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ThermalProbe: Exploring the Use of Thermal Identification for Per-user Energy Metering

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***Abstract*—Given the strong link between energy and behavior, sensing and metering per-user energy consumption is critical for understanding individual energy behavior and for customizing personalized feedback to promote energy-saving behavior. This paper explores the feasibility of *per-user energy metering* by proposing a per-user energy metering system that uses thermal-imaging and thermal-identification to track and associate energy usage among individual occupants in a shared working/living space. Each occupant wears a thermal tag that emits a unique temperature signature for user identification. The system introduces location-based per-user energy disaggregation that accounts per-appliance energy usage to individual energy consumer(s), i.e., occupant(s) nearby activated appliances. We have designed, prototyped, and tested the ThermalProbe system. Results show that the system meters per-user energy consumption with an average error of 12.66%.**

***Keywords*-thermal sensing; per-user energy consumption**

I. Introduction

Because human behavior drives energy demand, understanding and influencing human behavior as a cost effective means to reduce energy demand [1] have attracted the attention of broad-ranging researchers in science, technology, and behavioral disciplines. For example, turning off unnecessary lights is a simple yet effective approach to conserve energy. To track individual energy consumption, an accurate metering tool [1] is critical for bringing awareness about individual energy behavior and for designing personalized feedback to promote energy-saving behavior. However, recent studies [5], [16] proposed per-user energy metering systems which attribute the consumed energy to consumers through manual appliance usage labeling, which require high human effort to use these systems in our everyday lives. To automatically track appliance usage for each user, this study proposed ThermalProbe, a *per-user* energy sensing and metering system that estimates per-user energy consumption in a shared working and living space through an automatic thermal identification technique.

A previous work [2] introduced a thermal-based energy sensing technique called HeatProbe. HeatProbe first detects appliance on/off events by recognizing universal temperature increasing/decreasing patterns on the appliance surface (from the thermal camera) when turning on/off appliances. By matching those on/off events to corresponding power increasing/decreasing events indicated by an in-line power meter based on the events' temporal proximity, HeatProbe further disaggregates per-appliance energy consumption by summing up the energy usage between the times when an appliance is turned on and off. Inspiring from the concept on detecting appliance on/off states by recognizing universal temperature increasing/decreasing patterns, ThermalProbe extends the thermal-based sensing to per-user energy sensing and metering to identify the energy consumer(s), i.e., the user(s), for each detected appliance usage through a novel thermal identification technique. ThermalProbe includes the following extended functions. (1) It develops *thermal-identification* in the form of a tag worn around an occupant's neck (Fig. 1(a)). This tag emits unique thermal signals to the thermal camera which identifies individual occupants and tracks their relative locations to the activated appliances (Fig. 1(b) and (c)). (2) It introduces *location-based per-user energy disaggregation*, which includes location-based rules to account an appliance energy usage to occupant(s) nearby the activated appliances. For example, it is possible to specify and include a location-based rule for an appliance with an on-device switch (e.g., a desktop lamp), which attributes its energy consumption to the occupant closest to the activated appliance (e.g., the user sitting on the desk where the lamp is located) at the time when the appliance is turned on. The proposed system correlates energy consumption of appliances to their appropriate users by matching spatial proximity between the appliances (whose locations are indicated by their heat surfaces) and occupants (whose locations are indicated by their thermal tags) at the time when those appliances were turned on/off.

Several recent energy metering systems, such as ElectriSense [3] and ViridiScope [4], track per-appliance power usage by analyzing electro-magnetic signals produced during appliance operation. However, appliances in a shared working/living space may not be used by a single occupant. In this case, disaggregating per-user energy consumption becomes

