WaterSense: Water Flow Disaggregation Using Motion Sensors

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Abstract

Smart water meters will soon provide real-time access to instantaneous water usage in many homes, and *disaggregation* is the problem of deciding how much of that usage is due to individual fixtures in the home. Existing disaggregation techniques require additional water sensing infrastructure and/or a manual characterization of each water fixture, which can be expensive and time consuming. In this paper, we describe a novel technique called WaterSense to perform fixture-level disaggregation using only a handful of inexpensive motion sensors. WaterSense automatically infers how many fixtures are in each room, and how much water each fixture uses. We evaluate the system using a 7-day in-situ evaluation in 2 diverse multi-resident homes with a total of 10 different water fixtures and 467 fixture events and observe that our approach achieves 86% classification accuracy in identifying individual water fixture events and 80-90% accuracy in determining the water consumption of individual water fixtures.

Categories and Subject Descriptors

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

General Terms

Algorithms, Measurement, Experimentation

Keywords

Water Consumption Monitoring, Occupancy Sensing, Unsupervised Learning

1 Introduction

The world's usable water supply is decreasing at a faster rate than it can be replenished. Household water conservation is important to ensure sustainability of fresh water reserves, to save energy from water treatment and distribution, and to prevent fresh water habitats from being affected through excessive water use [3]. Residents have a number of practical options to conserve water, ranging from replacing high flow toilets and showers with low flow replacements, to reducing water usage for daily activities such as brushing teeth or washing dishes. To make informed decisions that maximize water savings, households first need a detailed understanding of how much water is used by each appliance and water fixture in the home.

Water utilities are increasingly installing smart water meters that provide real-time access to household water consumption, and 31 million smart water meters are expected to be installed by 2016 [2]. However, these meters are installed at the water mains and only provide aggregate water usage, primarily for billing purposes. *Disaggregation* is the problem of deciding how much of that usage is due to individual fixtures in the home. For high flow appliances such as washing machines, dishwashers, and sprinklers, existing flow trace techniques can be used to uniquely identify their usage time and water consumption [13]. However, monitoring the usage of multiple sinks, toilets, showers, and other fixtures that produce similar rates of flow in a home setting, is challenging. For this reason, existing disaggregation techniques require additional sensing on the water piping infrastructure, and/or a manual characterization of each water fixture [7, 8, 9, 11]. These techniques can be expensive, difficult to deploy, and time consuming.

In this paper, we present the WaterSense system that performs fixture-level disaggregation of smart water meter data using only simple motion sensors. Motion sensors are inexpensive ($5 each for X10 motion sensors [4]), easy to install, and already prevalent in many homes as part of home security or home automation systems. WaterSense does not require any additional sensing infrastructure on the water pipes or fixtures, and disaggregates fixtures in an unsupervised manner that does not require the collection of training data. The WaterSense technique is based on two basic insights: 1) fixtures with similar flow signatures (e.g. identical toilets) are often in different rooms, and 2) fixtures in the same room often have different flow signatures (e.g. a toilet vs. bathroom sink). Based on these insights, WaterSense clusters all water usage events based on both flow signatures *and* motion sensor signatures, and each of these clusters represents a unique water fixture in the home. One limitation of this technique is that it is not likely to differentiate two identical fixtures in the same room, such as double sinks in a bath-

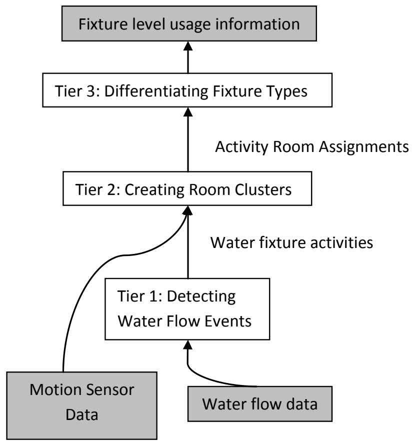


Figure 1. WaterSense uses a three tier inference algorithm to find 1) water flow events 2) clusters of flow volumes that often co-occur with certain motion sensors, and 3) different types of fixtures in the same room.

room. However, such distinctions may also be less important for the purpose of water conservation decisions. We use a novel Bayesian clustering algorithm to create robust clusters despite noise in the motion sensor data caused by both wireless packet loss and multiple residents moving in multiple rooms simultaneously. We deployed the WaterSense system in two different, natural home environments for 7 days each and found that the system can disaggregate flow at the water mains to individual fixtures with an average 86% classification accuracy.

