efficient detection of desk activities can be achieved by analysing the USR sensors' field of view. When the computer screen is adjusted to the user, *ScreenWork* typically shows close ultrasound reflections in both sensors' field of view, whereas *Away* shows no reflections in both USRs. For *DeskWork* we considered that the user moved from the position centrally in front of the screen to either side. Thus, the field of view of one USR, located at that side where the user is present will show reflections, while the other USR obtains none. This can be interpreted as the user is not requiring the computer screen, but rather performing some desk work, e.g., paper work, making phone calls, drinking coffee, etc. An advantage of this detection approach is its simplicity and comprehensibility for a desk user, thus resulting in a robust and easy to deploy solution for different

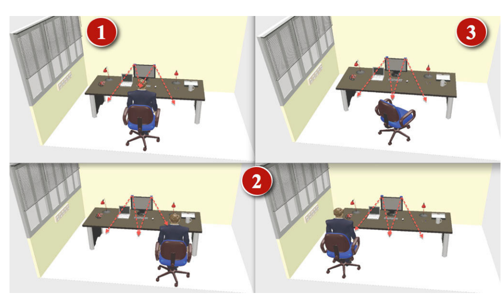

Figure 1. Illustration of office workplace configuration and user activities related to energy saving. Our proximity-controlled (PC) recognition system considered three basic desk activities: (1) *ScreenWork*, (2) *DeskWork*, and (3) *Away*.

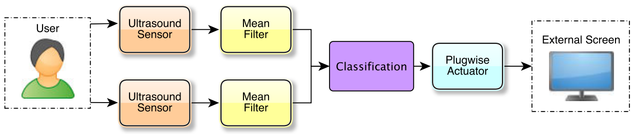

Figure 2. Online proximity-controlled (PC) recognition and actuation procedure. Two USR sensors measured proximity of a user to the computer screen. Activities at the desk were recognised online from the USR distance data. Control rules were used to actuate the computer screen according to recognised user activities.

workplaces. By attaching USR sensors to screens, their field of view is linked to the screen. Hence the ergonomic adjustments of a screen for a user helps to arrange suitable viewing angles for the USR sensors too.

Based on the recognised activities, our system produces control commands that were send to plug-in power meters to control, e.g. a computer screen. Thus, if *ScreenWork* was detected, the computer screen is automatically turned on, whereas *DeskWork* and *Away* results in the computer screen being turned off. A more detailed description of our proximity-based approach is provided in Sec. III-B below.

B. *Proximity-controlled system*

Figure 2 illustrates our proximity-controlled (PC) sensing, processing, and actuation prototype system for an individual office desk. The proximity estimates obtained from USR sensors were mean filtered and supplied to a classifier. For the online sensing and processing, we used the CRN Toolbox (CRNT) [15]. Activity classification was performed by thresholding both proximity estimates to recognise all three states (*ScreenWork*, *DeskWork*, *Away*) as described above. The classifier output was subsequently mapped into on/off switching states for the screen power controller.

IV. Evaluation study design

We performed a real-life intervention study to evaluate potential energy savings of our online PC recognition and actuation. Here, the methodology of this study is reported.

A. *System deployment*

We used two USR sensors model SRF08 [3] from Davantech and a Circle [4] plug-in power meter from Plugwise. Both devices were read out using CRNT.

USR sensors were mounted to top edges of computer screens, angled to face the user in ergonomic screen working conditions. The sensors covered a field of view of approximately 45° in the horizontal plane. Ranging was set to measure distances below 100 cm for both sensors. We obtained distance measurements from both sensors at a rate of 1.4 Hz, and we use a window size of 10 s for mean filtering. Both USR sensors were interfaced to the gateway,

[3] http://www.robot-electronics.co.uk/htm/srf08tech.shtml
[4] http://www.plugwise.com

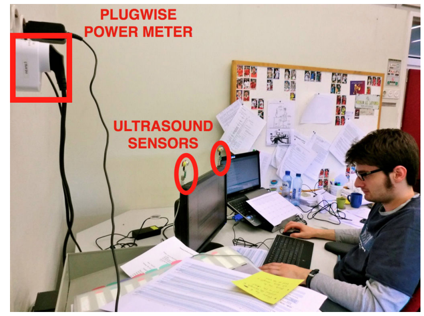

Figure 3. Example workplace area of one participant in our intervention study. Two USR sensors were mounted at computer screen edges, facing the user. A Plugwise power meter was used to control the computer screen power supply.

via commercially available USB-I2C [5] modules. These interfaces were powered from a USB port and provided a 5 V output for the USR sensors. The USRs consume a peak-power of ~1.375 W upon startup initialisation, and typically ~55 mW during operation (ranging mode).