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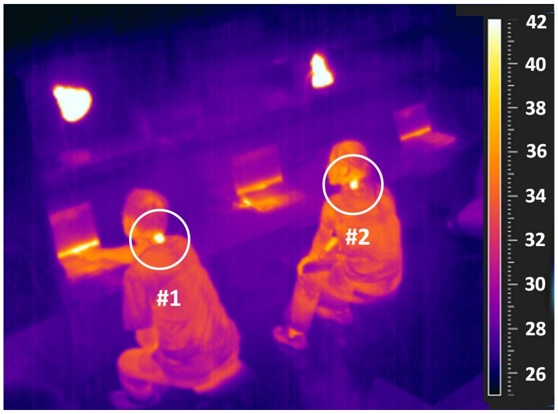
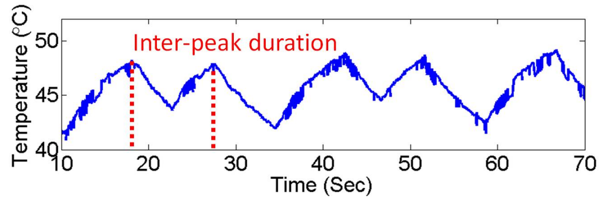
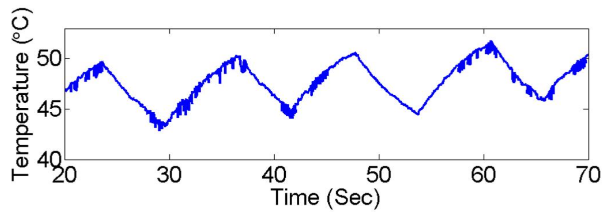


(a) Sample heatmap



(b) Temperature readings of the tag #1



(c) Temperature readings of the tag #2

Figure 1: The sample heatmap and temperature readings for tags #1 and #2. Two tags (two glowing dots indicated by the white circles) were worn by two different occupants (using their notebook PCs) in (a). The human identities are encoded in the combinations of various inter-peak durations modulated in the corresponding temperature readings of (b) and (c).

difficult given the lack of one-to-one mapping between appliances and occupants. Recognizing this difficulty, the Human-Building-Computer Interaction (HBCI) system [5] leverages mobile phones to record and track per-user energy consumption. However, this approach requires manual effort to scan an appliance's QR code prior to the activation of the appliance, and is therefore only semi-automated. In contrast, our ThermalProbe system aims to automate the process of per-user power sensing and metering - requiring no user feedback turning on/off the appliances.

The contribution of this study is to design, prototype, and evaluate a per-user power metering system. The proposed system extends thermal-based power sensing to include *thermal identification* and *per-user power metering*. This experiment includes 122 appliance usage sessions with 6 participants to evaluate the system's accuracy in thermal-identification and per-user power metering. Results show that the proposed system can correctly track user identity 82% of the time when they are in the view range of the thermal camera, while achieving an average 87.34% accuracy in per-user power disaggregation. Furthermore, we discuss the strengths and weaknesses of the thermal-based approach and lessons learned which can be leveraged by future energy monitoring projects.

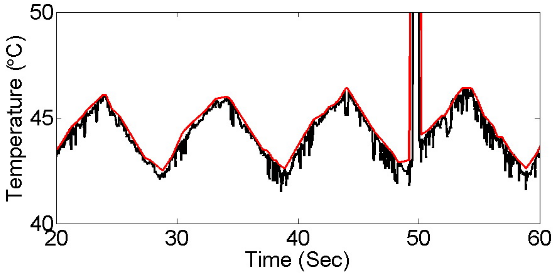
II. The ThermalProbe System Overview

The design of the ThermalProbe system includes three inference modules to estimate per-user power consumption: (1) the thermal power meter, (2) the thermal identification, and (3) the per-user power disaggregation. These three modules are described as follows.

