Office Multi-Occupancy Detection using BLE Beacons and Power Meters

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Office Multi-Occupancy Detection using BLE Beacons and Power Meters

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***Abstract*—Indoor occupancy provides information about human occupation in the closed space, most notably, office and residential buildings. This information is useful in dwindling unnecessary energy usage, such as consumption in unoccupied spaces or energy-wasting due to unnecessarily active appliances. We present an empirical experiment on office occupancy detection using simple office sensors. We choose generic power meters and mobile phones. First, we classify beacon signals received by mobile phones into a room location. A workspace map is assumed to be available to facilitate the mapping between room locations and the occupancy state of users' workspace. Second, we infer the individual occupancy state utilizing the aggregated electricity consumption of occupant-related devices (i.e., monitors) in shared offices. The later solution helps to keep costs and intrusiveness level low compared to deploying a power meter for each device or user. We experiment in an work environment with two shared offices, a personal office, and a social corner involving five volunteers. Given the acquired data, three techniques based on machine learning, optimization, and probabilistic approach are implemented and compared to evaluate their performance. The results indicate that localization and occupancy based on beaconing works best for three of the five volunteers, reaching 95% F-measure. Further findings shows that occupancy inference based on the aggregated power consumption performs well for the four volunteers when using Decision Tree classification, reaching more than 90% F-measure. Our effort on the fusion of two modalities gives a positive result for all five volunteers, ranging from 92% to 99% F-measure.**

***Index Terms*—Context aware, Occupancy detection, Power meter, Bluetooth low energy, Beacon, Office building**

I. Introduction

In the EU, commercial and residential buildings accounted for 40% of total energy consumption and were responsible for 36% of the total CO_2 emissions in 2012 [1]. It was also reported that commercial buildings had the most significant energy use intensity compared to buildings in residential or industrial sectors [2]. These two factors urge researchers to explore strategies for saving energy. A preliminary step to achieve that, is that of having precise information on building utilization. The most basic information to understand utilization is presence.

Detailed building utilization information results in (considerably significant) energy saving [3]–[5]. For instance, Gonzales et al. try to detect occupancy in open space offices using ultrasound sensors installed at each desk [4]. They turn ceiling lights ON only when the presence is detected at the corresponding desks and the outdoor light intensity is below the threshold (i.e., $5000 Lux$). The energy savings of up to 19.01 $kWh/m^2 \cdot year$ has been showed by controlling self-dimming ceiling lights in a room space with nine participants. Milenkovic et al. propose PIR sensors and power meters as sensory sources to detect context of users, such as per desk presence information (e.g., being present or away) and activity information (e.g., having a computer work or desk work) [5]. Through a simulation, it is reported that there is significant saving compare to PIR-based room lighting control. That is, up to 63.2% and 71.2% when we use presence per desk control and activity based control, respectively.

Overall, these studies highlight the need for information on building utilization, specifically occupancy detection, to reduce power consumption. There are several definition of indoor occupancy: (i) the level of occupancy in a building (i.e., people counting) [6], (ii) the binary occupancy state of a space (i.e., being *vacant* or *occupied*) [7], (iii) the number of occupants in a space [8], and (iv) the room location of people [9]–[11]. In a typical commercial office space, Passive Infrared is the typical sensor found to detect occupancy. This type of sensor provides binary occupancy status of a room space with less emphasis on occupant identification and counting (i.e., referring to definition (ii)).

When we look at an office environment thoroughly, one notices that there are several ubiquitous devices that potentially indicate employees' occupancy. For example, a mobile phone carried by a user (e.g., in the pocket or hand) can provide location information, while a monitor on a desk in a fixed workspace can also indicate the presence of the corresponding employee. The exploration of such available sources (e.g., using wireless beaconing or power metering) gives more

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information about occupancy than merely a PIR sensor. It is because the sensory sources are associated to the identification of an individual, giving additional information of who is involved in the observed context. Furthermore, the information tends to be more reliable and fine-grained than mere PIR-based presence detection.

To detect the aforementioned occupancy, beaconing and power metering sensing are required. First, beacon signal sensing needs to be done through a mobile phone to provide relative phone's approximate location to the known anchors. Anchors refer to any devices that transmit signals to mobile devices, such as WiFI access points or Bluetooth Low Energy (BLE) beacons. BLE beacon is a promising anchor as this is small, relatively cheap, so it can be flexibly and massively deployed for localization. Second, the amount of power consumed by monitors or outlet office appliances can be measured by a power meter. The meter can be installed either into each device or attached to the incoming power line. Attaching one meter per device, however, is considered to be very expensive and intrusive for the users (e.g., there will be a number of power meters around the workspace). Since it is common to have a dedicated electricity circuit for PC equipments (for example, to eliminate the risk of outages and to guarantee the quality of power supplied [12], [13]), it is reasonable to attach only one meter in the dedicated incoming power line at the room level. In this way, we can reduce investment costs and keep the level of intrusiveness low.

Nonetheless, the utilization of mobile phones and power meters, which are not originally designed to be occupancy sensors, cannot ensure accurate occupancy detection. An example is when people work with a fully charged laptop and thus do not consume energy from a power outlet. In this case, a system based only on power metering will not be able to detect occupancy. The localization based on wireless beaconing could also suffer from fast fading signals during propagation, making it more challenging to determine a location among adjacent rooms. We thus propose their combination and evaluate a solution using both. The mobile phone beaconing and power metering could be a perfect match that overcomes individual disadvantages as they observe the same objects of interest from different perspectives. That is, mobile phone observation is from an individual perspective, while power meter observation is from the building's infrastructure perspective. To the best of our knowledge, this is the first approach considering the combination of aggregated power metering and Bluetooth beaconing to detect multi-person occupancy in multiple offices, apart from our previous work which explored different scheme of sensor fusion [14].

The goal of the present study is to investigate the power consumption and beacon signals received by mobile phones as an indication of human presence in multi-user offices. We hypothesize that by combining such information, the occupancy detection can be improved in terms of accuracy and details. To test our hypothesis, we apply several techniques and investigate each source as well as the fusion of them in an actual office environment. We finally compare the performance of individual occupancy detection.