Instantaneous power consumption of individual computer screens was continuously measured using Plugwise Circles networks sampled at 0.1 Hz. Circles were interfaced to a gateway computer via ZigBee. The actuation of computer screens was controlled using the CRNT configuration as described above.

B. *Study design*

The study was performed in three different offices, with a total of seven participants that were regular users of the offices and desks. Within this sample, we found four different screen brands with a specified maximum power consumption between 34 W to 45 W. All computer screens were EnergyStar certified and therefore had a power consumption of 2 W or less in stand-by mode.

In total, 10 recording sessions were obtained distributed into two study conditions: a baseline study was performed for one working day at two desks to obtain consumption traces without controlling the screens. These measurements were further used for comparison to controlled study data. An intervention study was performed for all seven workplaces with the online proximity-based system. Each recording session last for one working day and consisted in controlling the computer screen according to the three recognised user activities. One participant in this study was recorded twice for baseline and intervention study, resulting in a total of eight recording days. Figure 3 illustrates the installation in one of the workplaces.

The proximity-based recognition and control approach was explained to each participant before the recording session. Participants were asked to work according to their usual habits. In addition, participants were asked to complete

[5] http://www.robot-electronics.co.uk/htm/usb_i2c_tech.htm

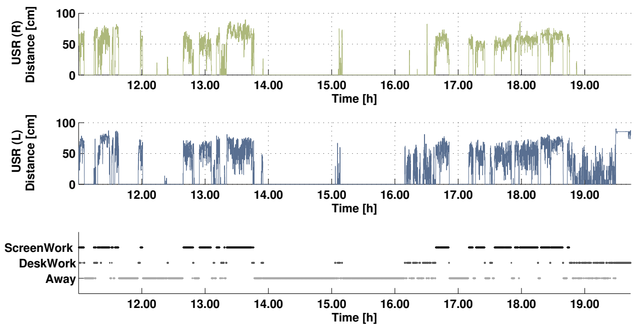

Figure 4. Example timeseries of proximity measurements from USR sensors located at top right (R) and left (L) sides of a computer screen. An illustration of the activity classification result is shown below. Overlaps between classes are a result of the visualisation only.

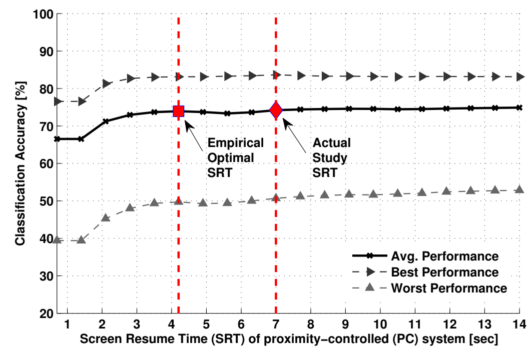

Figure 5. Accuracy performance trade-off regarding the screen resume times (SRT). Accuracy performance curves show participants' average, best, and worst performances.

an annotation sheet with a 2 min resolution, indicating the activities *ScreenWork*, *DeskWork* and *Away*.

V. Evaluation results

We analysed activity patterns and recognition during the intervention study and regarding the screen response time (SRT). In a comparative analysis, we evaluated our PC approach, against the computer-controlled (CC) scenario and a non-controlled (NC) baseline. Finally, we summarise participant opinions on our PC approach.

A. Activity patterns

Figure 4 illustrates the continuous proximity measurements obtained from the USR sensors in one selected workplace, together with the classification output.

We observed that in seven of 10 recording sessions, *ScreenWork* was dominantly reported by participants, accounting from ∼50% up to ∼83% time of the daily recording sessions. In the remaining three recording sessions, *Away* was reported most frequently, accounting from ∼43% up to ∼62% time of the daily recording session. The least reported activity by all participants was *DeskWork* accounting from ∼1% up to ∼30% time of the recording session. While this analysis confirms that screens are used most of the time, energy saving options can be found due to the short interrupts of *DeskWork* and *Away*, as our subsequent analysis shows.