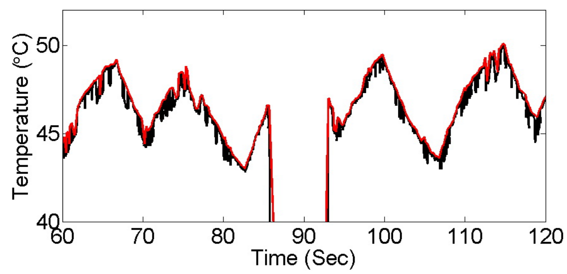
The *thermal power meter* implements the thermal sensing technique used in HeatProbe [2] to disaggregate per-appliance power consumption. This section provides a brief description and refers interested readers to the HeatProbe paper for details. The thermal sensing technique uses two sensors: a thermal camera and a power meter. By analyzing changes in the power meter readings, the system infers power events correlated to appliances being turned on or off. By analyzing heatmap images from the thermal camera, the system recognizes the heated surface area of a running appliance. Then, the system detects thermal events by observing the temperature changing patterns on the appliance's surface area where an increasing (decreasing) temperature pattern suggests that the appliance is turned on (off). Finally, matching the power and thermal events based on the events' temporal proximity disaggregates per-appliance energy consumption. The system also tracks the occupants' heated body segments that are excluded from appliance surfaces. When used together with an inline master power meter, HeatProbe further disaggregates per-appliance energy consumption by summing up the energy usage between the times when an appliance is turned on and off. The system also tracks the occupants' heated body segments that are excluded from appliance surfaces.

The *thermal identification* recognizes each individual occupant by detecting a unique temperature changing pattern emitted from the thermal tag worn on each occupant's neck as shown in Fig. 1(b) and (c). Section III describes the details on how thermal-identification encodes and decodes thermal signals.

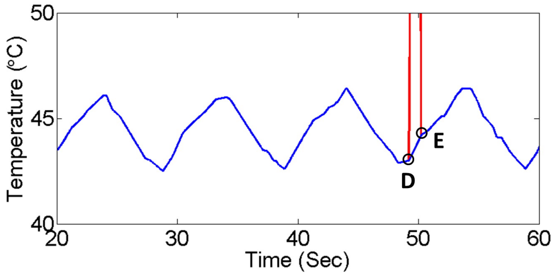
The *per-user power association* tracks per-user energy



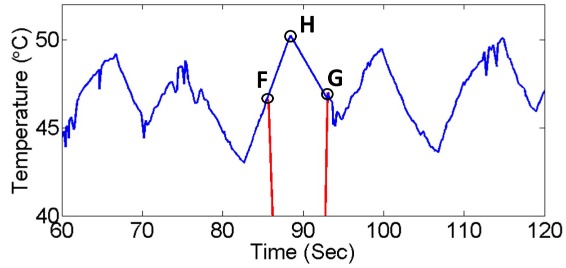
(a) Envelope detection (a static tag)



(b) Envelope detection (a moving tag)



(c) Temperature data recovery (a static tag)



(d) Temperature data recovery (a moving tag)

Figure 2: The temperature readings of a static tag or moving tag obtained after applying envelope detection (the upper graphs), and temperature data recovery (the lower graphs). The black lines are the raw temperature data. The red and blue lines indicate the temperature readings after applying envelope detection and temperature data recovery, respectively.

consumption over an energy audit period. It provides default location-based association rules. Optionally, energy administration staff can alter and specify the accounting rule for each appliance through an administrative user interface. Based on these rules, this module attributes the energy consumption of each appliance usage to specific users (i.e., the corresponding energy consumers) based on spatial proximity (i.e., location-based rules) or proportionally to a group of occupants present during appliance operation (i.e., administrator-specified rules). For example, in Fig. 1(a), the per-user power association attributes energy consumed by notebook PCs by matching spatial proximity between the notebook PCs and occupants at the time when the notebook PCs were turned on/off. Section IV describes the details of per-user power association.

III. Thermal Identification

Thermal identification recognizes each occupant by decoding a unique thermal signature emitted from his/her thermal tag. The following subsections describe thermal signal encoding and decoding schemes.