The rest of this paper is organized as follows. We introduce system design, methods, and metric in Section II. We describe our experiment in Section III. The result of the experiment and discussion are provided in Section IV. Section V presents the related work covering occupancy detection based on beaconing, power metering, and fusion of both. Finally, we summarize our work in Section VI.

II. Design and Implementation

We investigate several approaches to infer occupancy. Initially, we perform single-label occupancy detection based on BLE beacons reading. We then evaluate the occupancy detection based on power metering, which brings a perspective of occupancy of all employees. Finally, we combine the features of the two sources and input the fused features to a classification technique.

A. Notation

Given a set of individuals $J = \{j_1, j_2, \ldots, j_n\}$, a set of room locations $L = \{l_1, \ldots, l_r\}$, and a set of beacons $B = \{b_1, \ldots, b_d\}$, the signal strength of beacons received by any individual $j_i \in J$ sampled in any discrete time t, $t \subseteq \mathbb{N}$, is measured as a vector $\vec{\beta}_t^{j_i} = [b_1, \ldots, b_d]$. The localization function assigns locations to measurements as a classification problem $f_{loc}(\vec{\beta}_t^{j_i}) = l_t^{j_i}$ with $l_t^{j_i} \in L$.

Let $x_t^{j_i}$ be the power consumption of individual j_i at time t, the aggregated consumption X_t for all individual $j_i \in J$ is defined as $X_t = \sum_{i=1}^{n} x_t^{j_i}$, that is, as measured by a power meter installed in a circuit breaker. The occupancy detection function assigns Y_t to the power reading X_t, that is, $f_{occ}(X_t) = Y_t$, where $Y_t \in 2^n$. Y_t is a class label that represents the presence state of all individuals and can be transformed into binary occupancy state of n individuals, $Y_t = \left\{ y_t^{j_1}, y_t^{j_2}, \ldots, y_t^{j_n} \right\}$, where $y_t^{j_i} \in \{0, 1\}$ represents occupancy state of an individual j_i at time t.

Depending on the portrayal of context observation, classification problems can be defined as follows.

a) Single-label multi-class classification is defined as a task of assigning a single label l to a vector of BLE readings. Any received signal strength (RSS) discovered by a mobile phone uniquely refers to a single room location. Therefore, given the query vector $\vec{\beta}_t^{j_i}$, the task is to build a classifier $h_1 : \vec{\beta}_t^{j_i} \rightarrow l_t^{j_i}$.

Based on a known workspace map (i.e., the map maintained by a building receptionist pointing to an employee's work space in the building), we create a mapping function $m : l_t^{j_i} \rightarrow y_t^{j_i}$, where $y_t^{j_i} = 1$ if and only if location $l_t^{j_i}$ is associated with a room office of individual j_i in the map, and 0 otherwise.

b) Multi-label classification refers to a classification problem associated with a set of labels $y \subseteq \mathcal{Y}$, where $\mathcal{Y}$ is a set of disjoint labels with $|\mathcal{Y}| \geq 1$. Based on a power meter reading at time t, the aggregated power measurement X_t is associated with a set of disjoint labels $y_t^{j_i}$ for all individual $j_i \in J$. We transform the problem by concatenating

TABLE I
AGGREGATED POWER CONSUMPTION X_t FUSED WITH BLES' RSS $\beta_t^{j_i}$ IN FEATURE LEVEL

Instances	fused feature					Y_t
$t = 1$	X_1	$\vec{\beta}_1^{j_1}$	$\vec{\beta}_1^{j_2}$	...	$\vec{\beta}_1^{j_n}$	$j_1 j_2 j_3$
$t = 2$	X_2	$\vec{\beta}_2^{j_1}$	$\vec{\beta}_2^{j_2}$	...	$\vec{\beta}_2^{j_n}$	$j_1 j_2$
$\dots$						
$t = T$	X_T	$\vec{\beta}_T^{j_1}$	$\vec{\beta}_T^{j_2}$	...	$\vec{\beta}_T^{j_n}$	$j_1 j_4 j_5$

the set of labels $y_t^{j_i}$ to $Y_t = \left\{ y_t^{j_1}, y_t^{j_2}, \dots, y_t^{j_n} \right\}$. After the problem transformation, we are able to use traditional single-label classification approaches by treating Y_t as an independent label and building classification models based on Y_t. This approach is known as *label combination* or *label power-set* (LC) method [15] or the Combination Method (CM) [16]. Formally, given the power meter measurement X_t, the task is to build a classifier $h_2 : X_t \rightarrow Y_t$.

Finally, we investigate the fusion of the BLE beaconing system and power consumption measurement to improve the performance of occupancy inference per individual y^{j_i}. We combine the observation of all mobile phones $\vec{\beta}_t^{j_i}$ and aggregated power consumption X_t in feature-level sensor fusion [17]. The RSS from all individuals are concatenated to fit with the measured power consumption which is the consumption of all individuals, as illustrated in Table I.

B. Methods

We implement several techniques based on machine learning, optimization, and probabilistic approaches. A decision tree is adopted as this is a simple supervised technique that can handle high dimensional data without high computational loads. Combinatorial optimization is an optimization algorithm proposed in the Non-Intrusive Load Monitoring (NILM) field, which studies the separation of individual appliances from the aggregated power readings [18]. In addition, we consider a Markov model-based approach that assumes that the occupancy state can be determined only by the preceding state. These techniques are described next.

1) Classification Decision Tree Decision Tree (DT) is an approach assigning observations to the most commonly occurring class of training observations in the region to which it belongs [19]. It works by growing a classification tree using several criteria for making binary splits of the tree.

We utilize DT as this approach is efficient in the inference process once a tree has been built, especially in high dimensional feature sets with many instances. This approach also does not require any distribution assumption, and the classification tree may provide alternative splitting nodes when some beacons do not exist (i.e., due to out of beacon coverage). Furthermore, it performed well in a simple occupancy detection (i.e., in/out of a room) based on BLEs' signals [11].