2 Related Work

Several approaches have been proposed in the literature to infer fine-grained water fixture use in homes. The most basic approach is to use flow signatures, such as flow rate, flow duration or, in the case of high flow appliances such as washing machines and sprinklers, patterns of flow to identify types of fixtures and appliances [13]. However, flow signatures alone cannot disambiguate between different instances of identical sinks, toilets, or showers in the same home. Fogarty et al. [7] use microphones installed in a basement to classify water fixture use, and achieve good accuracy in identifying high consumption appliances, but low accuracy in differentiating between different instances of the same fixture category. Another recent approach [11] uses vibration sensors on pipes to disaggregate total flow measured at a central location in a novel, unsupervised manner. Both of these techniques, however, require additional sensing of the water infrastructure, which may require access to pipes in crawl spaces or walls. Furthermore, microphones and accelerometers are more power intensive than motion sensors and would either have a short battery life or would require wired power.

Froehlich et al. [8] avoid extensive sensing by using a single water pressure sensor that samples at 500Hz, plugged into a free spigot or water outlet in the home. However, this approach requires significant training data on the order of several days in a real world setting [9] to achieve high accuracy in inferring individual water fixture events. Our approach is an unsupervised technique that does not require training data.

3 WaterSense System Design

In this section, we describe both the underlying sensing components and the three tier inference approach used by WaterSense to infer fixture-level water usage from the water flow data stream and occupancy data streams. The WaterSense algorithm uses a three tier approach, as seen in figure 1, and the sensor components shown in figure 2. In **Tier I**, we perform edge detection on the water flow data stream, matching rising edges and falling edges to compute a sequence of water flow events. In **Tier II**, we present an algorithm that groups flow events based on the motion sensors with which they often co-occur. A key challenge is that motion sensor data is very noisy due to (i) false positives from multiple residents moving in different rooms simultaneously, and (ii) false negatives from low sensitivity on the PIR sensors or wireless packet loss. To address these challenges, we design a Bayesian approach that we call **ELoc** that uses both *instantaneous* and *historical* co-occurence of a each flow volume with each motion sensor. Finally, in **Tier III**, we differentiate the fixtures in each room into different types based on flow signatures.

Throughout this section, we will explain each of the system components in terms of an example involving two simultaneous toilet flush events. The data trace from the events is shown in Figure 3: the top three graphs show motion sensor data from the kitchen and two bathrooms, and the bottom graph shows the total flow levels that must be disaggregated. In this example, Tier I detects four edges with flow rates of 0.3 and 0.6 kl/hour, respectively, and identifies them as two different flow events. Tier II assigns the two water flow events to two different bathrooms based on their temporal proximity to motion sensor data in the two rooms, as well as the historical correlation between these flow rates and these motion sensors. Tier III identifies both flow events as toilets using the flow volume and duration.

3.1 Physical Sensor Components

Our WaterSense approach requires a water flow meter at the whole house water input line, and also motion sensors in each room that contains water fixtures. In our home deployments, we use a Shenitech Ultrasonic water flow meter [1] that uses the Doppler effect to measure the velocity and resulting flow of water through the pipeline. The flow meter reports instantaneous water flow (in cubic meters per hour) at a frequency of 2Hz using the home's Wifi connection to transmit data. We expect that utility water flow meters being deployed in a large scale [2] in homes will have a similar setup. Figure 2(a) shows the installation of the flow meter in one of our home deployments. In addition to the flow meter, WaterSense requires at least one motion sensor in each room containing water fixtures. In our deployments, we use off the shelf X10 motion sensors [4] inside rooms to detect occupancy, as seen in figure 2(b). The X10 motion sensors send a binary ON message whenever motion is seen with a minimal damping interval of 7 seconds between ON messages.

(a) Water Flow meter (b) Motion Sensor (c) Contact Switch for Ground Truth

Figure 2. WaterSense uses a single flow sensor at the water mains (a) and motion sensors (b). Sensors were placed on fixtures for evaluation purposes only (c).