A. Thermal Encoding

Our thermal tags adopt temporal encoding of thermal signals for user identification. Temporal encoding encodes identification information by varying the time interval between successive thermal pump-and-diffuse stages (analogous to electric stimuli spikes). Temperature variations were generated using a Peltier device. A Peltier device is a thermoelectric device with two plates. When an electrical current flows from one plate to the other (i.e., the thermal pumping stage), the top plate heats up to a temperature above the human body temperature, thus making the thermal tag visible to a thermal camera. When the electrical current stops (i.e., the thermal diffusion stage), the top plate loses heat and its temperature decreases. A thermal tag creates temporal signatures by altering frequencies of applying electrical voltage to its Peltier device. The results are temperature changing patterns (Fig. 1(b) and (c)) observable by a thermal camera, which then decodes these patterns for user identification.

In the proposed system, each occupant wears a thermal tag around his/her neck. Each thermal tag is sewed onto the fabric of an employee badge string. To avoid the camera occlusion problem where a user's thermal tag is hidden from the camera view, multiple thermal tags can be sewed to various positions on the employee badge string such that at least one thermal tag is visible to the ceiling-mounted thermal camera. For accurate user identification, we performed an experiment to evaluate how well our thermal tag works by measuring the so-called *interval detection error*, or the time difference between the tag-encoded time interval (i.e., the encoding interval when a thermal tag applies voltage to the Peltier device) and the camera-observed decoded time interval. Results showed that the average interval detection error was 0.39 second with a maximum error of 1.257 seconds. Additionally, results revealed that it took a thermal tag a minimum of 7 seconds to heat up and cool down its thermoelectric plates, thus completed a thermal pump-and-diffuse cycle. Based on these results, the proposed temporal encoding scheme uses a minimum temporal interval of 7 seconds with 2 seconds (i.e., $>$ 1.257 seconds) increment. In other words, the 2^{nd} temporal interval is 9 seconds; the 3^{rd} temporal interval is 11 seconds; and so forth. To uniquely encode 20 thermal tags, 2-code combinations with seven selected temporal intervals (7, 9, 11, 13, 15, 17 and 19 seconds) served as the basic temporal codes. The experiments in this study adopted twenty-one 2-code combinations, which was sufficient to uniquely encode 20 occupants.

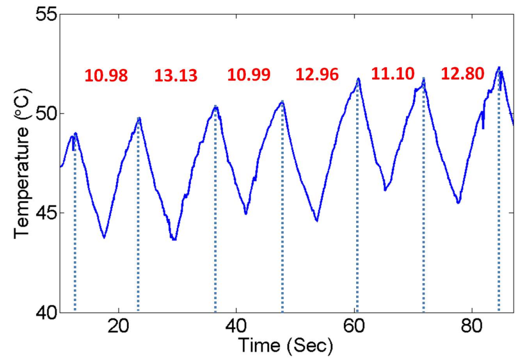
B. Thermal Decoding

Given an observed temperature stream, the proposed technique determines user identity by detecting the temporal code combinations of observed heat pump-and-diffuse intervals. There are four steps in this module: (1) envelope detection, (2) temperature data recovery, (3) inter-peak interval detection, and (4) user identification.

In the first step, envelope detection constructs an envelope (the red lines in Fig. 2(a,b)) by connecting successive local maximal values from the raw temperature readings. Since the infrared detector in a thermal camera takes time to collect enough IR radiation energy to determine an accurate temperature value, the sensing temperature of a moving tag (large zigzag values in Fig. 2(a)) can incur a high error. Additionally, passers-by can block a tag from the view of a thermal camera, resulting in temporary data loss. Fig. 2(b) shows the temperature curve (the black line) of a moving tag as the tag carrier is walking toward a seat, with a flat dip (i.e., temperature data loss) caused by a passer-by blocking the tag from the $87^{th} \sim 92^{th}$ second. To reduce sensor errors, the system applies envelope detection to smooth the temperature curve.

The second step addresses temporary data loss from camera occlusion. The system first locates the occluded time interval by finding large gradient changes during the temperature-increasing (-decreasing) phases. By locating the starting and ending points (points D and E in Fig. 2(c)) on the occluded time interval, the system applies linear interpolation to connect these two points (thus, forming the blue line in Fig. 2(c)), or to extend two lines from these two end points (thus, forming the blue lines $\overline{FH}$ and $\overline{GH}$ in Fig. 2(d)). These two methods recover and estimate lost data.