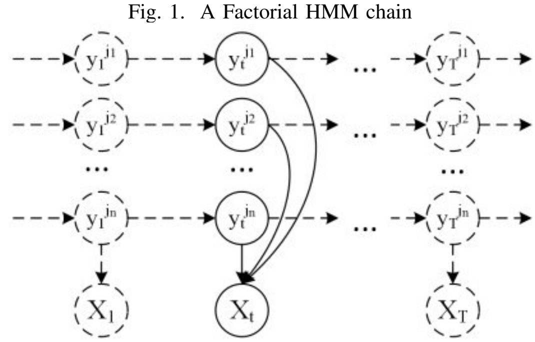
2) Combinatorial Optimization Optimization approaches have been used to investigate aggregated power consumption for loads disaggregation or appliance states recognition, for example [18], [20]. We examine Combinatorial Optimization (CO), an algorithm that finds a combination of states that minimize the difference between the aggregated power readings P_t and the sum of predicted power consumption [18]. Formally, it is defined as:

$$Y_t' = \arg min \left| P_t - \sum_{i=1}^{n} x_t^{j_i} y_t^{j_i} \right| \quad (1)$$

3) Factorial HMM A Hidden Markov Model is a stochastic modeling with unobserved (or hidden) states. The presence of an employee based on his/her power consumption can be regarded as an HMM problem with measured power readings being observable values and presence states as unobserved states (i.e., could be only measured by power energy that he/she consumed). In our case, however, the aggregated power readings are the total power consumption of any employees living in a workspace under measured. Hence, the model needs to be generalized to Factorial HMM [21]. Figure 1 shows the illustration of FHMM chain, where the aggregated power reading X_t is affected by the unobservable presence state of individuals $y_t^{j_i} \forall j_i \in J$.

The exact computation of FHMM can be implemented as the cross product of the state variable of each individual. This computation forms an equivalent HMM chain which each state represents one combination of the employees' occupancy states. Although this approach grows exponentially with the number of occupants, it is still tractable for a few participants, as in this work. The optimal sequence of hidden states can be estimated from the FHMM using the Viterbi algorithm [22].

Fig. 1. A Factorial HMM chain



C. Metrics

To provide a comprehensive evaluation of the occupancy detection performance, we provide measurements of single-label classification and the base class investigation of multi-label classification.

1) Single-label classification The accuracy and f-measure for localization and occupancy inference from individual beaconing system (i.e., per-person) are defined as follows:

- $Accuracy = \dfrac{TP + TN}{TP + TN + FP + FN}$
- $Recall = \dfrac{TP}{TP + FN}$
- $Precision = \dfrac{TP}{TP + FP}$

- $F - measure = 2 \cdot \dfrac{precision \cdot recall}{precision + recall}$
- $kappa = \dfrac{actualAccuracy - randomAccuracy(RA)}{1 - RA}$

In binary occupancy $y_{t,j}$, TP/TN (True Positive / True Negative) is the number of instances for which $present/absent$ are correctly predicted, and FP/FN (False Positive / False Negative) is the number of instances for which $present/absent$ are miss-classified. The performance of a specific room occupancy is then computed using the F-measure as harmonic mean of precision and recall.

In multi-class problems, such as in localization $l_t^{j_i}$, we consider Cohen's kappa. This metric handles multi-class and imbalanced class problems very well [23]. The actual accuracy is defined as the success rate of actual predictor, while the random accuracy is referred as the success rate of random guesses according to the frequency of each class.

2) Base-class evaluation of multi-label classification Multi-label inferences are broke down into individual occupancy using an extension of the single-label measures [24].

Let $Y_t = \{y_{t,j_1}, y_{t,j_2}, \ldots, y_{t,j_n}\}$ be the set of true labels for an instance at time t and $Y'_t = \{y'_{t,j_1}, y'_{t,j_2}, \ldots, y'_{t,j_n}\}$ be the set of predicted labels from classifier h at the same time t. The *hit* $H_t^{y_{t,j_i}} = 1$, if $y_{t,j_i} = y'_{t,j_i} = 1$, and 0 otherwise. Likewise, let the *true condition positive* $\hat{Y}_t^{y_{t,j_i}} = 1$, if $y_{t,j_i} = 1$, and 0 otherwise, and let the *predicted condition positive* $\hat{\hat{Y}}_t^{y_{t,j_i}} = 1$, if $y'_{t,j_i} = 1$, and 0 otherwise. The base-class recall and precision become:

- $Recall(y_{j_i}) = \dfrac{\sum_t H_t^{y_{t,j_i}}}{\sum_t \hat{Y}_t^{y_{t,j_i}}}$
- $Precision(y_{j_i}) = \dfrac{\sum_t H_t^{y_{t,j_i}}}{\sum_t \hat{\hat{Y}}_t^{y_{t,j_i}}}$
- $F - measure = 2 \cdot \dfrac{precision(y_{j_i}) \cdot recall(y_{j_i})}{precision(y_{j_i}) + recall(y_{j_i})}$

III. Experiment

An experiment was done to evaluate the occupancy detection in a real-life office environment. We considered an office space as shown in Figure 2. It consists of two shared offices, one single-occupant office, one social corner, and a hallway interconnecting the spaces. The shared offices were regularly occupied by four PhD students and a postdoc researcher, while the personal office was a workspace of the head of the research group. In the coffee corner, there is a coffee machine, refrigerator, and microwave. None of these appliances are related to the occupancy of specific people as this room is a public space.

