Discerning Electrical and Water Usage by Individuals in Homes

Juhi Ranjan
University of Virginia
Charlottesville, USA
juhi@virginia.edu

Erin Griffiths
University of Virginia
Charlottesville, USA
erg3wb@virginia.edu

Kamin Whitehouse
University of Virginia
Charlottesville, USA
whitehouse@virginia.edu

Abstract

Energy auditing and feedback is an effective and low cost technique that has the potential to save 20-50% energy in homes. Several new sensing technologies can now detect and disaggregate energy usage in homes at a fixture level, which is helpful for eco-feedback in homes. However, without disaggregating and assigning fixture energy usage to individuals (*fixture assignment problem*), it is hard for residents to discover individual energy saving actions. In this paper, we explore the hypothesis that fixture assignment can be performed based on coarse-grained room-level location tracking – even when a fixture is used and multiple people are in the same room. To test this hypothesis, we perform a study with 5 groups of 2 participants each, who lived together for 7-12 days in a test home. We find that fixture assignment can be performed with an average accuracy of 87% using room-level tracking. In comparison, fixture assignment has 12% accuracy with house-level tracking (who is home vs not home) and 97% accuracy with coordinate-level tracking (who is standing at the oven vs fridge).

Categories and Subject Descriptors

H.4 [**Information Systems Applications**]: Miscellaneous

General Terms

Measurement, Experimentation

Keywords

Fixture Usage Assignment, Energy Disaggregation

1 Introduction

In today's world of centralized air conditioning systems, appliances, gadgets and more square footage, homes have become high energy consumers. Not only does this result in hefty utility bills for the home residents, but also consumes 40% of the total US energy budget, and 70% of all electricity usage [3]. Engaging home residents in energy conserving behavior has the potential to affect 20-50% of the home's total energy usage. However the main challenge in this technique is that with the current level of energy feedback (via aggregate utility bills), residents do not know how energy is used/wasted in the home. This makes discovering energy saving behavior difficult.

It is believed a system that disaggregates a home's total energy usage at a *per-person, per-fixture* level, will allow individuals to discover and reduce the energy footprint of their fixture usage behavior in homes [11]. A key challenge in disaggregating energy usage among individuals in a multi-person home, is sensing *who* is using a fixture. We call this the *fixture assignment problem*. Recent advances in sensing technology have been able to disaggregate the coarse-grained aggregate energy consumption in homes, to a fixture level; it is possible to discover which fixtures are present in the home [22], recognize when they are used [7, 6], and discern how much energy or water was consumed during each use [16, 15]. However, unless every fixture is instrumented with an RFID tag [19] or a biometric sensor [21], the fixtures themselves can not detect who is using them. An indirect approach for performing fixture assignment is to assign the individual located closest to a fixture ,when it is used. In such an approach, the key question then becomes: what should be the granularity of the location tracking system in homes?

In this paper, we demonstrate that we can perform fixture assignment based on coarse-grained room-level location tracking – even when two people are present in the room where a fixture is used. Many WiFi fingerprinting based, cellphone, and emerging Bluetooth Low Energy (BLE) systems, such as the Apple's iBeacon system can already achieve room-level location tracking. Our results offer promise that these coarse-grained location systems can be used to perform fixture assignment, even if fine-grained coordinate level indoor location tracking remains impractical and expensive in the current state of the art.

Our basic approach to fixture assignment is to first find unambiguous assignments, where a fixture is used with only one person present in the same room. These unambiguous cases are then used to learn fixture usage patterns that can help disambiguate cases where two or more people are in the room. The patterns can be general trends (e.g. Person A does all the cooking) or can be similar to object-use fin-

BuildSys'14, November 5–6, 2014, Memphis, TN, USA.
ACM 978-1-4503-3144-9.
http://dx.doi.org/10.1145/2674061.2674066

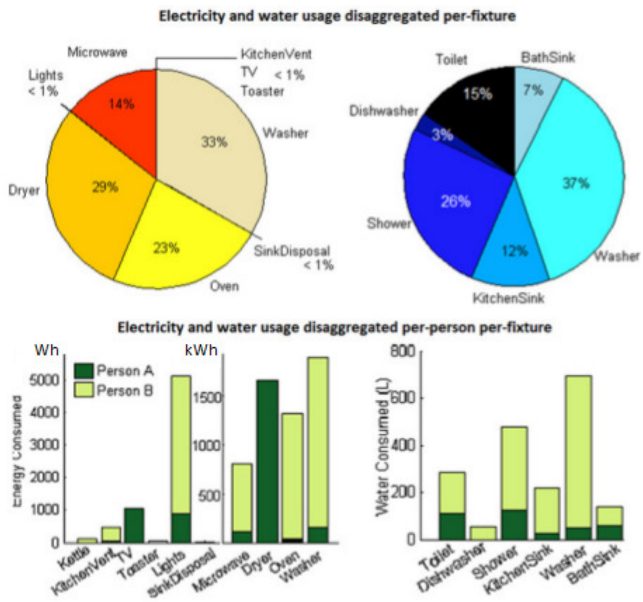

Figure 1. Energy disaggregation (of one of the participant groups): Per-person per-fixture disaggregation makes it evident that Person B consumes most of the electrical and water fixture energy in the house except for TV and Dryer, which are used only by Person A

gerprints [13] (e.g Person A likes long, hot showers) and can even include multi-object fingerprints (e.g. Person A uses the sink often while cooking).

To test our approach, we performed a study with 5 groups of 2 participants each, who lived together for 7-12 days in a test home. We equipped the test home with an RFID-based tracking system that tracked the location of each participant with three different granularities: house-level (home vs. not home), room-level (kitchen vs. bathroom), and coordinate-level (at the oven vs. at the fridge). We also instrumented 39 different fixtures including light fixtures, water fixtures (for e.g. sinks, showers, and toilets), and electrical appliances (for e.g. the oven, stove, and fridge). Coordinate-level tracking was deployed for 15 of those 39 fixtures. Participants were required to wear RFID ankle bracelets [20] for up to 12 days, and were otherwise asked to follow their normal daily routines.

While only 70% of fixture usage was unambiguous (i.e. only a single person was in the room), we found that fixture assignment could be performed with 87% accuracy on average by using our learning algorithms. In comparison, fixture assignment based on house-level tracking achieved only 12% accuracy due to fixtures being used when multiple people are home at the same time. Coordinate-level tracking achieved fixture assignment accuracy of 97%. In 3% of cases, two people were standing immediately next to the fixture when it was used. Thus, fixture assignments performed with room-level tracking had comparable accuracy as coordinate-level tracking, but at potentially much lower cost.

2 Related Work

Energy usage feedback in residential buildings is considered an effective means to induce energy saving behavior in home residents [9]. The concept of energy usage at home disaggregated at fixture level, has been incorporated in many eco-feedback systems, such as the Aware-Cord [8], which displays fixture level ambient energy usage, and WattBot [18] which is a mobile phone based fixture and room level home energy feedback system.

Hay et al. explored breaking down electricity consumption for occupants of a commercial building working at different shifts in the day [10]. They used access logs to infer the occupancy of the building, and explored the usage of different policies to allocate shared resource usage. The static apportionment policy divides the entire energy consumption equally among all the people who have desks allocated in the building, regardless of how much they use the building. Dynamic occupants policy divides a building's instantaneous power consumption amongst only the current occupants of the building. But this approach penalizes people who are present in the building at odd hours, such as early morning, as the entire building's energy load including the static energy consumption is divided between a few people only.

While these general policies might work for a commercial buildings where a large percentage of the building's energy consuming systems, such as the heating and ventilation system are not individually controlled by its occupants, homes are different. In homes, individuals are in control of the all fixtures and appliances that contribute to the total home energy consumption. Therefore, the need for discerning who is using a fixture becomes very relevant in homes. In this direction, Hay et al. present their concept of a personal energy meter (PEM) which can record and apportion an individual's energy usage [11]. Their concept not only includes a person's energy footprint inside a home, but also the energy footprint outside of home - such as that of transportation.

Hsu et. al conducted a study with a mobile application that provides estimations of personal electricity consumption in a research laboratory [14]. In this study, metadata about each appliance owned by a user such as computer, printer and phone was stored in a central repository, and the energy consumption for these appliances tracked using their proposed system architecture. The total energy consumed everyday by all these devices is apportioned and displayed on the user's smartphone. They propose that this method gives users the alternative to operate specific appliances which are more energy efficient.

Cheng et. al use coordinate level tracking in a study and apportion energy usage for users in an office building [1]. To determine which person is using an appliance, they use a proximity detection system where users carry a magnetic beaconing system which are detected by special receivers near appliances. The disaggregation policy is simple - assign the energy used to the nearest person detected. We recognize that coordinate level localization is very accurate in determining the individual who used an appliance. However, it is also an expensive technique which requires carrying specialized wearables at home, in the current state of the art. We explore the idea that we can use a more coarse-grained room level localization system and achieve comparable results. Room location tracking in homes can be done much cheaper by utilizing the existing technology infrastructure at

Figure 2. Sensor Deployment: All major electrical and water fixtures in the test home were instrumented. The stove knobs and fridge doors were fitted with rare earth magnets, and detected by reed switch sensor. Light fixtures were monitored with optical fiber based directional light sensor. Appliances such as hair dryer, were detected using power meters. Sinks and toilet flush tanks were instrumented with in-line water flow sensors

homes, such as Wi-fi fingerprinting.

Lee et al. propose tracking people's movements in the rooms of a house to disaggregate electrical energy [17]. They use people's most frequent movements in the rooms of a home to identify individual bedrooms, and assign all electrical usage in those rooms to the person. In a shared space, they use room location tracking to identify possible person present in the room while an electrical appliance is being used. If multiple people are present in the room when an electrical fixture is used, they simply split the energy usage equally between all people present in the room. Our work differs from this study, in that, even in the presence of multiple people in a room, we attempt to guess the exact individual who is actually responsible for a fixture event. Dividing all the energy usage equally masks individual contributions to energy usage and makes it harder for individuals to recognize energy impact of their individual fixture usage. We explore learning based policies of fixture usage assignment that intend to use history of appliance usage to make an intelligent guess about which individual might be using the appliance.

3 Approach

We aim to compare the performance of different granularities of location tracking systems in discerning the individuals using electrical and water fixtures in a home. We fuse location tracking information of individual along with electrical and water fixture usage events, to assign fixture events to residents within a home. The main challenge is disambiguating who used a fixture when two people are detected within the same proximity of a fixture at the time of its use. We use different heuristics to learn past fixture usage behavior in order to disambiguate such events.

Step 1 - Fixture Usage Detection

In the scope of this paper, we assume that we have prior knowledge about a fixture's presence, identity and location within a home. All the fixture sensors in the house, report fixture usage status at a second's granularity. For every electrical fixture sensor i in the system that produces a time series $E^i = e^i_1, e^i_2, e^i_3, ..., e^i_t$, we apply DBSCAN algorithm [4] to find clusters of fixture usage events. For each of the sensor data streams produced by a sensor i, DBSCAN produces a series of events ev^i. Let EV^i be the ordered set of all events $ev^i = (t^i_{start}, t^i_{end}, m^i)$, where t^i_{start} and t^i_{end} are the start and end timestamps of the electrical fixture usage event, and m^i is the total electrical energy (watts) consumed in the event.

For each water fixture sensor i, we have two streams of sensors reporting hot water volume (wh^i) and cold water volume (wc^i) at the fixture at a second's granularity. Therefore every water fixture sensor i produces a time series $W^i = (wh^i_1, wc^i_1), (wh^i_2, wc^i_2), (wh^i_3, wc^i_3), .., (wh^i_t, wc^i_t)$. We apply DBSCAN on W^i to generate water fixture usage events wv^i. Let WV^i be the ordered set of all events $wv^i = (t^i_{start}, t^i_{end}, m^i)$, where t^i_{start} and t^i_{end} are the start and end timestamps of the water fixture event end, and m^i is the total water (liters) consumed in the event.

For appliances such as fridge and freezer which do not register an immediate change in appliance power, sensors on the appliance report back appliance door open events a^i. Let A^i be the ordered set of all door open events $a^i = (t^i_s, t^i_e, 0)$, where t^i_{start} is the timestamp of opening the appliance door, and t^i_{end} is the timestamp of closing the appliance door. F is the set of all fixture usage events, i.e., $\{EV, WV, A\} \in F$.

Step 2 - Location Tracking

In terms of tracking residents in homes, we compare three levels of location inferring systems: 1. House occupancy level, 2. Room location level, and 3. Coordinate level. RFID anklets worn by participants at home, and RFID detection zones created at pertinent locations was used to perform these three levels of location in homes. We use a RFID tracking system, evaluated in prior work [20], to obtain highly accurate location information for our studies.

House Level Tracking

House level tracking of individuals is detecting when the individuals are at home or away. This level of tracking is at a very coarse level granularity, and is one of the most inexpensive level of tracking. The fixture assignment accuracy at

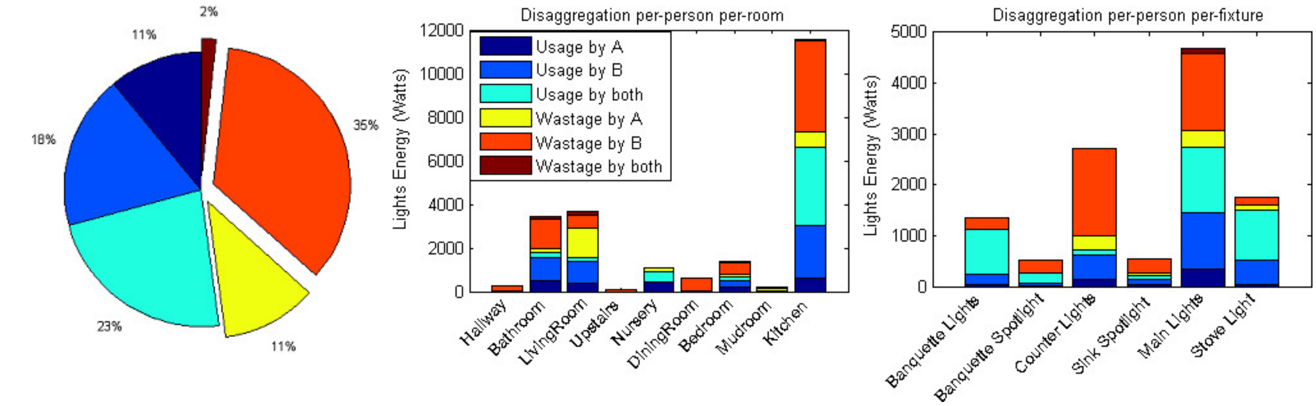

Figure 3. Case study of lights' energy: (a) Aggregate energy analysis reveals that person B uses light energy comparable to person A, but wastes three times more energy than A, (b) Energy disaggregated per person, per room indicates that lights energy in Dining room and Hallway are mostly wasted, (c) Energy disaggregated per person, per fixture in the kitchen shows that the stove and banquet lights are used more efficiently

this level of tracking depends on how often individuals stay at home alone. This is an inaccurate tracking mechanism when all the individuals within a home have similar hours of stay.

Let $HouseOccupancy$ be the set of all home occupancy sessions (t^i, t^j, p_X), where a person p_X occupies the house from time t^i to t^j. To detect home occupancy sessions of people, we track their movements across the entry doorways of the house. For each entry doorway ed^i, there are two RFID zones $(rf^i_{Exterior}, rf^i_{Interior})$ on either sides of the doorway: $rf^i_{Exterior}$ lies on the outer part of the house, and $rf^i_{Interior}$ lies on the inner part of the house. We know a person p_X enters a house at time t^i, when we observe a doorway crossing $dc^i = (p_X, ed^i, rf^i_{Exterior}, rf^i_{Interior}, t^i)$, where $rf^i_{Exterior}$ detects p_X first, followed by $rf^i_{Interior}$, at time t^i. We know that p_X was present in the house from t^i to t^j, when p_X is detected at a doorway crossing $dc^j = (p^j_X, ed^j, rf^j_{Interior}, rf^j_{Exterior}, t^j)$, where $rf^j_{Interior}$ detects p_X first, followed by $rf^j_{Exterior}$, such that t^j ¿ t^i. More details of the algorithm to detect a doorway crossing can be found in [20].

Room Location Tracking

Room location tracking goes one step beyond what house level tracking does. In this level of tracking we have precise knowledge of when a person occupies individual rooms in a house. Room location is a very important level of tracking in homes, because a 'room' is a logical unit of space within a house which encompasses certain categories of activities which people perform within that space. These activities define the type of appliances and fixtures present and used in the room.

Let $RoomOccupancy$ be the set of all room occupancy sessions $(p^i_X, r^i_x, t^i_{enter}, t^i_{exit})$, where r^i_x is the room occupied by the person p^i_X from time t^i_{enter} to t^i_{exit}. To sense when people occupy rooms in a house, we detect them as they walk across the indoors doorways, to move in and out of rooms. For each doorway id^i, between rooms r^i_x and r^i_y, there are two RFID zones (rf^i_x, rf^i_y) on either sides of the doorway. RFID zone rf^i_x lies on r^i_x's side of the doorway., and rf^i_y lies on r^i_y's side of the doorway. We know a person p_X walks across a doorway id^i into the room r^i_y from room r^i_x, when a doorway crossing event $dc^i = (p_X, id^i, rf^i_x, rf^i_y, t^i)$ is generated in the doorway. Here rf^i_x is the first RFID zone that detects the person, rf^i_y is the second RFID zone that detects the person, and t^i is the time when p_X is detected at doorway. To detect how long a person stays in the room r_y, we look for the subsequent doorway crossing event made by the same person out of the room $(p_X, id^{i+1}, rf^{i+1}_y, rf^{i+1}_z, t^{i+1})$. Based on these two doorway crossing events, we can infer that person p_X was in room r_y from t^i to t^{i+1}.

Coordinate Level Tracking

Coordinate level tracking can locate a person at a precise spot with sub meter accuracy within a house. Given this ability, we can locate a person in the spot right next to where the fixture is used. Although this may seem as 'the most ideal level' of tracking, it is still prone to errors. Sometimes two people may stand very close next to each other while one person using a fixture, and may even share the use of the fixture, for e.g. two people may cook together. In such cases, co-locating people with fixtures even within sub-meter range would result in ambiguous fixture assignment.

To track people at a coordinate level, as they stand next to fixtures, we created RFID detection zones $(rz_1, rz_2, rz_3, ..., rz_n)$, with sub-meter radius. Each fixture i associated with a coordinate specific RFID zone rz_i. Each RFID zone i, produces a stream of RFID tags reads $rz^i = (r^i_1, r^i_2, r^i_3, ..., r^i_n)$ when a person wearing RFID anklets stands near the corresponding fixtures. We use DBSCAN to cluster these tag reads into coordinate detection events $cd^i = (rz^i, p^i, t^i_{steppedOn}, t^i_{steppedOff}) \in CoordinateEvents$, where rz^i is the the RFID zone where a person was detected standing, p^i is the person identified at rz^i, $t^i_{steppedOn}$ and $t^i_{steppedOff}$ are the timestamps when p^i was first and last detected at rz^i in this cluster of RFID tag reads.

Step 3 - Fixture Assignment

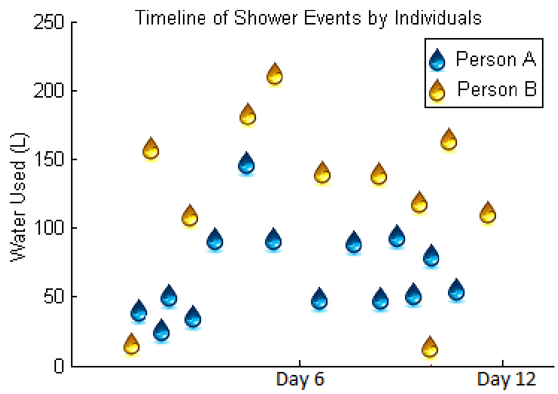

Figure 4. Person A showers more frequently than B. However A's total shower water usage (916 L) is lower than B's (1327 L). This is because B tends to take longer showers compared to A

House Level Only

For all events $f^i = (t^i_{start}, t^i_{end}, m^i) \in F$, we detect which individuals are present in the house. If $\exists(p^j, t^j_{enter}, t^j_{exit}) \in HouseOccupancy$, such that $t^j_{exit} > t^i_{start} > t^j_{enter}$, then person p^j was present in the house when the fixture was used. If only one person is detected in the house when a fixture event f^i takes place, the fixture usage is assigned to that person. $FixtureAssignment$ is the set of all fixture assignments (f^i, p^i). If there are multiple people in the house when a fixture f^i is used, then it is declared an ambiguous fixture event, and added to the set $AmbiguousEvents$.

Room Location Only

For all fixture usage events $f^i = (t^i_{start}, t^i_{end}, m^i) \in F$ that takes place in a room r_{fi}, we detect which individuals are present in the room. If $\exists(r^j_{fi}, p^j_y, t^j_{enter}, t^j_{exit}) \in RoomOccupancy$, such that $t^j_{exit} > t^i_{start} > t^j_{enter}$, then person p^j was present in the room when the fixture was used. If only one person p^i is detected in the room r_{fi}, when a fixture event f^i takes place, the fixture usage is assigned to the same person. $FixtureAssignment$ is the set of all fixture assignments (f^i, p^i). If there are multiple people in the room r_{fi}, when a fixture f^i is used, then it is declared an ambiguous fixture event, and added to the set $AmbiguousEvents$.

Coordinate Level Only

For all fixture usage events $f^i = (t^i_{start}, t^i_{end}, m^i) \in F$, we detect which individuals are present at the associated RFID zone rz_{fi}. If $\exists(rz^i, p^i, t^i_{steppedOn}, t^i_{steppedOff}) \in CoordinateEvents$, such that $t^i_{steppedOff} > t^i_{start} > t^i_{steppedOn}$, then we know person p^i was located right next to the fixture when it was used. If only one person p^i is detected at the RFID zone rz_{fi}, when a fixture is used f^i, the fixture usage is assigned to the same person. $FixtureAssignment$ is the set of all fixture assignments (f^i, p^i). If there are multiple people standing at the RFID zone rz_{fi}, when a fixture f^i is used, then it is declared an ambiguous fixture event, and added to the set $AmbiguousEvents$.

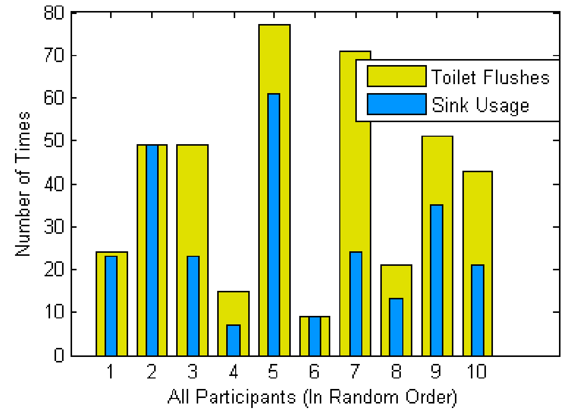

Figure 5. Fixture assignment can be used to track hygiene habits, for e.g. how many times do people wash their hands after using the toilet flush

Step 4 - Applying Heuristics

For all fixture events $f^i \in AmbiguousEvents$, we apply different heuristics to make an intelligent guess as to who might have used a fixture.

Naive heuristic: This is a simple heuristic, which does not require any preconditions to operate. Given a set of multiple people $(p_1, p_2, .., p_n)$ detected in the same proximity, where a fixture event f^i takes place, this heuristic randomly assigns the fixture usage to any one of the people present nearby.
$Naive(f^i) = RandomSelection(p_1, p_2, .., p_n)$.