The third step decodes temporal code by measuring the length of each thermal pump-and-diffuse interval (Fig. 3(a)). The fourth step looks up the detected temporal code in a code book to find the best-matched user identification. The system computes a similarity table, shown in Fig. 3(b), in which each entry computes the matching count between the measured codes and the assigned codes of each user. The most likely user, e.g., user #3, is the one with the highest matching count among all users.



(a) Processed temperature readings

ID	Assigned temporal codes	Matching count
#1	9, 11	3
#2	9, 13	3
#3	11, 13	6

(b) Matching table

Figure 3: The detected heat-transferring durations and matching table. All detected transferring durations appear in red numbers and are placed at the corresponding stage. The corresponding matching table is in (b). Each row records related information for indexing a user, including the ID, the assigned temporal codes, and the matching count.

IV. Location-based Per-user Power Disaggregation

Per-user power disaggregation uses relative distance between occupants and activated appliances to determine which occupant(s) is the energy consumer(s) for each appliance usage session. To better describe the usage relationship between the activated appliances and its energy consumers, this study defines default location-based accounting as well as general user-specified accounting. If the energy administrators want to customize the accounting rule for any appliance, they can specify user-specified rules through a user interface. Otherwise, the system will apply the default rule. These default and user-specified rules are described as follows.

A. Default Location-based Accounting

The default location-based accounting determines the most likely occupant who turned on an appliance. If the appliance is activated by a physical switch on the appliance, the system finds the occupant who touches the appliance at a time instance closest to the time when the appliance is turned on (i.e., the turn-on time). This occupant-touch time must also fall within 60 seconds of the appliance turn-on time, in which the 60 seconds were empirically determined to account for the time shift in the event detection and matching algorithms. Then, the energy consumed in this appliance usage session will be apportioned to that appliance-touching occupant. If the appliance is activated by a remote control or the system cannot find any occupant who touches the activated appliance, the system finds the occupant who stays closest to the appliance for the longest period during the activated interval of the appliance.

The default location-based accounting has this limitation: if the activated appliance serves and benefits a group of users, e.g., several home occupants watching a TV together, the energy consumed by this communal appliance should not be attributed only to the occupant who activates the TV but should be proportionally attributed to the home occupants based on the amount of their time present in front of the TV during the appliance's operation. We address this limitation in the user-specified accounting described below.

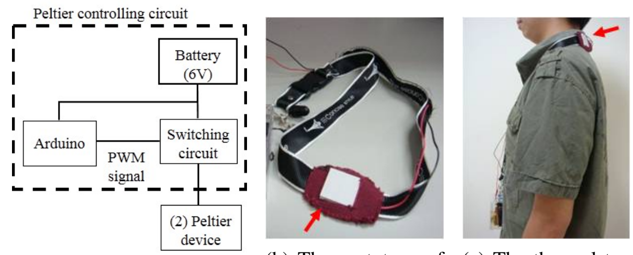
B. User-Specified Accounting

The user-specified accounting enables an energy administrator to customize how to divide energy consumed by an activated appliance among possibly multiple house occupants who are present and nearby the appliance's location. The system provides a user interface to specify this energy accounting rule. First, the energy administrator selects a target appliance, e.g., TV, from a sample thermal image. Then the energy administrator marks the appliance's *service area*, inside where occupants will benefit from this appliance's output and thus will equally share the appliance's energy usage. For example, a TV's service area could be a living room sub-area in front of the TV.

If the appliance is later moved by occupants, our system does not track its new location. As a result, the energy administrators need to input the energy accounting rule again using the user interface on a new thermal image (i.e., the appliance's current location can be marked on the new thermal image) described in the previous paragraph. Our future work plans to place a special thermal tag (which heats up and cools down in a specified temporal pattern) on the appliance for tracking its new location.