In the shared offices with fixed workplaces, we assumed that PCs' power footprints could reveal occupancy states of users. Therefore, we measured the consumption of individual monitor screens using the electricity meter Plugwise[1] Circle [25]. We summed up the measurements to represent an equivalent composite power consumption of target loads (in this case, monitor screens) measured at one single point, as illustrated in Figure 3. The figure illustrates that the unstoppable (i.e., any devices required to operate/stand by at all times, such as a fridge and coffee machine) and non-target appliances (i.e., any power consuming devices that are not related to personal computer activity and thus not showing individual occupancy, such as lighting and heating/cooling system) are connected to the outside of line $L2$. Such a dedicated circuit $L2$ to power computer appliances is useful to reduce the risk of outages, thus improves productivity [12], [13]. We left the appliance arrangements of these rooms, in which, one volunteer may own multiple screens, and several monitors might draw a similar consumption, as shown in Table II. We set the sampling rate to $10s$ intervals to comply with the Dutch National Regulation on smart meters [26]. If some readings were missing, for example when an unexpected failure happened during the measurement, we imputed the last observation up to at most 10 minutes. This is based on the 'unchanged state' belief, which is a reasonable assumption in the occupancy detection based on electricity in a smart office [27].

Fig. 2. Office layout

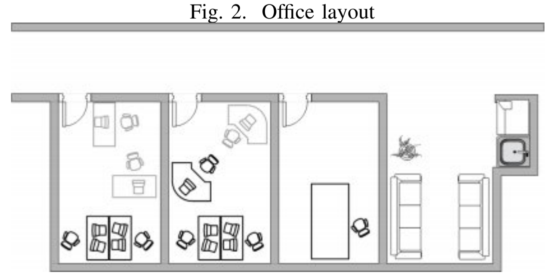
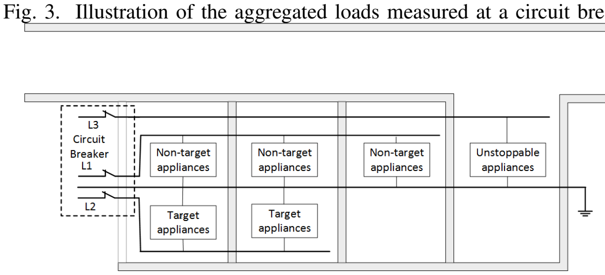


Fig. 3. Illustration of the aggregated loads measured at a circuit breaker



We also equipped the volunteers with a mobile phone installed with an Android application, as given in Table II. The

TABLE II
List of mobile devices and monitor screen power rated

ID	Phone (Android SDK version)	Monitor screen power rated
j_1	S6 edge+ (Android 7.0, API 24)	11.8 W and 21 W
j_2	LG Nexus 5x (Android 7.1.1, API 25)	20.6 W and 24 W
j_3	A5(2016) (Android 6.0.1, API 23)	34.8 W
j_4	Xperia XZ (Android 8.0.0, API 26)	64 W
j_5	Galaxy S3 (Android 4.3, API 18)	14 W

main functionality of the mobile phone is to measure the RSS from the surrounding BLE beacons. There were 12 beacons

[1] www.plugwise.com

from Estimote[2] configured homogenously and installed on the ceiling of the observed rooms (three offices, and a social corner) and hallway. The beacons' signal transmission power was set to -16dBm (i.e., weaker than the default settings to extend battery life) with default 950ms broadcasting interval. The mobile application's scanning and waiting period were set at 1500ms and 5000ms, respectively, to support the detection of occupancy state changes every 5s.

The application also served as a ground truth collector where the users reported their updated location during the observation. To deal with a condition when volunteers forgot with their presence report, we preprocessed the ground truth by comparing presences with the evidence from power consumption measurements. We did manually override any implausible ground truth (e.g., overnight presence due to a forgotten $leaving$ state update). Once the data was cleaned, we need to generate ground truth for aggregated power consumption. Firstly, we find out the associated office room for each individual in the predefined workspace map. We thus transform the location l^{j_i} to occupancy y^{j_i}, $i = 1, \ldots, n$. Finally, the ground truth of overall occupancy Y_t is formed by the concatenation of binary presence state of each individual j_i, forming $|Y_t| = 2^n$.

During the experiment, the mobile application was consistently running (for example, to support users' productivity). We also keep the mobile phones charged whenever volunteers were sitting in their workspace. This is common place for smart office in which a wireless charger is provided on a work desk [28].

To make sure any sensory data (i.e., power consumptions, beacons' RSS, and ground truths) were stored in an appropriate way, we developed gateways that transform specific sensory data format to a generic time series format. We stored the data in an Apache Cassandra[3] database which offers scalability and high availability.

With this setup, we collected data from 1st October 2018 until the 26th October 2018. To avoid over-confidence (i.e., a higher performance due to the easily inferred room vacancy during the night), we only considered working hours, from 7 am to 9 pm. The collected data from power meter is active power, which shows the amount of power (measured in $Watts$) that flows through any power meter plug instances. Beaconing application on mobile phones measures the signal strength from each BLE beacon. The data is an array in which the elements represent the signal strength from any discoverable beacon. We overrode the value of undiscoverable beacons with very weak signal strength, with the default value of -120dBm.

Based on the collected data, we developed classification models and evaluated occupancy inference based on only beaconing, power metering, or a combination of both data sources. The evaluation was on the untouched test data. For a decision tree and CO, we shuffled the data followed by splitting the data into 85% and 15% for train and test set, respectively. For Factorial HMM, as the time sequence need to be retained, we split the first 85% portion of data as a train set and the remained 15% portion as the untouched test set. Furthermore, for the decision tree that requires parameters, we tuned parameters using Scikit-learn RandomizedSearchCV on the training data portion [29]. The aim was to search for the best parameters (e.g., separating criterion, minimum samples leaf, and maximum tree depth) in developing a decision tree in cross-validated train set. For the other techniques, we provided several inputs, such as the number of expected occupancy states per person (i.e., present or absent) for FHMM, and the devices' power rated for CO.

IV. Results and Discussions

Depending on the type of sensors and its observed data, the occupancy detection in an office space was investigated in single-label and multi-label classification. It was then followed by fusing multiple inputs to achieve accuracy improvement in occupancy detection.