3.2 Tier I: Detecting Water Flow Events

The goal of **Tier I** is to transform the raw water flow time series $F(t)$ (in kl/hour) from our flow monitor to a sequence of timestamped *water flow events* W containing events of the form $W_i = (st_i, end_i, f_i)$, where st_i and end_i denote the start and end timestamps of the event, while f_i denotes the mean flow rate during event W_i. Tier I uses the Canny edge detection algorithm [6] on time series $F(t)$ to compute a sequence of timestamps E^t when potential edges are present. The *edge value* E_i^v for a given edge timestamp E_i^t is then computed as the difference between the median flow rate of the time intervals after and before the edge timestamp given by equation 1 below.

$$E_i^v = |median(F(E_i^t : E_{i+1}^t)) - median(F(E_{i-1}^t : E_i^t))| \quad (1)$$

The rising and falling edges from E are partitioned into two separate sets RE and FE respectively, matched using a min cost bipartite matching approach the Hungarian algorithm [12]). We set each edge value to its absolute value when we partition the edges to rising and falling edges. The edge weight between a rising edge RE_i and a falling edge FE_j is defined to be $-log(p_{ij})$, where p_{ij} is the match probability, obtained assuming a normal distribution on the relative difference between rising and falling edges:

$$p_{ij} = \mathcal{N}((RE_i^v - FE_j^v)/min(RE_i^v, FE_j^v), 0, \sigma) \quad (2)$$

Additionally, we ensure that rising edges occur before falling edges in each match, and that edges from two different water flow events are not matched with each other. Specifically, we set p_{ij} to 0 if (i) $RE_i^t > FE_j^t$, or (ii) $min(F(RE_i^t : FE_j^t)) <= \beta RE_i^v$. Currently, we set parameters $\sigma = 0.3, \beta = 0.5$ that works well across multiple homes. Any unmatched sink edges whose corresponding ON or OFF edges coincide with a flush event, are mapped accordingly to a feasible higher flow event of opposite polarity, if such an event is detected. From the resulting matches (RE, FE), we compute water flow events $W_i = (st_i, end_i, f_i)$ by setting $st_i = RE_i^t$, $end_i = FE_j^t$, and $f_i = mean(RE_i^v, FE_j^v)$. Durations T_i for each water flow events W_i are also computed as $end_i - st_i$ for use in the subsequent inference tiers.

In our example data trace in Figure 3, Tier I infers two distinct water flow events for the two toileting events in bathroom 1 and bathroom 2, with different start and end times. It does this by detecting two rising and two falling edges each with flow rates of 0.62 kl/hour and 0.32 kl/hour respectively.

3.3 Tier II: Creating Room Clusters

The goal of **Tier II** is to assign a room $\hat{r}_i \in M$ to each water flow event W_i computed in Tier I, using both W_i and the set M of relevant motion sensor data streams as input; we design the ELoc Bayesnet shown in figure 5 to make this room assignment. In our current approach, we only consider motion sensors in rooms containing water fixtures. Going back to our example data trace in Figure 3, Tier II correctly assigns water flow events W_1 and W_2 inferred by Tier I to bathroom 1 and bathroom 2 respectively. However, this assignment is not intuitive just from figure 3 alone; both bathroom 1 and bathroom 2 are occupied during the two flush events. Tier II first clusters all water flow events based on their duration and flow rate value, and then computes how likely these clusters are to co-occur with the M motion sensor data streams. Event W_1 with a duration of 54 seconds and flow rate of 0.62 kl/hour belongs to a (0.6 kl/hour, 40 second) cluster that is more likely to be in bathroom 1 than bathroom 2; similarly, the other 0.32 kl/hour flush event is more likely to co-occur with the bathroom2 based on long term evidence. The ELoc Bayesnet, which uses both the instantaneous occupancy evidence from motion sensors, and also the historical room to flow signature likelihoods, accurately assigns the flush events to the two bathrooms. On the other hand, when multiple water fixtures such as flushes across multiple rooms do have closer flow signatures, such as the two 0.5-0.7 kl/hour flushes in Home 2, the Bayesnet can still use the immediate occupancy evidence to match motion sensors to flow events with high accuracy.

In the Bayesnet shown in figure 5, r_i denotes the room of water flow event W_i. D_i encapsulates the temporal distance between event W_i and the $|M|$ motion sensors, while $c_i \in C$ is a hidden variable that denotes the flow signature cluster to which the current event W_i belongs. Each motion sensor stream M^s consists of a sequence of timestamps when motion sensor s transmitted an ON event to our base station. We compute room assignments $\hat{r}_i$ for each event using a maximum likelihood approach:

$$\hat{r}_i = \arg\max_{r_i} \sum_{c_i} P(r_i|c_i).P(W_i|c_i).P(c_i).P(D_i|r_i) \quad (3)$$