V. Implementation Details

The ThermalProbe system consists of (1) a FLIR A325 thermal camera [6], and (2) an *ACme* wireless inline power meter [11]. The thermal camera was attached to a sliding rail mounted on the ceiling to sense heated appliance surface areas resulting from appliance operation. The thermal images captured by the camera (through an Ethernet interface) were



(a) The schematic block diagram

(b) The prototype of the thermal tag

(c) The thermal tag worn by the user

Figure 4: The schematic block diagram and prototype of a thermal tag. The Peltier controlling circuit is wired to the Peltier device (marked by red arrow) along the black stripe as shown in (b). This tag is worn by a user with the Peltier device placed on his neck in (c).

sent to a backend data processing server. In the current prototype, the server records and processes sensor data. This study also develops image processing software based on OpenCV libraries to process recorded thermal images. As for power monitoring, the inline power meter transmits power readings to the server through the Zigbee radio every second. A corresponding wireless Zigbee-based data receiving module attached to the server receives power readings. The server records these power readings for subsequent processing by the power usage detection module.

Each thermal tag includes one 3cm x 3cm Peltier heat pump device (marked by the red arrow in Fig. 4(b)) and a Peltier controlling circuit. The controlling circuit consists of an Arduino Uno microcontroller board [7], a switching circuit, and a power supply. The Arduino microcontroller uses Pulse-Width Modulation (PWM) signals to control the heat-pump frequencies. These PWM signals are fed into a switching circuit sitting between the battery power and the Peltier device to dynamically regulate the voltage driving signals as shown in Fig. 4(a). Pumping heat requires a non-negligible amount of energy. To save energy, the thermal tag does not need to pump heat after its occupant has been identified by the thermal camera. By dynamically skipping unnecessary heat-pumping actions, the system can further reduce the heat-pumping frequency and save more energy. In the future, we will improve the design of the thermal tag by adding a wireless control interface to dynamically optimize power consumption. To improve its wearability, we sew the thermal tag onto a badge string (Fig. 4(b) and (c)).

VI. Evaluation

To measure the accuracy of the ThermalProbe system, the experiments conducted in this study involved three appliance usage scenarios with multiple users.

Table I: Experimental appliance usage scenarios for three types of environments.

Environment	(1) cubicle spaces	(2) room spaces	(3) kitchen spaces
Participating Appliances	2 PCs	2 Notebooks	1 water heater
	2 monitors 2 desk lamps 1 heater 1 toaster 1 printer	2 desk lamps 1 television 1 shredder 1 printer	1 toaster 1 electric oven 1 microwave 1 television
# of participants for each round	2 people	2 people	3 people
# of on/off events per round	25	16	20

A. Appliance Usage Scenarios

To test the feasibility of the ThermalProbe system, we conducted scripted experiments in the lab (due to the cost issue described later). Table I lists three appliance usage scenarios. We collected data from 122 different appliance usage sessions in which the session durations ranging from one to 72 minutes, with an average length of about 22 minutes. These scenarios differ in terms of operating appliances, the number of participants, the number of appliance usage events, and the energy accounting rules. Each scenario included a scripted sequence of appliance usage actions for participants to perform. Six participants were recruited for these experiments. All participants were graduate students in our department. Each set of scenarios included two repeated rounds involving different pairs of participants.

Appliance usage scenario #1 (office cubicles). Two participants worked in two adjacent cubicle spaces with the thermal camera mounted on the ceiling monitoring their electricity usage. Appliances included two PCs, two LCD monitors, and two desk lamps. One heater, one toaster, and one printer were placed between the two cubicles. Among these appliances, the heater was designated as a communal appliance through the administrative user interface. The appliance usage script for participant #1 was to (1) turn on/off a PC, (2) turn on/off a LCD monitor, (3) turn on/off a desk lamp, and (4) print documents from the shared printer. The appliance usage script for participant #2 was to turn on/off (1) a PC, (2) a LCD monitor, (3) a desk lamp, (4) a heater, and (5) toast bread using the toaster.