A. Single-label classification

A single-label classification approach infers exactly one location of a set of possible rooms in an office. As the inference is based on beacon readings from one mobile phone, it has an *individual perspective*. That is, one sensor (in this case, a mobile phone) shows only the context of an individual.

Table III shows the results of room-level localization and occupancy detection relative to self-owned office based on a decision tree on the RSS data. It can be seen from the table that the result is not always precise, especially for individual j_2 and j_3. The kappa statistic value dropped, reaching 0.56. For these individuals, the mobile phones associated with them occasionally missed beacon measurements. It occurred in a short period (i.e., about 30 minutes) during occupancy. This mistake might be due to a human error (e.g., forgetting to start the application or accidentally stopping the measurement) or system failure (e.g., the application crash or operating system service interruption).

Our further investigation indicated that while the localization of some occupants showed good results (i.e., more than a kappa value of 0.885), the per class f-measure was only average and tended to be not consistent. In the neighboring personal office (i.e., the head of the group's office), individual j_1 and j_4 could be localized with a notable difference performance, that is, 75.8%, and 89.9% f-measure, respectively. While for locating in the social corner, the f-measure for both people were about the same, reaching 68%. Several reasons may affect the results, such as physical room condition (e.g., a door was closed/opened), signals blockage by the human body (e.g., when the phone was located in the pocket), or noises from the environment (e.g., a microwave nearby was operating). These factors are difficult to observe and control, but they can impact the localization results.

When we focused on the occupancy of users' own office (i.e., the 4^{th} and 5^{th} column in Table III), the f-measures for

[2]www.estimote.com

[3]https://cassandra.apache.org/

TABLE III
CLASSIFICATION $\vec{\beta}^{j_i}$ TO SHOW l^{j_i} AND y^{j_i} USING A DECISION TREE

ID	localization l^{j_i}		Occupancy y^{j_i}	
	accuracy	kappa	office ID	f-measure
j_1	.941	.885	A	.948
j_2	.846	.561	A	.646
j_3	.826	.595	B	.706
j_4	.985	.938	B	.955
j_5	.990	.969	B	.975

a specific class were high for individual j_1,j_4, and j_5, reaching 95%. For individual j_2 and j_3, we can see that the self-office detection based on BLE was still limited, only about 65% f-measure. These results indicated that self-office occupancy detection was generally better than localization in terms of correctness. It might be explained that during occupancy, participants stayed for a longer time in their office than in other places. They might put the phones on the table, so there was a line-of-sight between mobile phones and the beacon transmitter.

B. *Multi-label classification*

In multi-label classification, the system has an *overall perspective* of users' occupancy where each label Y'_t represents any combination of individual presence states. Figure 4 shows an output of classification Y'_t based on the aggregated monitor consumption. Each class label refers to a set of individual occupancy labels. It is encoded based on binary numbering system where individuals are sorted in ascending order and represented from the Least Significant Bit (LSB). For example, the encoded label of five individuals are sorted as j_5, j_4, j_3, j_2, j_1, thus label 28 = $[1, 1, 1, 0, 0]$ represents individual j_5, j_4, and j_3 were present.

As it can be seen from Figure 4, the classification became worse when trying to classify several class labels, particularly those which involved the presence of individual j_4. That is, it is apparent from the figure that it happened in class-$8, 11, 24, 27$, and 28, which are classified as class-$0, 3, 16, 19$, and 20, respectively.

To further investigate the performance of individual occupancy detection, we used the base class evaluation proposed in [24]. In this way, we break down Y'_t to compare per individual occupancy, and fuse with different sensory sources. The details are described as follows.

1) Occupancy detection from a total monitor consumption In order to asses occupancy detection based on aggregated monitor consumption, we analyzed the power readings with CO, FHMM, and DT.

Table IV provides the breakdown of occupancy per individual j_i. It can be seen from the table that CO provided the worst occupancy inference for all individuals, reaching about 40% F-measure for individual j_2, j_3, and j_4. FHMM were comparable to DT, except for individual j_3 and j_4 in which DT outperformed FHMM by more than 20% F-measure. For all individuals, DT was the best predictor among the other.

The most interesting aspect from Table IV is that individual j_3 and j_4 were not detected very well. This is consistent with the overall occupancy detection in Figure 4. It means that most of the presence of individual j_4 at the office could not be detected solely based on power consumption footprints. A possible explanation for this might be that the individual j_4 was often in the workspace without using external monitors. This observation may support the intuition that power consumption cannot discover the occupancy of a person who do not leave power usage fingerprints.

TABLE IV
OCCUPANCY INFERENCE BASED ON ONLY PLUGWISE)

ID	Technique	Precision	Recall	F-measure
j_1	CO	0.8496	0.4319	0.5726
	FHMM	0.9923	0.9097	0.9492
	DT	0.9911	0.9728	0.9819
j_2	CO	0.4155	0.3277	0.3664
	FHMM	0.9976	0.8953	0.9437
	DT	0.9696	0.9377	0.9534
j_3	CO	0.4375	0.4548	0.446
	FHMM	0.8837	0.4953	0.6348
	DT	0.9595	0.8416	0.8967
j_4	CO	0.383	0.7084	0.4972
	FHMM	0.3984	0.8081	0.5337
	DT	0.8428	0.6957	0.7622
j_5	CO	0.7763	0.7878	0.782
	FHMM	0.7273	0.964	0.8291
	DT	0.9267	0.9496	0.938

2) Fusion of sensory sources To improve the occupancy inference, we considered the observational data from individual BLE beaconing data and fusion the features. Table V presents the occupancy detection results obtained from only power metering, BLE beaconing, and a fusion of both. It is shown that occupancy detection using BLE on individual j_2 and j_3 was only reaching about 71-79% f-measure. While the detection of j_4 using power metering resulted in 76% f-measure. Surprisingly, the inference output using fused features outperformed classification using either only Plugwise data or BLE beaconing data. It happens for all the five volunteers, reaching 99% f-measure on the detection of individual j_1 and j_5.