We first describe how the variables D_i and the set of water flow clusters C are computed, in order to obtain the three conditional probabilities required in equation 3 above. D_i is composed of two $|M|$ dimensional *binary vectors* D_{i1} and

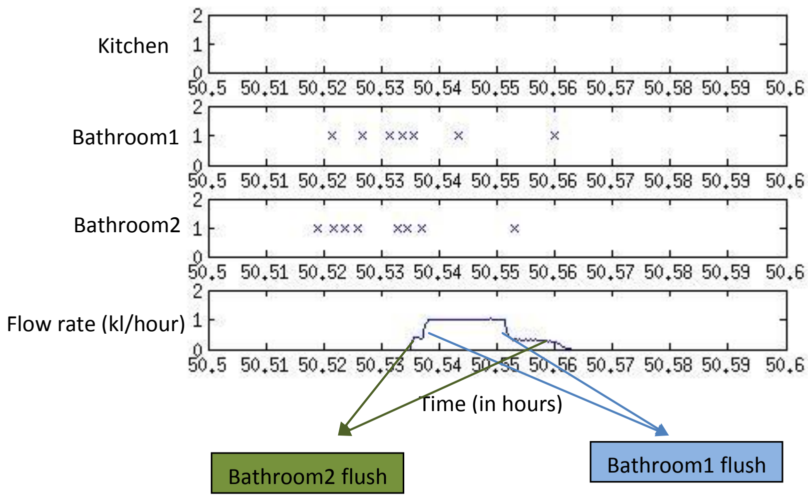


Figure 3. A 6 minute data trace from Home 1 shows the water flow data and binary occupancy data from two simultaneous flush events. Tier I detects four edges with flow rates of 0.3 and 0.6 kl/hour, respectively, and identifies them as two different flow events. Tier II assigns the two water flow events to two different bathrooms based on their temporal proximity to motion sensor data in the two rooms, as well as the historical correlation between these flow volumes and motion sensors. Tier III identifies both flow events as toilets using the flow volume and duration.

Home #	Number of Residents	Number of rooms with fixtures	Number of sinks and flushes	Pipe material and width
Home 1	2	3	5	¾" Copper
Home 2	4	3	5	¾" PEX

Figure 4. Our deployments involved two homes with multiple residents. Both homes had a kitchen sink and two bathrooms with both sink and toilet.

D_{i2}, which denote if the minimal temporal distance between the start time and end time of each water flow event and motion sensor stream M^s is below a threshold time dT (set to 12 seconds in our current approach):

$$D^s_{i1} = (min(|M^s - st_i|) < dT)\forall s \in M \tag{4}$$

$$D^s_{i2} = (min(|M^s - end_i|) < dT)\forall s \in M \tag{5}$$

We assume independence between the binary vectors D_{i1} and D_{i2}, and also assume that the room assignment to motion sensor j is independent of binary vectors D^s_i, when $s \neq j$. Applying Bayes rule and our independence assumptions, we get:

$$P(D_i|r_i = j) = \prod_{k=1}^{2}(P(r_i = j|D^j_{ik}) * P(r_i = j)|P(D^j_{ik})) \tag{6}$$

Currently, we fix the parameter $P(r_i = j|D^j_{ik} = 1) = 0.9$ $\forall j,k,i$, which works well across multiple homes. We currently discount $P(r_i = j)$ as a constant and set the prior probability $P(D^j_{ik} = 1)$ to be proportional to the number of ON events from each motion sensor:

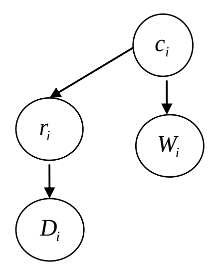
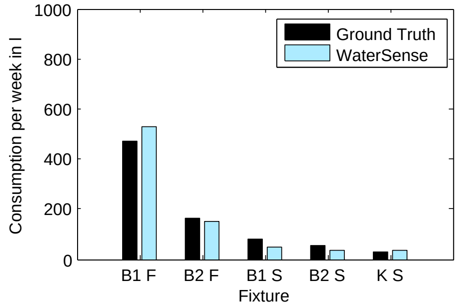


Figure 5. Our ELoc Bayesnet clusters water flow events based on both flow volume and co-occurence with motion sensors.