Blame 'X' Myopic heuristic: This heuristic keeps a short term memory (a day) of all the unambiguous fixture usage assignments made for each person. $(f^i, p^i_x) \in ShortTermMemory$. When a fixture is used, this heuristic refers to $ShortTermMemory$ for the person p_x who has used this fixture most on that day. If there are no records for the fixture f^i in $ShortTermMemory$, i.e., $!\exists(f^i, p^i_x) \in ShortTermMemory$, then we use $Naive(f^i)$ to make the fixture assignment.

LastPersonXmin heuristic: If an unambiguous fixture assignment is made to a person within a certain time frame of an ambiguous fixture usage, this heuristic assigns the ambiguous fixture usage to the same person. To assign an ambiguous fixture usage f^i at time t_{fi}, this heuristic searches for any instance of an unambiguous fixture assignment in $FixtureAssignments$ within a time window from $t_{fi} - X_{minutes}$ to $t_{fi} + X_{minutes}$. If $\exists(f^j, p^j_x)$, such that $f^j = (t^j_{start}, t^j_{end}, m^j)$ and $t_{fi} - X_{minutes} > t^j_{start} > t_{fi} + X_{minutes}$, then the ambiguous fixture usage f^i is assigned to p^j_x.

Blame 'X' Hyperopic heuristic: This heuristic keeps a long term memory of all the unambiguous fixture usage assignments made for each person. $(f^i, p^i_x) \in LongTermMemory$. When a fixture is used, this heuristic refers to $LongTermMemory$ for the person p_x who has used this fixture most till date.

If there are no records for the fixture f^i in *LongTermMemory*, i.e., $!\exists(f^i, p_x^i) \in LongTermMemory$, then we use $Naive(f^i)$ to make the fixture assignment.

Case Studies

Lights Energy Analysis:

Personalized light usage feedback can reveal a lot of potential for savings. Quite often, lights once switched on, remain on even when when rooms are unoccupied. We can detect exactly which person forgets to switch the light off when they leave the room. Figure 3 shows the breakdown lights energy usage and wastage by individuals from one of our studies. To discover wastage, for every minute that a light fixture is on, we detect who is present in the room. If one or more persons are present in the room, then its energy is assigned to the set of people present in the room. If the room is empty, and the light is on, then it is labeled as wastage. This wastage is attributed to the last person who left the room without switching off the light. In this case study, we observe that 50% of the total lights energy in the house is wasted by the individuals. Although person *A* and *B* use lights in the rooms almost equally, person *B* wastes about 35% of the total lights energy, which is three times more than what *A* wastes. A room level breakdown further reveals that person *B* usually leaves the lights on in some rooms such as the Dining room and Hallway without ever using the lights in those rooms. *A* wastes more light in the Living room than *B*. Most of the light usage and wastage takes place in the Kitchen. A further analysis of individual light fixtures in the Kitchen reveals that certain lights fixtures are used more efficiently than others. For e.g., there is hardly any wastage detected for Stove Light and Banquet Light. However, most of the light energy of Sink Spotlight and Counter Light is wasted by *B*.

Habit Monitoring: A 'per person per fixture' assignment can be helpful in learning individual habits and preferences of people in a house. In Figure 4, we can detect non-obvious trends in shower water usage. Although person A showers 1.2 times more than person B, B uses 1.4 times more shower water than A. We can also monitor if people are following hygienic habits. In Figure 5, we can see that for 65% of the toilet flushes made by participant 7, there were no sink events detected within 45 seconds of the toilet being flushed.

4 Experimental Setup

To evaluate our hypothesis for performing a 'per person per fixture' disaggregation, we used a living lab model for data collection. We instrumented lights, appliances and water fixtures with sensors in a residential house and rotated five sets of two participants each, who lived in the same house for 7-12 days each. Compared to controlled experiments, this approach gave us in-situ data of the participants, who lived their lives normally in the house.

Participants

Five sets of two participants were recruited to live in the house for 12 days each. Each set had only two participants living in the house at the same time for two reasons - some of the participants were married/dating, and for others we were limited by the number of bedrooms in the house. While most participants lived in the house for 12 days, one participant in study set 2 had to leave the study for work obligations after 7 days. Although the participants in study sets 3 and 4 lived in the house for 12 days each, we lost 5 days data in set 3, and 2 days data in set 4 due to an internal network failure in the living lab.

Sensing Infrastructure

Lights: We used light on/off sensing HOBO UX90-002M data loggers [12] to sense the lights in the house. These loggers are installed right next to the light bulbs, and have a programmable threshold for light intensity to detect when a light is on. We used off-the-shelf optical fiber pipe attachments (as shown in Figure 2 b.) with the light sensors to filter out external light and make sure the sensor received light only from the fixture being sensed.

Appliances: We use different sensing methods for different types of appliances. *Appliances with hinged doors* such as fridge, dishwasher, washing machine etc. were instrumented with state sensing HOBO UX90-001 data loggers [25]. A rare earth magnet was attached to the door of the appliance, and the reed sensor was attached on the fixed part of the appliance. We also used the magnetic reed switches to instrument the stove, by fixing rare earth magnets inside the stove knobs, and reed switches next to the knob from inside the frame of the stove. *Small appliances plugged to wall receptacles* such as electric kettle, toaster etc. were instrumented with CSV A-8 current sensor [2] to sense when these appliances were powered on and off (as shown in Figure 2 a.) *Major power consuming appliances* such as microwave, oven, dryer etc. had individual power lines connecting to the circuit board, which was monitored using a TED Energy Monitor [23]. This monitored the power consumption on all circuits and reported data to a central repository via ethernet.

Water Fixtures: We instrumented all the water fixtures in the house such as sink faucets, toilet flush tanks, and showers, and obtained water flow information at each fixture at a second's granularity. To do so we installed in-line water flow sensors FTB4700 and FTB4707 [5] just before the outlet valve of each fixture. The data from these sensors were logged using UX120-017M 4-channel pulse data logger [24].

Location Sensing: The ability to conduct this study relied mainly on being able to sense the locations of residents in the house at different granularity levels. Each participant in this study wore a pair of RFID anklets with unique RFID tag numbers. We track the location of the participants in the house by tracking the RFID anklets worn by them using under the floor RFID antennas. We track participants in the house at three levels -

1. *Coordinate Level* - We created binary-state RFID detection spots near many of the fixtures in kitchen and bathroom.

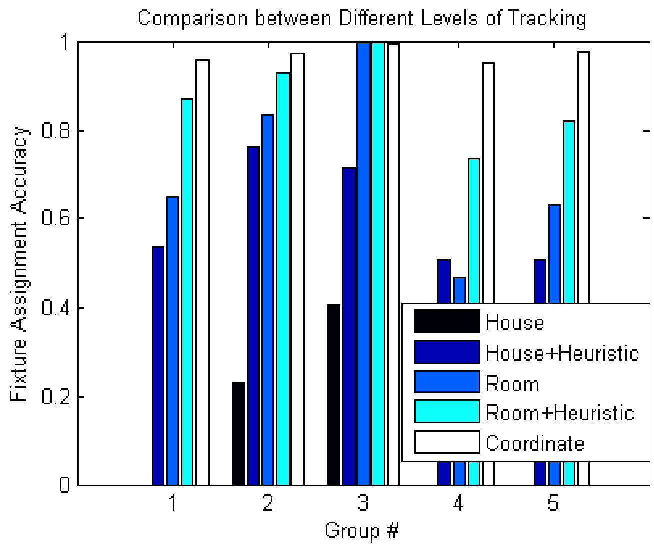

Figure 6. Evaluation results: House level tracking has an average fixture assignment accuracy of 12%. Room location level tracking alone has 70% accuracy. Heuristics augmented room location tracking has an average accuracy of 87%. Coordinate based tracking has an average of 97% accuracy across all groups

This ensured that we detected a person only when they stood at a given RFID detection spot in the house.
2. *Room Location Level* - In this level of tracking, we sense the room locations of the participants by detecting their RFID anklets as they cross the doorways, using the RF-Doormat room location sensing system proposed in [20]. This sensing system uses proximity based RF threshold systems: two RF thresholds placed on either sides of a doorway, determine if a person crosses a door to change his/her room location.
3. *House Occupancy Level* - In this level of tracking, we sense when people are present at house or away, by monitoring their movement into or out of the house at the entry doorways of the house using the RF Doormats.

5 Evaluation

To evaluate our hypothesis, we use fixture events obtained from 'monitored' appliances which have coordinate level tracking systems installed near them. These include toilet, bathroom sink, hair dryer, fridge, freezer, microwave, oven, toaster, coffee machine, electric kettle, coffee grinder, kitchen sink faucet, stove, range hood light, and dishwasher. Post study analysis revealed that none of the participant groups had used the coffee machine or the coffee grinder, and therefore these got excluded from evaluation. To test the fixture assignment of different tracking systems - house, room, coordinate and heuristics augmented house and room level tracking, we use the metric '*fixture assignment accuracy*': percentage of fixture usage events assigned to the right person. To evaluate coordinate tracking, we use the number of events logged by the sensors on monitored fixtures as the ground truth. A video recording system would have been ideal for getting ground truth. However, privacy concerns of 'being watched' inside rooms, and specially the bathroom,

Group 1	P1	P2	Ambiguous	Total #
P1	91	1	47	139
P2	14	256	126	396

Group 2	P1	P2	Ambiguous	Total #
P1	248	0	34	282
P2	1	58	26	85

Group 3	P1	P2	Ambiguous	Total #
P1	64	0	0	64
P2	0	65	0	65

Group 4	P1	P2	Ambiguous	Total #
P1	62	1	56	119
P2	5	60	78	143

Group 5	P1	P2	Ambiguous	Total #
P1	196	11	90	297
P2	13	230	134	377

Table 1. Analysis of room location based fixture assignment: The confusion matrix represents the fixture assignments for individuals when the room is singly occupied. Ambiguous fixture usage (when multiple people are present in same room) is the main reason why room location tracking has lower fixture assignment accuracy than coordinate system. Group 4 has 0 ambiguous events, and therefore 100% room location based fixture assignment accuracy

were the main reasons why we did not use cameras. For evaluating fixture assignment accuracy of all other tracking systems, we use the data from coordinate tracking system as the ground truth.

To get fixture assignments for coordinate tracking system, we incrementally search for a person detected by the coordinate tracking system near the fixture starting from 5 secs to 15 seconds of the event timestamp. This flexibility in the search time window is to deal with the time sync differences between the different logging systems. If a single person is found standing near the fixture used, then the event is assigned to the same person. An event remains unassigned (ambiguous) if two people are detected within the search timeframe of the event. As can be seen from Figure 6, coordinate tracking system has an average accuracy of 97% across all groups of participants. The 3% of ambiguous fixture assignments could have been caused due to several reasons, such as one person operating the fixture as the other person walks by, or two people jointly operating a fixture, such as sharing a stove while cooking a meal together.

In the room location tracking system, if a single person is detected in the room when a monitored fixture is used, it is assigned to the same person. A fixture event remains unassigned if multiple people are present in the same room at the time it is used. The room location system achieves an average fixture assignment accuracy of 71.60%. It achieves 100% accuracy in group 3, where there are no ambiguous events detected. Errors in detecting people entering a room, or exiting the room, may lead to mistakes in assigning the

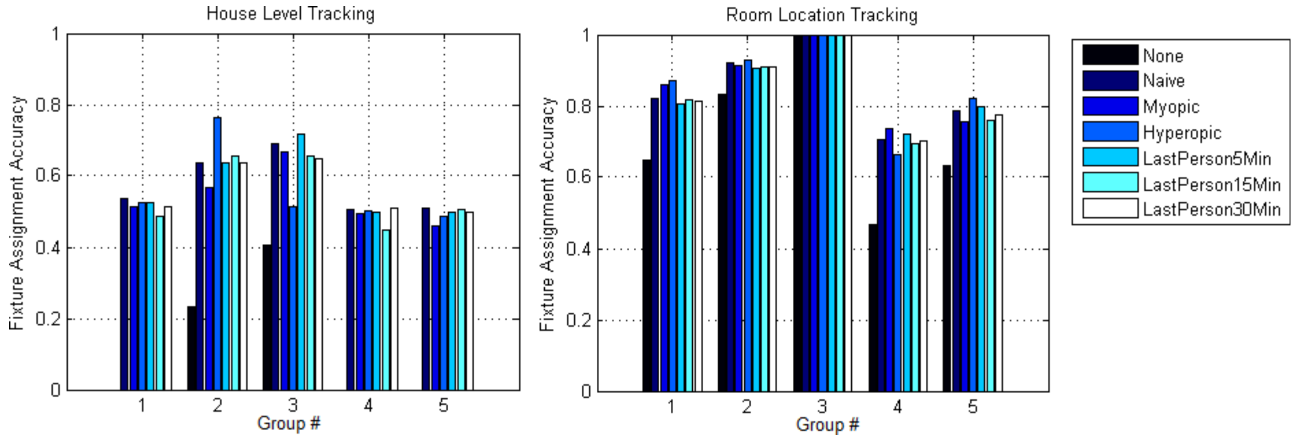

Figure 7. Heuristics analysis: (a) House Level Tracking - Heuristics achieve about 75% accuracy in groups 2 and 3, which have 23% and 40% accuracy without any heuristic. In group 1, 4 & 5, heuristics obtain 50% accuracy indicating that none of them worked better than random assignment. (b) Room Location Tracking Heuristics achieve over 85% accuracy in groups 1, 2 and 3 due to a high number of unambiguous fixture assignments. In group 4, heuristics achieve 72 % accuracy because of a small percent (45%) of unambiguous fixture assignments

fixture to the right person. As can be seen in Table 1, these cases are few and limited to 2% of the total monitored fixture usage. Adding heuristics to room location tracking, improves the average fixture assignment accuracy to 87%.

In the house level tracking system, if a single person is detected in the house during fixture usage, the system assigns it to the same person. If multiple people are present in the house when a fixture is used, the event is unassigned. House level's fixture assignment accuracy is 0% for groups 1, 4 and 5 - which means both participants in these groups were present in the house every time a monitored fixture was used. The fixture assignment accuracy is higher for groups 2 and 3 at 20% and 40% respectively. For these study groups, the corresponding room location system's accuracy is also higher at 92% and 100%. Later in our exit interviews we came to know that in group 3, one participant had left town for two days. As a result, the house was singly occupied for 30% of the study, resulting in a higher fixture assignment accuracy at the house level.

House level tracking system when augmented with heuristics, has an average of 60% accuracy. This is a significant improvement over the average of 12.5% in unassisted house level tracking. In fact, group 4's heuristic assisted house level accuracy is higher than that of unassisted room location based system. Group 2 achieves 76% accuracy which is comparable to the 83% achieved by the unassisted room location tracking system. Groups 1, 4 and 5 achieve an accuracy of 50% which is what we expect if we were to randomly assign all fixtures usages between any two people. Details of heuristics assisted house level tracking will be discussed later in this section.

Analysis of Heuristics

In Figure 7, we compare the performance of all heuristics for house level and room location tracking systems. All heuristics except for Naive, refer to unambiguous usage of fixtures at different timeframes to determine fixture assignment in ambiguous cases. In the case of house level tracking,

Group 1	*BlameX Hyperopic*	P1	P2	Total #
	P1	91	48	139
	P2	21	375	396

Group 2	*BlameX Hyperopic*	P1	P2	Total #
	P1	282	0	282
	P2	26	59	85

Group 4	*BlameX Hyperopic*	P1	P2	Total #
	P1	85	34	119
	P2	35	108	143

Group 5	*BlameX Myopic*	P1	P2	Total #
	P1	246	51	297
	P2	113	264	377

Table 2. Improved room-location based fixture assignments: The use of simple heuristics with room location tracking resulted in fixture assignment accuracy of 87% in group 1 and 92% in group 2. This is comparable to 96% and 98% accuracy achieved respectively in coordinate level tracking system

all heuristics in study groups 1, 4 and 5, have fixture assignment accuracies of 50%. This is expected since all heuristics other than Naive, depend on a history/database of unambiguous fixture assignments, which is 0% for these groups. In the absence of any unambiguous history, they all resort to the Naive heuristic to make the fixture assignment determination. Group 2 has 22% unambiguous fixture assignments, therefore enabling the heuristics to use the history to learn fixture usage behavior. Hyperopic heuristic, which uses long term history to disambiguate works best for this group. This implies that these participants typically follow a consistent pattern of fixture usage over time. In the case of group 3, we have 40% unambiguous fixture assignments, however Hyperopic performs even worse than Naive. This might indicate that the unambiguous fixture assignments were made during

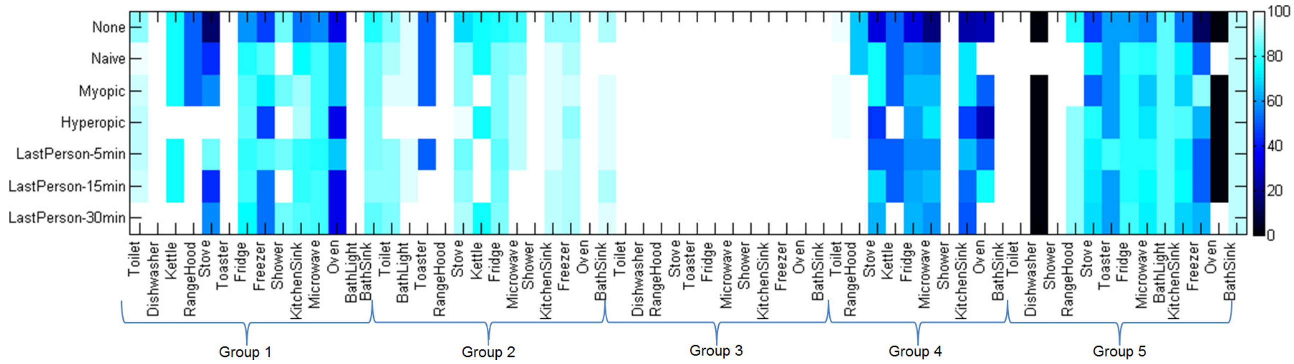

Figure 8. Fixture level breakdown of event assignment accuracy, for different heuristics for all groups, shows potential for developing complex heuristics which are sensitive to typical usage pattern of individual fixtures

a time when other person was not present. Therefore the history of appliance usage could be skewed and a short sighted heuristic such as LastPerson5 min has higher accuracy.