B. Activity recognition performance

We confirmed the activity classification performance of our proximity-based approach by comparing the recognition results to manual paper-based annotations of participants made during the recording day. On average, our system achieved a recognition performance of 75%. While *ScreenWork* and *Away* were recognised at $\geq$ 80%, classification rates dropped for desk activities of some participants to ∼50%. We attributed this reduced performance to the variable activity patterns during desk work in our real-life study leading to mismatches with *Away* mostly. The results nevertheless confirm that the system can reliably determine *ScreenWork*, which is essential to use our approach for reliable screen control.

C. Screen resume time (SRT)

With SRT, we describe the time elapsed from the moment the user moves in front of the screen until the computer screen is activated. Thus SRT should not be confused with the screen power-on delay[6]. SRT is particularly important to our approach since it has a direct impact on user's ability to switch to computer work.

Figure 5 shows the system performances of our PC system with respect to increasing SRT values. As the plot illustrates, larger SRT values lead to higher classification accuracy too since the proximity measurements averaging window is increased. Larger SRT lead to reduced system reactions once a user approaches the screen though. In our study, SRT was set to 7 s, which was found acceptable for most participants (see Sec. V-E). However, the SRT analysis shows that a similar recognition rate could be obtained at ∼4 s already, which would increase responsiveness. For reference, the worst-case power-on delay is specified by screen manufacturers at ∼2 s.

D. Comparative analysis of energy savings

A comparative analysis was performed regarding potential energy savings when controlling computer screens in office environments. We considered the following scenarios.

Proximity-controlled (PC) scenario: The computer screen is controlled by our proximity-based approach that considers user activities. The screen is turned off (0 W) if the recognition system detects *DeskWork* or *Away*, and is turned on (typical on-state power consumption) when the recognition system detects *ScreenWork*. In order to

[6]http://en.wikipedia.org/wiki/Response_time_(technology)

evaluate the potential savings in this scenario, we used the intervention study data.

Computer-controlled (CC) scenario: For CC, we consider that the computer screen is controlled through the computer's operating system using screen time-out settings. Thus, the screen is sent to stand-by mode (2 W) as soon as the computer's operating system detects no user input during the time-out period. To estimate energy consumption for CC, we simulated time-outs according to behaviour patterns of all seven study participants across all recording sessions (see Sec. IV-B). Simulations were based on the activities reported by participants and typical on-state and standby mode power consumptions of each participant's computer screen.

Non-controlled (NC) scenario: For NC, a screen is not controlled by any power management. To estimate power consumption in this scenario, we used the typical on-state power consumption of the study screens. In the study baseline (Sec. IV-B), we determined user habits at the workplace, i.e., how often does the user turns off the screen, and how much time is spend in *ScreenWork* state. Participants reported *ScreenWork* for 72% and 74% of the total recording session time. We observed that users did not turn off their computer screen while being recorded.

Results: For the CC scenario, screen time-out was swept between 1 to 20 min. The 20 min time-out corresponds to standard energy saving recommendations. Figure 6 illustrates the average power required for PC, CC, and NC scenarios. As expected, higher time-outs lead to decreases in power saving for CC. The results confirm that PC saves most energy, even for small CC time-outs. Both, PC and CC scenarios clearly outperform the NC baseline.

In Table I, the typical on-state power consumption per screen model used at individual desks are summarised. We show here the PC and CC scenario. For CC, we considered the 1 min and 20 min screen time-out extremes only and derived the relative energy saving for the PC scenario for each. Overall, our proximity-based approach could save ∼25% compared to CC with 1 min time-out, and ∼43% compared to CC with 20 min time-out. When compared to the non-controlled baseline, PC can save ∼55% on average.

The savings for PC can be explained by its instantaneous operation upon user activity changes, i.e. the screen is turned off after the SRT time when the user is not in front of the screen. In contrast, the CC scenario requires to wait for a screen time-out in the range of minutes to infer the not used condition. Furthermore, in our PC scenario a screen is switched off (0 W), rather than kept in standby mode (2 W). We observed that the standby consumption was typical for various screens considered in our study. Even if screen standby consumption could be lowered, savings for the PC scenario would remain.

Table I confirms that the energy saving potential is related to the activity variance of individual participants. We derived activity variance by considering the three activity states

Table I
COMPARATIVE ANALYSIS PER PARTICIPANT CONSIDERING PROXIMITY-CONTROLLED (PC) AND COMPUTER-CONTROLLED (CC) SCENARIOS. FOR CC, 1 MIN AND 20 MIN SCREEN TIME-OUTS WERE CONSIDERED. THE LAST COLUMN REPORTS THE ACTIVITY VARIANCE BETWEEN THE STATES *ScreenWork*, *DeskWork*, AND *Away* (σ^2).