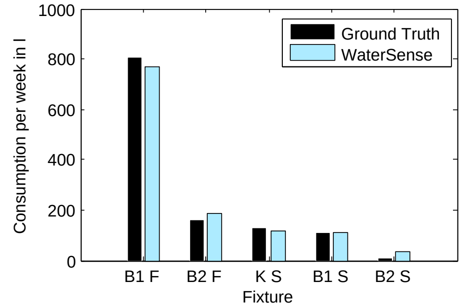
$$P(D^j_{ik} = 1) = |M^j||(\sum_{s \in M}|M^s|)\forall k,j,i \tag{7}$$

We compute the set C of flow signature clusters by clustering the water flow event W_i based on two features: the event duration T_i, and the event value f_i. We use quality threshold (QT) clustering with a fixed relative distance width of 0.25 on both duration and edge value [10]. QT clustering makes a *hard cluster assignment* of $q_i \in C$ to each event W_i. Thus $P(c_i|W_i) = 1$ when $c_i = q_i$ and zero otherwise. In the future, we intend to explore alternative clustering algorithms with soft cluster assignments for use in the Bayesnet.

Finally, $P(r_i|c_i)$ is obtained by first assigning events W_i to rooms rd_i using D_i alone ($rd_i = \arg\max_{r_i} P(r_i|D_i)$), and then computing $P(r_i|c_i)$ using a frequency count on how many events from cluster q_i are assigned to each of the motion sensors in M. If we denote the set of events W_i such that $(rd_i = j \wedge q_i = x)$ is true to be $RC_{j,x}$, and the set of events W_i such that $q_i = x$ to be CL_x, then we get the remaining proba-



(a) Home 1



(b) Home 2

Figure 6. The water consumption feedback provided by WaterSense for the various fixtures monitored in the two homes closely matches the ground truth for most high flow fixtures. End users can use such a display to start considering cost effective ways to conserve water. (B stands for bathroom, K for kitchen, S for sink, and F for flush)

bilities required in equation (3) as:

$$P(r_i = j | c_i = x) = |RC_{j,x}| / |CL_x| \quad (8)$$

$$P(c_i = x) = |CL_x| / |W| \quad (9)$$

From equations (6), (7), (8), (9), and our hard cluster assignments for events using QT clustering, we assign maximum likelihood room labels $\hat{r}_i$ using equation (3). In the future, we propose to learn the parameters for $P(r_i|c_i)$ using a non-linear convex optimization algorithm to maximize the likelihood of observing the sensor data , given by $L = \prod_{i=1}^{|W|} P(W_i, D_i)$. Another interesting direction is to explore alternative distance vector features D_i to potentially improve accuracy further.

3.4 Tier III: Differentiating Fixture Types

The goal of **Tier III** is to infer fixture types, such as a sink or a flush, for each water flow event W_i from Tier I. In the current simplistic implementation, we first infer a flush event cluster FL_j in each room j, if any, by looking for an event cluster contained in that room with an average flow rate greater than 0.3 kl/hour and an average duration greater than 30 seconds, with an event frequency of at least 10% of events from the room. Events belonging to this cluster FL_j are assigned as flush events, while the remaining low flow events are assigned as sinks. The fixture types from Tier III and the room assignments from Tier II together constitute unique water fixtures in the home, and we use these assignments to present users with feedback on the time of use of individual water fixtures distributed around a home. We also provide users with feedback on total water consumption of individual fixtures by multiplying the fixture use durations T_i of each unique water fixture with the corresponding flow values f_i.

4 Evaluation

To evaluate our WaterSense approach, we deploy our system in two homes for 7 days each. Both homes had multiple residents, multiple bathrooms, and a wide array of water fixtures and appliances. Details of the two deployments are summarized in Figure 4. To execute WaterSense in these homes, we deployed a single water flow sensor on the water mains and a motion sensor in each room. In Home 2, one of the motion sensors in a bathroom malfunctioned during our week long deployment, so we used a motion sensor in an adjacent bedroom with a partial view of the bathroom in our analysis. To evaluate the system, we deployed ZWave contact reed switches [5] , as shown in Figure 2(c) to record the actual times that each fixture was used. We compute ground truth water consumption for each fixture by integrating total water flow into the house when each fixture was used. In the case of simultaneous toilet and sink events when we do not observe explicit sink edges, we ignore the short duration usage of the sink. These cases constitute a small fraction of events and we do not believe that it significantly changes the overall water consumption profiles. In this experiment, we installed ground truth sensors on only 3 sinks and 2 toilets in each home and only evaluate accuracy for these fixtures. Other fixtures and appliances were also used during the experiment period, and we observe several anecdotal instances of fixtures such as the shower or the sprinkler system being inferred in these homes. However, we currently limit our evaluation only to those ground truth events observed from the ZWave system. Ground truth events that do not change the total water consumption of the house are ignored, since they do not affect the water consumption feedback to the end user. In the future, we intend to expand our evaluation to a larger set of fixtures and appliances.