In heuristics assisted room location tracking, Hyperopic heuristic performs the best in three of the five study groups. In group 1, Myopic and Hyperopic perform better than Naive, whereas the LastPerson heuristics are at par with Naive. In groups 2 and 5 all heuristics are comparable to Naive, with Hyperopic performing slightly better than Naive. The problem with Hyperopic is that the most dominant user is assigned all the ambiguous fixture usages, even those made by the minority user. Looking at the confusion matrix for group 2 in Table 1 and Table 2, we observe that P2 is the dominant user of all fixtures, and gets assigned all ambiguous fixture events (even those of P1). This indicates the need for insightful heuristics which even consider assigning ambiguous fixture events to a minority user. In group 3, the unassisted room location system achieves 100% fixture assignment accuracy, indicating that there were no ambiguous events at this tracking level. Therefore, all heuristics performed at par with the unassisted room location system. In group 4, Myopic heuristic performs better than the other heuristics. This indicates that in this group, the dynamics of who uses a fixture varied over time.

Analysis of Heuristics for Individual Fixtures

One possible way to improve fixture assignment accuracy, is to apply different heuristics for different fixtures. In Figure 8, we show a detailed breakdown of event assignment accuracy per fixture for all heuristics across all studies. While BlameX Hyperopic achieved the highest accuracy across most groups of participants, we can clearly see that for many appliances other heuristics worked better. And this seems intuitive for general purpose appliances such as fridge and freezer. Here historical data gives little information in predicting future fixture usage, for e.g. predicting who would feel thirsty and open the fridge for a glass of juice. This suggests that complex heuristics will be better at performing event assignments. In future work, we want to develop systems that can apply a medley of different heuristics for individual fixtures, based on fixture usage patterns.

6 Discussion

In this paper, we investigated the hypothesis that we can perform fixture assignment based on coarse-grained room-level location tracking even when two people are in the same room when a fixture is used. We compare the fixture assignment accuracy for three different granularities of tracking - at the house level, room location level and coordinate level. While we recognize that coordinate tracking is the best level of tracking required to assign fixture usage to individuals, we can achieve comparable results using a more coarse grained room location level tracking system. We observe that room-location tracking alone cannot assign fixture usage when multiple people are present in the same room, and has a 70% average fixture assignment accuracy. However, the use of fixture usage history based heuristics, improve the average assignment accuracy to 87%. These heuristics look at short term and long terms usage history of a fixture to determine which person should be assigned the fixture event. In three sets of participants, a long term usage history based heuristic 'BlameX Hyperopic' had 89% fixture assignment accuracy. These results are indicative of the potential that simple heuristics have in overcoming the limitations of a room location tracking system.

Anecdotal data in Figure 8 reveals that when it comes to applying heuristics to fixtures, there's more to it than meets the eye. Any single heuristic does not perform the best assignment for all appliances. This is because different appliances in multi-person household are 'shared' by residents in different ways. For example, one person may cook for everyone in the household, and in this case a stove's fixture usage can be better disambiguated by a long term history based heuristics. The fridge on the other hand, may be used by everyone in the house, with no obvious bias by any one individual, and therefore a random or naive approach in disambiguating fridge usage might be the best approach.

Trying to develop a heuristic with a comparable accuracy to coordinate tracking based system is challenging: this is a modeling problem to understand how people use fixtures when there are other people present in the same room. Since this modeling would require more longer study periods than two weeks, in ongoing work we are generating more extensive data sets. Our goal for future work is to test whether the system can learn personal 'signatures' of every fixture's usage by individuals to improve fixture assignment when multiple people are in the room simultaneously.

Limitations of the study

We recognize that our study sets of two people are not representative of all possible types of multi-person households, such as those with grandparents. kids or pets living together as well. We were limited by the number of bedrooms in the house. Recruiting participants who were willing to leave their homes, and live somewhere else for 2 weeks was also a big challenge. We were a bit concerned about whether participants would behave naturally while living in another house (Hawthorne effect). However, in the exit surveys, all the participants said that their lifestyle in the living lab was very similar to what they had at their own residence, except that some participants did not have certain appliances at their own homes. A participant said, “Yes, it is indicative of use at home, except for the fact that we do not have a dishwasher or laundry appliances. We probably used the laundry machines more frequently than we normally would due to the fact that it was a rare opportunity to do all our laundry for free :)”. The time of study for one participant set coincided with a month long winter break at the university, where the participants said that they were at home longer than the usual work week - “no deviation from use in own house except maybe hours of occupancy since this was winter break period”. We believe the participants would have also had longer hours of home occupancy at their own homes during the winter break, and therefore we do not consider this a serious deviation from natural behavior. Participants also said that the RFID based location tracking system did not distract their behavior - “RFID receivers beneath the floor did not bother us at all - it’s easy to forget they are there”.

7 Conclusion

In this paper, we aim to disaggregate electrical and water fixture usage among individuals in a home. We use the fusion of information from location tracking system and fixture usage to demonstrate, that fixture usage events can be assigned to individuals in a home using a coarse grained room level location tracking system with 87% accuracy, even when multiple people are present in the same room where the fixture is used. We apply heuristics that learn how people use fixtures in unambiguous assignments (when only one person was present in the room), and make an informed guess to assign ambiguous fixture usage to individuals. While we recognize that fixture assignments can also be performed using coordinate level tracking, we believe that a coarse granularity of tracking would have lower cost implications.

8 Acknowledgments

We would like to thank all the participants who helped us with this study. This work is supported by the National Science Foundation under Grants 1038271 and 0845761, and the NSF Graduate Research Fellowship Program under Grant 0809128.

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