These results are likely to be related to incomplete information from one individual source. While the power metering was unable to detect presence in missing sensory readings, the beaconing system also failed when RSS readings were missing in the observation. The feature fusion can improve the occupancy detection performance by taking the benefits from each sensor input.

V. RELATED WORK

Power meters and mobile phones are among ubiquitous devices available for monitoring modern energy buildings and supporting employees in a dynamic working environment. Apart from their basic function as a power consumption measurement device and a proximity marketing, they have also been used for occupancy detection.

Researchers have investigated occupancy in offices by adopting smartphones with the beaconing system due to the

Fig. 4. The confusion matrix of classification Y_t' based on aggregated Plugwise using Decision Tree

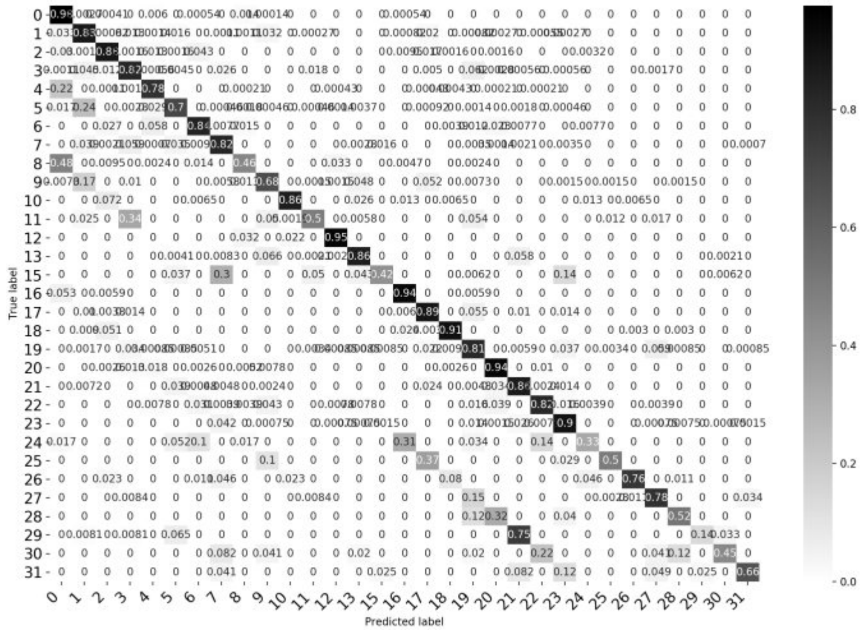


TABLE V
SENSOR FUSION DECISION TREE-BASED OCCUPANCY INFERENCE

ID	Source	Precision	Recall	F-measure
j_1	Plugw	0.9911	0.9728	0.9819
	BLE	0.9843	0.9377	0.9604
	Fusion	0.9883	0.9889	**0.9886**
j_2	Plugw	0.9696	0.9377	0.9534
	BLE	0.8963	0.7155	0.7958
	Fusion	0.9742	0.9508	**0.9623**
j_3	Plugw	0.9595	0.8416	0.8967
	BLE	0.9016	0.5928	0.7153
	Fusion	0.9675	0.8809	**0.9222**
j_4	Plugw	0.8428	0.6957	0.7622
	BLE	0.9809	0.9483	0.9643
	Fusion	0.9661	0.97	**0.9681**
j_5	Plugw	0.9267	0.9496	0.938
	BLE	0.989	0.9647	0.9767
	Fusion	0.9906	0.9889	**0.9897**

proliferation of wireless Bluetooth Low Energy (BLE) technology. Filippoupolitis et al. addressed occupancy detection for emergency management using BLE [30]. The idea was to keep track of the occupancy area of a building so that emergency personnel can reach occupants efficiently in a dangerous situation. They deployed a total of eight BLE beacons in two sectors, each covering about $11m \times 16m$. Of five areas in a sector, the task was to classify an area using *k*-Nearest Neighbor (*k*-NN), logistic regression, and Support Vector Machine (SVM). They proposed average and standard deviation of RSS across moving windows in time-series data as features. They assigned 80% of the dataset as a training set and left the rest as a test set. Finally, the classification results was provided in a confusion matrix. The results indicate that *k*-NN and SVM (radial basis function kernel) was better than linear classifier logistic regression, with accuracy values ranging from 0.74-0.93 in sector two.

In [11], Conte et al. inferred binary occupancy of a room in an office building by evaluating the RSS of beacons. While the two techniques, a decision tree and *k*-NN, provided decent results, the computational loads were the opposite. That is, *k*-NN based solution is heavy as the process needs to scan the entire dataset. In the decision tree, the resource peaked only when it built a tree model. Once the model has been established, the classification in deployment phase is effortless. In our work, we choose to use a decision tree but in a more complex problem. Furthermore, we investigate aggregated power consumption and fusion of both modalities as an option to infer occupancy in an office area.

Choi et al. investigated occupancy in an office using BLE beacons for saving energy in a building [31]. The energy saving was proposed by controlling power states of a PC, monitor, and light based on the occupancy. They investigate occupancy inference based on the detection of event entering/exit region, instead of developing machine learning techniques. Several energy-measurement units were deployed to measure energy consumption during the three-month period of observation. Although they presented the potential energy saving of 31.9% and 15.3% for the PCs and lights, respectively, they did not show the evaluation of occupancy inference performance. Such an evaluation is necessary to make sure the saving effort does not compromise users' productivity and comfort.

Power meters have also been proposed to detect multi-occupancy in a shared office room, either deployed per desk [27] or or per appliance [32]. Akbar et al. investigated occupancy detection of four employees in an office using power meters [27]. The power meters have a capability to observe real power, active power, root mean square of of voltage and current, and phase angle. *k*-NN and SVM with various kernels were implemented to classify three occupancy states, namely away, present, or standby. Generally, k-NN outperformed the SVM models, reaching 94% F-measure using the combination of all the five measurement variables. However, there was no break down of individual occupancy. Compared to our work, the power meters installation in this work were more intrusive as it required one meter per person. Furthermore, we consider a longer measurement data collection and a fusion data with BLE beacons.