The true and estimated water consumption levels for each fixture are shown in Figure 6. The order of the fixtures is sorted based on their actual flow. WaterSense estimated water flow at each fixture with a median accuracy of 81.5% in Home 1 and 89.9% in Home 2. More importantly, however, WaterSense preserves the relative ordering of fixtures in terms of maximum consumption; it correctly indicates, for example, which sink or toilet causes the most water usage. End users can use the output of WaterSense to understand what the high consumption fixtures in their home are. If combined with intuitive displays that show users *when* each fixture was being used, and in which daily *activity*, we expect to provide users with actionable recommendations to save water, such as leaving the sink closed while washing or brushing, or providing low flow replacements for certain showers and flushes. For example, in Homes 1 and 2, res-

Fixtures	K S	B1 S	B1 F	B2 S	B2 F
K S	8	0	0	8	1
B1 S	1	19	0	2	0
B1 F	0	1	49	0	0
B2 S	3	1	0	16	2
B2 F	0	0	0	1	14

(a) Home 1

Fixtures	K S	B1 S	B1 F	B2 S	B2 F
K S	81	10	0	3	0
B1 S	7	78	0	5	0
B1 F	1	0	85	0	5
B2 S	0	1	0	6	0
B2 F	0	0	2	1	13

(b) Home 2

Figure 7. WaterSense accurately classifies water flow events for most of the monitored water fixtures across the two homes as seen in the fixture level confusion matrices. Confusion between fixtures of the same type in different rooms is common due to overlapping occupancy. Confusion between fixtures of different types, such as a sink and a flush, due to overlapping flow signatures, is less common. (B stands for bathroom, K for kitchen, S for sink, and F for flush)

idents might be able to infer that it might be most efficient to replace the high flow toilet in bathroom 1, while in Home 2, residents can also infer that replacing the high flow toilet in bathroom2 would have about the same effect as using the sinks in bathroom1 and the kitchen more efficiently with a better understanding of how they are used.

Figure 7 shows the confusion matrix for classifying individual fixture usage events. We observe that classification accuracy is high for the majority of fixtures in the home. Most misclassifications that did occur were due to simultaneous occupancy in multiple rooms from fixtures with similar flow signatures, such as high confusion between sink usage in the kitchen and bathroom2 in Home 1. In Home 1, we find zero confusion between the flush fixtures in the two bathrooms even in the presence of simultaneous occupancy as seen in the example data trace in Figure 3, while in Home 2, there is about 7% confusion between the two flush fixtures. The reason is that in Home 1, the two flush fixtures have a larger difference in flow signatures (0.3 and 0.6 kl/hour flow rates), while in Home 2, the two flush fixtures have similar flow signatures of 0.6-0.7 kl/hour; the Bayesnet in Home 2 relies more heavily on the noisy instantaneous occupancy than in Home 1, resulting in slightly more errors. In general, these misclassifications do not cause significant degradation in water consumption accuracy because they are infrequent and roughly symmetric across the diagonal, and so they often cancel each other out.

5 Conclusions and Future Work

In this paper, we present an unsupervised approach to infer the fine-grained fixture level breakdown of water consumption in homes by effectively combining cheap occupancy sensors and whole house water flow meter data. Our approach shows significant promise in an early evaluation carried out in two homes over 7 days each, and is able to accurately infer both the time of use and water consumption of individual fixtures. In the future, we expect to build upon the existing approach by performing an extensive evaluation of our system that includes ground truth sensing on fixtures such as the shower, washing machine, and dishwasher to address potential challenges posed due to simultaneous fixture use from these high consumption fixtures. There are also improvements to be made in our inference approach, including fixture identification in Tier III, alternative temporal distance features used in the bayesnet, and additions to the algorithm to handle simultaneous or compound flow events. It would also be interesting to consider non-binary PIR sensors that report the actual intensity of infrared changes, as opposed to the existing binary motion sensors; with non-binary PIR sensors, it would be possible to perform a joint clustering of the flow rate and the infrared intensity, to achieve higher accuracy in identifying individual fixtures within a room, and also better disambiguate cases where there is simultaneous occupancy in multiple rooms. With these additions, we expect our WaterSense approach to be a viable approach to provide fine grained water consumption information and recommendations to end users to help conserve water.

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