Appliance usage scenario #2 (a meeting room). Two participants discussed their project in a meeting room with a thermal camera mounted on the ceiling monitoring tracking their electricity usage. Appliances included two notebook PCs, two desk lamps, one TV-size screen, one printer, and one paper shredder. Among these appliances, the television was assigned as a communal appliance through the administrative user interface. The appliance usage script for participant #1 was to turn on/off (1) a notebook PC, (2) a desk lamp, (3) the TV-size screen, and (4) use the printer to print a document. The appliance usage script for participant #2 was to turn on/off (1) a notebook PC, (2) a desk lamp, (3) the paper shredder, and (4) print another document.

Appliance usage scenario #3 (a kitchen). Three participants operated various appliances in a kitchen with a thermal camera mounted on the ceiling monitoring their electricity usage. Appliances included a water boiler, a toaster, an electric oven, a microwave, and one TV. The appliance usage script for participant #1 was to (1) boil water using the electric water heater, (2) toast bread using the toaster, and (3) heat food in the microwave. The appliance usage script for participant #2 was to (1) use the microwave oven and (2) heat food in the electric oven, and (3) watch some TV. The appliance usage script for participant #3 was to (1) make toast with the toaster, and (2) heat food in the electric oven.

B. Evaluation Metrics

This study measures the following system performance metrics.

- **User identification error**: This measures the percentage of time the system correctly (or incorrectly) identifies occupants from their thermal tags.
- **Per-user power metering error**: This measures the error percentage of the system-detected (per-user) power consumption versus the ground-truth (per-user) power consumption.

C. Results

Table II: Confusion matrix for the user identity error.

Room \ Date	Presence	Non-presence
Presence	0.82	0.03
Non-presence	0.18	0.97

User identification error. Table II presents a confusion matrix that measures the percentage of time the system correctly (or incorrectly) detects the presence (or non-presence) of a participant with his/her thermal tag. The time accuracy of detecting the presence of participants is 82%, with a small false positive rate (3%). The slightly lower time accuracy (82%) is mainly due to time intervals when a participant is walking. When participants are mobile, the observed temperature signals produce a larger error than those from stationary participants [6], and therefore result in high incorrect temporal codes. However, our findings show that participants tend to stay at fixed locations while they are using appliances that are plugged into the wall sockets. Therefore, these incorrectly-decoded time intervals when occupants are mobile does not seriously affect system accuracy in tracking per-user power consumption.

Per-user power metering error. Table III presents the accuracy of metering per-user power consumption. The actual

Table III: Per-user power metering error for all sharing scenarios. S_i, R_i, and P_i mean the identifications of scenario, rounds, and participants, respectively. True (Estimated) column means the true (estimated) energy consumption. `Diff` column means the difference between true and estimated energy consumption. `Error` (`Avg_error`) column means the estimated error percentage (average estimated error percentage for an appliance usage scenario).

S_i	R_i	P_i	True (kJoule)	Estimated (kJoule)	Diff (kJoule)	Error (%)	Avg_error (%)
S_1	R_1	P_1	949.94	857.64	92.30	9.72	10.02
		P_2	1151.95	1069.97	81.98	7.12	
	R_2	P_3	992.48	1048.38	55.90	5.63	
		P_4	889.56	732.61	156.94	17.64	
S_2	R_1	P_2	477.04	405.86	71.18	14.92	7.82
		P_3	579.07	540.24	38.83	6.71	
	R_2	P_4	462.35	481.44	19.09	4.13	
		P_5	586.04	553.59	32.44	5.54	
S_3	R_1	P_1	698.37	690.06	8.31	1.19	17.63
		P_2	452.12	456.28	4.16	0.92	
		P_3	152.27	90.15	62.12	40.80	
	R_2	P_4	688.32	838.39	150.07	21.80	
		P_5	387.81	246.07	141.74	36.55	
		P_6	147.77	141.07	6.70	4.53	
All	-	-	-	-	65.84	12.66	-

count (estimated count) column gives the actual (estimated) energy consumption. The error column computes the difference between the actual and estimated energy consumption. The error % column gives the estimated error percentage.

