Exploring Privacy Breaches and Mitigation Strategies of Occupancy Sensors in Smart Buildings

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ABSTRACT

Occupancy sensors are an integral part of many smart building applications, including energy and space optimizations. However, as more occupancy data is collected at an increasingly fine-grained level, possibilities of potential privacy breaches also increase. In this paper, we propose an attack in which the adversary associates an individual with the occupancy sensor by combining the occupancy data with other public information that could easily be obtained online. We conduct an experiment using real-world data to demonstrate that the proposed attack is not only feasible, but the adversary can efficiently identify a small set of sensor IDs that contains the ID of interest given a relatively small amount of additional information. We also summarize a number of mitigation strategies against the proposed attack.

CCS CONCEPTS

• General and reference → Experimentation.

KEYWORDS

IoT, privacy, occupancy, building

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1 INTRODUCTION

Smart buildings are becoming increasingly prevalent as an integral part of society. Equipped with various sensors and actuators, smart buildings enable automated building controls including light, Heating, Ventilation, and Air Conditioning (HVAC), and space optimization [1]. This results in personalized comfort controls for the

building occupants as well as economic savings for the owners of buildings. However, as more fine-grained data at individual levels are collected for building automation, dangers of potential privacy breach also increase [2].

One type of sensor that has been identified as a potential privacy risk is the occupancy sensor [3]. Occupancy sensors detect presence of an individual which enables dynamic control of light and HVAC systems based on the detected occupancy information. However, the collected occupancy data could potentially be used for inference of individual's occupancy patterns and tracking of individuals [4].

In this paper, we study privacy implications of occupancy sensors in smart buildings. In particular, we are interested in a setting where each individual is given a primary location where the person is expected to be throughout the day, such as cubicles or offices.

In many cases, the automation control is indifferent to the identities of building occupants. For example, detection of a presence is sufficient to trigger the light to be turned on at the sensed location. The automated building control does not require the knowledge of *who* is triggering the occupancy sensor, but only requires the information that a presence is detected at a particular location.

For this reason, the database containing user-identifying information is typically kept separately from the database storing occupancy information, and there is no communication between those databases. Because of this separation, it is easy to believe that unless the adversary compromises both databases, it is difficult to infer the mapping between the set of sensors and the identities of individuals. The findings of this paper demonstrate that maintaining separate databases is insufficient for mitigating privacy leakage from occupancy sensors.

Figure 1: Figure illustrating the privacy implications of the presence data.

Specifically, we make the following set of contributions.

- (1) We propose a new privacy breaching attack in smart buildings when the gathered occupancy information does not

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contain unique identifiers of individuals. In the proposed attack, the adversary combines the sensed occupancy data with auxiliary information which is often public. This attack enables the adversary to identify the sensor ID whose location is associated with the individual, which in turn, leads to leakage of sensitive information (Figure 1).

- (2) We perform an experiment using real-world data to validate the feasibility of the proposed attack. The experiment shows that even with a small set of auxiliary information, the adversary can obtain a significant amount of information regarding the sensor ID at the primary location of the targeted individual.
- (3) We propose a set of mitigation strategies against the proposed attack including the use of differential privacy and time-based encryption and deletion of the stored occupancy data.

2 RELATED WORK

Use of occupancy sensors for various building applications has been a subject of active research for both academia and industry [3, 5–8]. Occupancy-driven building applications include both energy [5] as well as space optimization [7]. As occupancy data is being widely implemented, identifying privacy leakage and developing potential mitigation strategies against the potential privacy breaches have been gaining increasing attention [3, 4].

In [3], an optimization framework was proposed where the goal is to minimize the information regarding the location traces of individuals while guaranteeing performance of the HVAC system. However, the paper starts with the assumption that the mapping between the locations and individuals are available to the adversary.

A differentially private mechanism for streaming data was studied in [9], and the proposed mechanism was implemented on the building occupancy data in [10]. In this work, differential privacy ensures that an occupancy pattern in a particular zone is statistically similar whether an individual is in the zone or not. In this paper, we study the problem of linking an individual and the sensor ID at each presence sensor level.

3 MODEL AND PRELIMINARIES

In this section, we present the adversary and building models. We also define the notations that will be used throughout the paper.

3.1 Building Model

We consider a building that is divided into multiple locations where each location is equipped with a presence sensor. We assume that a presence sensor is capable of inferring whether or not the location is currently occupied, but is not capable of inferring which specific individual is triggering the occupancy. An example of such a sensor would be a motion detector which uses ultrasonic or microwave technologies. Each individual is given a primary location where the individual will be spending most of the time when the individual is in the building. For example, a primary location might be a designated office, a particular room, or a particular cubicle.

The set of presence sensors are denoted as S . Each sensor periodically detects presence in its neighborhood. The occupancy pattern

of sensor $s_j \in S$ at time t is denoted as o_j^t and is defined as

$$o_j^t = \begin{cases} 1, & \text{if sensor } s_j \text{ detects presence at time } t \\ 0, & \text{else.} \end{cases}$$

Similarly, we define $o_j^{[t_0, t_f]} = 1$ if occupancy is continuously detected during the time interval $[t_0, t_f]$ and $o_j^{[t_0, t_f]} = 0$ otherwise.

3.2 Adversary Model

Any application that consumes the occupancy data could potentially use the data other than its intended purposes. The goal of the adversary is to infer the sensor ID that is installed at the primary location of the targeted individual i denoted as s_i . It is assumed that the adversary can query any sensor ID to observe the presence information at any given time t .

The adversary also has a set of auxiliary information of the individual i , which is denoted as $\mathcal{A}_i$. