Supero: A Sensor System for Unsupervised Residential Power Usage Monitoring

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1. INTRODUCTION

Research [12] has shown that providing the electricity consumption of each appliance to the home owner fosters conservation. Previous power usage monitoring approaches can be broadly classified into *direct sensing* and *indirect sensing* categories. The direct sensing approaches apply in-line power meters [14; 2; 8] in between the appliance and power outlet, which however cannot be used on many permanently installed appliances such as ceiling lights. The indirect sensing approaches infer the power usages by detecting appliances' electricity usage patterns [7; 15; 4; 5] or the emitted ambient signals [6; 16]. As these approaches are affected by the characteristics of electrical wiring and appliances, they need either in-situ labor-intensive training [7; 5] or a comprehensive database of power characteristics of appliances [7; 4]. Although several recent studies [10; 9] aim to achieve autonomous monitoring without in-situ training, they typically require sensors to be carefully installed for each appliance, which may result in high installation cost [11] and reduced usability for non-professional users.

This extended abstract presents the design and implementation of *Supero* – a System for Unsupervised PowER mOnitoring using a smart meter and wireless light/acoustic sensors that are *ad hoc* deployed in the home. However, as homes are a highly dynamic and complex environment, sensors likely produce false alarms or miss important events. Moreover, as the sensors are deployed in an *ad hoc* manner, it is highly difficult to associate an event detected by possibly multiple sensors with the appliance that generates the event. Supero adopts a multi-sensor fusion scheme to mitigate the impact of noise and remove possible sensing errors. By using advanced unsupervised clustering algorithms, Supero identifies the events generated by the same appliance. Moreover, Supero autonomously associates the classified events with appliances through an optimization framework. Provided with a small amount of easily obtained prior information such as sensor-appliance distances and the rated powers of a small subset of appliances, these unsupervised algorithms work together to disaggregate the total household energy consumption to individual appliances.

We implemented Supero using TelosB/Iris motes [13] and a TED5000 smart meter [1], and evaluated Supero in five homes with significantly different square footage and electric power consumption. Long-term (up to 7 days) experiments in an apartment and a ranch house show that Supero estimates the energy consumption with errors less than 7.5%. Our results also demonstrate that Supero can be easily deployed by non-professional users in short time.

*The first two authors are listed in alphabetic order.

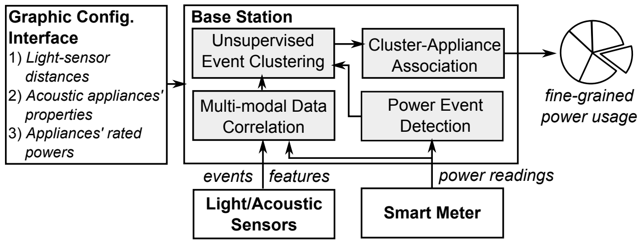

Fig. 1: Architecture of Supero.

2. THE DESIGN OF SUPERO

Supero is composed of a number of wireless sensors distributed in the home, a wireless smart meter, and a base station receiving the information from the sensors and the smart meter. In this work, we only consider light and acoustic sensors while other sensing modalities such as infrared can be easily incorporated by Supero. Fig. 1 illustrates the architecture of Supero. First, sensors sample signals and detect the events that are possibly caused by switching appliances. If a light sensor detects a significant change of light intensity, it sends the event feature, which is the change of light intensity, to the base station. For an acoustic sensor, if signal energy is high, it continuously sends event feature, which includes signal energies and zero crossing counts in four sub frequency bands of the acoustic signal. When Supero is requested to generate a power usage report, the base station executes the following algorithms based on the collected data and the prior information input by user.

2.1 Multi-Model Data Correlation

To deal with the false alarms and miss detections of sensors (e.g., light events caused by opening/closing window blinds and acoustic events triggered by human conversations), we employ a two-tier fusion approach to correlate the multi-modal events from different sensors. In the first tier, the events from multiple sensors of the same modality in a short moving window are regarded to be generated by the same source. This OR fusion scheme can largely mitigate the impact of miss detections of individual sensors. The features measured by all sensors of the same modality are then concatenated to form the *feature vector* for each event. The second tier correlates the results of the first tier with the power measurements from the smart meter to remove false alarms. Specifically, if the change of power at the time of an

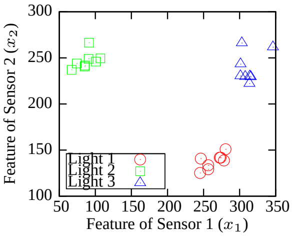

Fig. 2: Features of two sensors and clustering result.

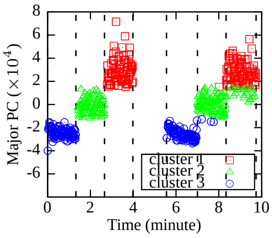

Fig. 3: Clustering result for a 3-speed fan.

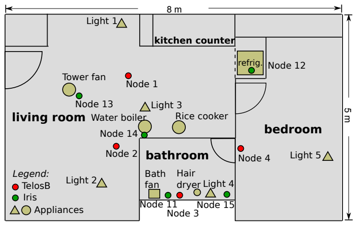

Fig. 4: Apartment deployment.