Each scenario involved two rounds of repeating the same appliance usage script but with different participants. The average error percentage from all scenarios is 12.66% and the average error in energy consumption is 65.84 kilojoules. Among these rounds, these percentage errors larger than 10% are caused by either (1) incorrect user identification or (2) higher appliance power metering errors for some appliance usage sessions in a round. For example, the microwave energy consumption ought to go to participant #5 in scenario #3 but it was incorrectly identified as being used by participant #4, and therefore causes large estimation error for participants #4 and #5.

VII. Related Work

A. Power Meters

In response to increasing energy costs, many people are becoming more concerned about how much energy they consume. Many commercialized power meters, such as Cent-a-Meter [8], The Energy Detective (TED) [9], Kill-a-Watt [10], etc., aim to help people understand their energy consumption. However, research studies [11], [12] point out problems with existing commercial power meters. First of all, most home occupants have little or no experience in installing monitoring devices in the breaker panel, and installation presents safety concerns. Considering the installation difficulty for end-users, Patel *et al.* [12] designed an easily-deployable power meter. This power meter consists of a sensor unit with a wireless radio interface that can be attached to the outside of the breaker panel. Another problem with the current commercial power meters is that it is difficult to systematically collect energy data for analysis.

B. Appliance-level Energy Consumption Systems

Systems that disaggregate energy consumption at the per-appliance level provide fine-grained feedback about users energy behaviors. Non-intrusive load monitoring (NILM) [13], [14] analyzes power readings from in-line power meters by detecting sudden changes in voltage or current. NILM then identifies appliance on/off or inner state changes, and classifies them at the appliance/device level and total power disaggregation. NILM relies on a database of appliance usage signatures for classification. Berges *et al.* [17], [18] and Roberts *et al.* [19] investigated how to build signature databases for NILM systems. Based on NILM, Rowe *et al.* [15] improved the training phase by exploiting an electromagnetic field (EMF) sensor. ElectriSense [3] takes advantage of this phenomenon to track different appliance usages by extracting features using machine learning toolkits.

ThermalProbe is based on the HeatProbe [2] system. HeatProbe applies a thermal sensing method to disaggregate the power consumption of each appliance. ThermalProbe extends disaggregation to the per-user level. ThermalProbe and HeatProbe differ from previous methods in that they apply a novel thermal sensing approach. Furthermore, neither system requires a training or calibration phase.

C. Per-user Energy Consumption Systems

Several recent studies monitored per-user power consumption in an effort to promote individual power-saving behavior. Hay *et al.* [16] discusses how building sensor systems can be potentially used to track individual energy consumption and proposes several apportioning policies that divides energy consumption among building occupants. The Human-Building-Computer Interaction (HBCI) system [5] provides each appliance with a QR code encoded with an URI. By scanning the QR code with a mobile phone, users are able to log the starting and ending times of each appliance usage. By apportioning the energy consumption of appliances based on usage time, this smart phone app can provide per-user energy usage feedback. ThermalProbe includes a thermal identification scheme to automatically track user appliance usage. ThermalProbe lowers installation costs because it does not require installing a tag on each appliance. Furthermore, ThermalProbe does not need manual scanning or labeling to track appliance usage, therefore automating the per-user power apportioning process.

VIII. Conclusion

This study explores the feasibility of per-user energy metering by proposing ThermalProbe, a novel energy meter system that estimates per-user energy consumption in a shared working/living space. In the ThermalProbe system, each occupant wears a thermal tag that emits a unique temperature signature for user identification. Then, the system implements location-based energy accounting that allows energy administrators to specify location-based accounting rules and to assign appliance energy usage to nearby occupant(s). Experimental results from three multi-user scenarios achieved average 87% accuracy in metering per-user energy consumption.

Though the current per-user energy metering error (12.66%) leaves much room for further improvement, we believe that the ThermalProbe system offers an alternative and promising thermal-sensing approach to tackle the problem of tracking per-user energy consumption.

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