Zhao et al. experimented occupancy detection of individual employees in an open office space during the three-month observation period [32]. They attached quite intrusive power meters to any single appliances categorized as computers, task lights, and others (fans, screens, chargers, printers). In total, there were 28 appliances belong to 10 employees measured with plug-based power meters. Based on the measurements, they created machine learning models (e.g., decision tree, support vector machine, and naive Bayes-based algorithm) to detect four states, namely: (i) present with computer work, (ii) present without computer work, (iii) remote computer work without being present, and (iv) absent, no computer work. Given the predicted presence state of each occupant, they applied some regression algorithms to reveal overall occupancy levels in the office. The experiment results indicated that the decision tree algorithm mostly outperformed the other methods in occupancy detection. The average accuracy was 90.29%, and the Kappa statistic value was 0.69. As for occupancy level prediction, the statistical correlation between the prediction values and the ground truth values showed the correlation coefficient of 0.95 by using appliance consumption data. While the reported results are pretty decent, the initial cost to invest scales with the number of appliances to be monitored. Furthermore, they did not consider fusion with other sensory modalities that prospectively improves the prediction. This is particularly useful in the case of detecting an employee being present without using power consumption (e.g., reading a book without using a task light).

Finally, our empirical investigation about fusing has been presented to fuse the two sensory sources to obtain more precise occupancy detection than the individual can serve [14]. It showed that the fusion can slightly improve occupancy, but not always. In this work, we proposed to fuse the same sensory modalities at an early stage (i.e., before inferring a local decision), by combining the features of each source.

VI. Concluding Remarks

The experimental evaluation indicated that BLE based occupancy detection generally performs better in personal offices rather than in other rooms (e.g., a neighboring office and social corner). The reason is that people spend relatively more time in their own office during work hours, giving more stable signals during occupancy. The drawback of this modality is when mobile phones do not receive beacon signals (which happened more frequently for two out of five volunteers). In this case, the mobile phone might assign *out of observation* state, which results in false negatives. This may become problematic when too aggressive energy saving mode based on false negatives leads to occupants' discomfort.

Power meter based occupancy detection performed reasonably good. The multi-label classification problem was treated as single-label classification, after a problem transformation, known as label combination. The challenge was when a person did not use any appliances, thus did not consume electric power. In this case, the presence will not be detected with the power meter.

Given the measured data from the mobile phones and power meters, we have opportunities to concatenate all feature vectors, followed by inputting the fused vector to occupancy detection techniques. It was shown that this feature-level fusion improved the accuracy of occupancy detection of all individuals. In this case, the drawbacks of each sensory source (e.g., missing beaconing signals and unavailable power consumption fingerprints) can be overcome.

There are, however, several limitations in to the present work. First, the approach is designed to work in a fixed workspace. The reason is that the inferred occupancy based on BLE is relative to occupants' own office layout. Second, the approach relies on the availability of an incoming electricity line dedicated to PC equipment. Without such an installation scheme, more power meter units are required to observe occupancy-related appliances. Third, as the multi-label classification problem (i.e., the detection of J's occupancy labels) is transformed into a single-label multi-class problem (i.e., the classification of 2^J independent classes), there is a tendency to overfit the training data. This because the model cannot learn labels which did not occur in the training data. When the entailed appliances change, the model will change; thus, new training data is required.

Further work is required to establish the viability of automatic appliance signature collection and classification model construction. It is also interesting to investigate the occupancy detection performance in various office settings involving more diverse and more number of office appliances, in other terms, to study the portability of the proposed solution. Furthermore, a thorough investigation needs to be done to observe what affects beaconing-based detection performs differently on some particular person. (e.g., minimizing interference that affects signal propagation and making sure all participants consistently use the application to collect the data during the experiment period).

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REFERENCES

[1] D. D'Agostino, P. Zangheri, and L. Castellazzi, "Towards nearly zero energy buildings in europe: A focus on retrofit in non-residential buildings," *Energies*, vol. 10, no. 1, 2017.

[2] A. Kamilaris, B. Kalluri, S. Kondepudi, and T. K. Wai, "A literature survey on measuring energy usage for miscellaneous electric loads in offices and commercial buildings," *Renewable and Sustainable Energy Reviews*, vol. 34, pp. 536–550, 2014.

[3] P. Jaramillo and O. Amft, "Improving energy efficiency through activity-aware control of office appliances using proximity sensing - a real-life study," in *2013 IEEE Int. Conf. on Pervasive Computing and Communications (PERCOM) Workshops*, March 2013, pp. 664–669.

[4] L. I. L. Gonzalez, U. Großekathöfer, and O. Amft, "An intervention study on automated lighting control to save energy in open space offices," in *2015 IEEE International Conference on Pervasive Computing and Communication Workshops (PerCom Workshops)*, March 2015, pp. 317–322.

[5] M. Milenkovic and O. Amft, "An opportunistic activity-sensing approach to save energy in office buildings," in *Proceedings of the Fourth International Conference on Future Energy Systems*, ser. e-Energy '13. New York, NY, USA: ACM, 2013, pp. 247–258. [Online]. Available: http://doi.acm.org/10.1145/2487166.2487194

[6] A. Schoofs, D. T. Delaney, G. M. P. O'Hare, and A. G. Ruzzelli, "Copolan: Non-invasive occupancy profiling for preliminary assessment of hvac fixed timing strategies," in *Proc. of the 3rd ACM Workshop on Embedded Sensing Systems for Energy-Efficiency in Buildings*.

[7] Y. Agarwal, B. Balaji, R. Gupta, J. Lyles, M. Wei, and T. Weng, "Occupancy-driven energy management for smart building automation," in *Proc. of the 2nd ACM Workshop on Embedded Sensing Systems for Energy-Efficiency in Building*, ser. BuildSys '10, 2010, pp. 1–6.

[8] A. Ebadat, G. Bottegal, D. Varagnolo, B. Wahlberg, and K. H. Johansson, "Regularized deconvolution-based approaches for estimating room occupancies," *IEEE Trans. on Automation Science and Engineering*, vol. 12, no. 4, pp. 1157–1168, Oct 2015.

[9] X. Lu, H. Wen, H. Zou, H. Jiang, L. Xie, and N. Trigoni, "Robust occupancy inference with commodity wifi," in *2016 IEEE 12th Int. Conf. on Wireless and Mobile Computing, Networking and Communications (WiMob)*, Oct 2016, pp. 1–8.

[10] S. K. Ghai, L. V. Thanayankizil, D. P. Seetharam, and D. Chakraborty, "Occupancy detection in commercial buildings using opportunistic context sources," in *2012 IEEE Int. Conf. on Pervasive Computing and Communications Workshops*, March 2012, pp. 463–466.

[11] G. Conte, M. De Marchi, A. A. Nacci, V. Rana, and D. Sciuto, "Bluesentinel: A first approach using ibeacon for an energy efficient occupancy detection system," in *Proc. of the 1st ACM Conf. on Embedded Systems for Energy-Efficient Buildings*, ser. BuildSys '14, 2014, pp. 11–19.

[12] R. Walawalker, V. Iyer, and M. Murthy, "Utility interface and power quality: The flip side," in *Frontiers of Power Conf.* Engineering Energy Laboratory, Oklahoma State University; 1998, 2002, pp. VII–VII.

[13] "Informatics for the clinical laboratory - a practical guide for the pathologist — daniel cowan — springer," https://www.springer.com/gp/book/9780387953625, (Accessed on 05/23/2019).

[14] A. R. Pratama, W. Widyawan, A. Lazovik, and M. Aiello, "Multi-user low intrusive occupancy detection," *Sensors*, vol. 18, no. 3, 2018.

[15] J. Read, B. Pfahringer, G. Holmes, and E. Frank, "Classifier chains for multi-label classification," in *Machine Learning and Knowledge Discovery in Databases*, W. Buntine, M. Grobelnik, D. Mladenić, and J. Shawe-Taylor, Eds. Berlin, Heidelberg: Springer Berlin Heidelberg, 2009, pp. 254–269.

[16] J. Read, B. Pfahringer, and G. Holmes, "Multi-label classification using ensembles of pruned sets," in *2008 Eighth IEEE Int. Conf. on Data Mining*, Dec 2008, pp. 995–1000.

[17] D. L. Hall and J. Llinas, "An introduction to multisensor data fusion," *Proc. of the IEEE*, vol. 85, no. 1, pp. 6–23, Jan 1997.

[18] G. W. Hart, "Nonintrusive appliance load monitoring," *Proc. of the IEEE*, vol. 80, no. 12, pp. 1870–1891, Dec 1992.

[19] G. James, D. Witten, T. Hastie, and R. Tibshirani, *An introduction to statistical learning*. Springer, 2013, vol. 112.

[20] Kosuke Suzuki, Shinkichi Inagaki, Tatsuya Suzuki, Hisahide Nakamura, and Koichi Ito, "Nonintrusive appliance load monitoring based on integer programming," in *2008 SICE Annual Conf.*, Aug 2008, pp. 2742–2747.

[21] Z. Ghahramani and M. I. Jordan, "Factorial hidden markov models," in *Advances in Neural Information Processing Systems*, 1996, pp. 472–478.

[22] L. R. Rabiner, "A tutorial on hidden markov models and selected applications in speech recognition," *Proc. of the IEEE*, vol. 77, no. 2, pp. 257–286, 1989.

[23] J. Cohen, "A coefficient of agreement for nominal scales," *Educational and Psychological Measurement*, vol. 20, no. 1, pp. 37–46, 1960.

[24] "Learning multi-label scene classification," *Pattern Recognition*, vol. 37, no. 9, pp. 1757 – 1771, 2004.

[25] A. R. Pratama, Widyawan, A. Lazovik, and M. Aiello, "Power-based device recognition for occupancy detection," in *Service-Oriented Computing – ICSOC 2017 Workshops*, 2018.

[26] P1 companion standard dutch smart meter requirements. Accessed: Sep. 22, 2019. [Online]. Available: https://www.netbeheernederland.nl/_upload/Files/Slimme_meter_15_32ffe3cc38.pdf

[27] A. Akbar, M. Nati, F. Carrez, and K. Moessner, "Contextual occupancy detection for smart office by pattern recognition of electricity consumption data," in *2015 IEEE Int. Conf. on Communications (ICC)*, June 2015, pp. 561–566.

[28] How qi wireless charging contributes to the world's most sustainable office building. Accessed: Sep. 22, 2019. [Online]. Available: https://www.makezens.com/wp-content/uploads/2015/11/how-qi-wireless-charging-contributes-worlds-most-sustainable-office-building.pdf

[29] F. Pedregosa, G. Varoquaux, A. Gramfort, V. Michel, B. Thirion, O. Grisel, M. Blondel, P. Prettenhofer, R. Weiss, V. Dubourg, J. Vanderplas, A. Passos, D. Cournapeau, M. Brucher, M. Perrot, and E. Duchesnay, "Scikit-learn: Machine learning in Python," *Journal of Machine Learning Research*, vol. 12, pp. 2825–2830, 2011.

[30] A. Filippoupolitis, W. Oliff, and G. Loukas, "Bluetooth low energy based occupancy detection for emergency management," in *2016 15th Int. Conf. on Ubiq. Comp. and Communications and 2016 Int. Symp. on Cyberspace and Security*, Dec 2016, pp. 31–38.

[31] M. Choi, W. Park, and I. Lee, "Smart office energy-saving service using bluetooth low energy beacons and smart plugs," in *2015 IEEE Int. Conf. on Data Science and Data Intensive Systems*, Dec 2015, pp. 247–251.

[32] "Occupant behavior and schedule modeling for building energy simulation through office appliance power consumption data mining," *Energy and Buildings*, vol. 82, pp. 341 – 355, 2014.