Appliance	KAW	Supero		
Name	kWh	Watts	kWh	Error
Light 1	4.14	154	4.17	0.5%
Light 2	4.96	150	4.96	0.1%
Light 3	6.15	155	6.24	1.4%
Light 4	1.45	62	1.45	0.1%
Light 5	0.39	105	0.39	0.2%
Boiler	0.48	1493	0.48	0.5%
Tower fan	0.15	30	0.21	50%
Rice cooker	1.00	499	0.98	2.2%
Hair dryer	0.09	467	0.07	19%
Fridge	12.22	143	11.8	3.7%
Bath fan	N/A	50	0.12	N/A
Router	2.12	12	2.03	4.3%
Avg error				7.5%

Fig. 5: Energy breakdown during 7 days.

event is below a small threshold, the event will be discarded. The appliances that cannot be easily or reliably detected by light and acoustic sensors (e.g., rice cookers) are referred to as *unattended appliances*. A significant power change is regarded to be caused by an unattended appliance if there is no simultaneous light or acoustic event. We refer to such power changes as *unattended events*.

2.2 Unsupervised Event Clustering

Due to the *ad hoc* deployment strategy and spatial distribution of sensors/appliances, different appliances can be sensed by different subsets of sensors. For a particular appliance, the feature vectors of the events generated by the same appliance are clustered in the feature space. Fig. 2 shows the feature vectors measured by two light sensors when three standing lights nearby are turned on and off. Fig. 3 shows the major principle component of acoustic feature vectors when a 3-speed fan iterates among all its speed levels. We can clearly see that the feature vectors are clustered. By using unsupervised clustering algorithms (e.g., k-means), the events generated by an appliance can be classified into the same cluster. The colors in Fig. 2 and Fig. 3 represent the clustering results. For acoustic modality, we adopt a Parzen-window-based approach to detect the *time edge* between two consecutive clusters (e.g., vertical lines in Fig. 3), which corresponds to the switching events of acoustic appliances. Supero also classifies the unattended events using k-means algorithm based on the absolute change of power.

2.3 Autonomous Event-Appliance Association

Supero associates the classified events with respective appliances based on event features and prior information. The light intensity measured by sensor i is given by $y_i = \beta P_j d_{ij}^{-\alpha}$, where P_j is the power of light j and d_{ij} is the distance between sensor i and light j, α and β are two coefficients. The association between light clusters and appliances is represented by a binary square matrix A, where the element $A_{m,j}$ indicates whether cluster m is associated with light j. By denoting R_m as the set of sensors that detect the events in cluster m, the error caused by associating cluster m with light j is defined as $e_{m,j} = \sum_{i \in R_m} |\beta P_m d_{i,j}^{-\alpha} - \mu_{m,i}|$, where P_m is the median value of the absolute power changes of the events in cluster m, $\mu_{m,i}$ is the average of light intensity changes measured by sensor i for the events in cluster m. The light cluster-appliance association is formally formulated as: *Find α, β and A to minimize the total error $\sum_{\forall m, \forall j} A_{m,j} e_{m,j}$, subject to that $\forall m, \sum_{\forall j} A_{m,j} = 1$ and $\forall j, \sum_{\forall m} A_{m,j} = 1$.* For fixed α and β, the sub-problem is a linear assignment problem, which can be solved by the Hungarian algorithm [3]. Iterating α and β in their possible ranges yields the final solution. This approach autonomously calibrates the environment-dependent coefficients α and β.

Although acoustic signal also follows the power law, in contrast to light, it is typically a by-product in the operation of appliances. Hence, the coefficient β varies significantly across different acoustic appliances and the linear assignment formulation is not applicable to acoustic modality. Sensor i is *primary sensor* of appliance j if the absolute change of signal energy of sensor i is always the largest when j changes its state and must not be the largest when any other appliance changes state. By identifying the primary sensors according to user's intuition based on the sensor and appliance locations, the events detected by them can be easily associated. The events detected by non-primary sensors are first clustered according to their absolute power changes and associated according to appliances' rated powers. Similarly, the clusters of unattended events are associated according to appliances' rated powers.

3. IMPLEMENTATION AND EVALUATION

The sensors are implemented using TelosB and Iris motes [13]. TED5000 [1] is used to measure the total household power consumption. The base station algorithms are implemented in GNU Octave. We build a couple of radio-enabled Kill-A-Watt (KAW) meters [14], which are applied to each appliance to provide groundtruth data.

We first deployed 4 TelosB and 5 Iris motes in a 40 m^2 single-bedroom apartment (as shown in Fig. 4) to evaluate the accuracy of Supero. The sensors are placed on the floor, table, chairs and toilet. The positions of sensors are not carefully chosen except for tower fan, fridge and boiler, as these appliances cannot be detected even when the sensor is just several centimeters away. Fig. 5 shows the result of a 7-day experiment, during which two residents led normal life in the apartment. In the 7 days, 713 false alarms out of total 859 light events were raised by light sensors, where 703 false alarms are identified by the multi-modal data correlation. From Fig. 5 we can see that Supero can accurately estimate the energy consumption of lights. Two bath fan events were incorrectly associated with the tower fan, because Node 13 (i.e., the primary sensor for tower fan) heard loud noises in living room at the same times. The two false associations introduce errors to the tower fan and hair dryer. The average error of energy consumption is 7.5%.

We also deployed Supero in another 80 m^2 two-bedroom apartment and an 150 m^2 one-story three-bedroom ranch house. The average error in the ranch house is 6.1%. Five different sensor placements in the apartment show that the user has considerable flexibility in choosing the sensor positions. Moreover, we recruited two homeowner volunteers to deploy Supero in their homes including a single-bedroom apartment and a two-story house with basement. They finished the deployment and configuration in 1.5 and 3 hours, respectively. Validation shows that their deployments are able to yield correct sensing results.

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