USERS	PC (TYP) [KWH]	CC (1') [KWH]	CC (20') [KWH]	PC VS. CC(1') [%]	PC VS. CC(20') [%]	σ^2
P1	0.175	0.217	0.295	19	41	0.93
P2a	0.095	0.118	0.181	19	47	0.79
P2b	0.271	0.280	0.316	3	14	0.48
P3	0.032	0.192	0.271	83	88	0.72
P4	0.188	0.197	0.232	4	19	0.84
P5	0.091	0.142	0.192	36	53	0.94
P6	0.094	0.129	0.225	27	58	0.80
P7	0.167	0.183	0.212	9	21	0.41
Total	0.139	0.182	0.240	25.24	42.74	—

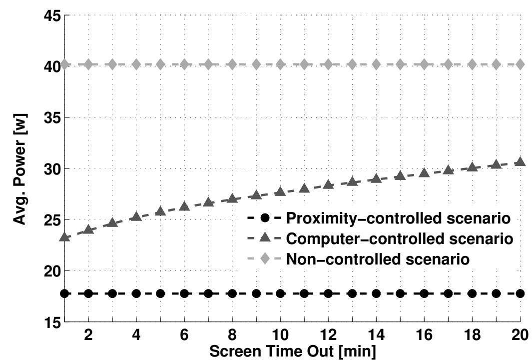

Figure 6. Comparative analysis of the average power required for an office screen in each scenario: proximity-controlled (PC), computer-controlled (CC), and non-controlled (NC). The average power was derived as mean over the study recording duration. For the CC scenario, simulated screen time-outs are shown from 1 min to 20 min. PC and NC do not depend on screen time-out.

ScreenWork, *DeskWork*, and *Away* as reported by participants. Larger variance σ^2 in activities was directly related to higher energy saving potential using our proximity-based approach. That is, the more a user switches between activities, the higher are saving benefits of our PC scenario. In contrast, in a CC scenario varying user activities within the screen time-out period cannot be detected.

E. User opinion on the power management

We surveyed the user perception of our power management system regarding their preferences and use of commonly available computer power management features. We received feedback from three participants of our intervention study and grouped main topics of the responses in: (1) knowledge of computer power management features, (2) screen resume time of the proximity-based control.

Knowledge of power management features. All participants considered that they have sufficient knowledge about the power management features of their computer's operating system. Two participants reported to change settings or operate the screen according to their activity. Only one participant reported that he/she was habituated to manually turn off the screen when leaving the office. Another reported: "I setup the system to turn off the monitor if I am absent for more than 2 min, but I don't really change them that much. ". One participant preferred to manually control the screen by setting power management to never enter sleep mode. This feedback conforms with our baseline measurements, where users did not actively control screens.

Screen resume time. From the responses, we observed that participants tried to influence the system's response by moving from one desk side to the other and by moving objects into a sensors field of view. Most participants rated the response time of the system as acceptable. One of the participants said: "the reaction time could be better, although current state is not bad enough to register as an annoyance". We concluded that the screen resume time is a key concern to users that can hamper their workflow.

VI. Discussion and Conclusions

In this work, we explored the practical deployment of an energy-saving ubiquitous system in office spaces. Our intervention study in real offices confirmed that a proximity-controlled computer screen management can save more energy than classic computer-controlled schemes. In our study, participants in the non-controlled group did not operate screens manually. While it is likely that manual control would have occurred in a larger study population, our proximity-controlled approach is likely to save more energy. The results of our post-study investigations confirmed that the resume delay can be shortened to $\sim$4 s at similar recognition rates. Further investigations should use this shorter resume times.

Although proximity-controlled screens are an industry standard in hand-held devices and smartphones, it has not been considered for office desk screens. While some novel desk screens use PIR sensors, our work confirmed that proximity-control using ultrasound can conceptually outperform PIR-based motion detection as USRs measure actual presence [13]. Potentially, active infrared sensing could be used as an alternative means for proximity sensing.

Modern office work implies frequent task changes, such as meetings and short leaves from the desk area, where the immediate reaction of our proximity-controlled approach has clear energy saving advantages. Since screens are widely used in a large office buildings, we expect that benefits of proximity-based systems remain, even when considering novel low-power screens operating at 25 W or less.

Acknowledgements

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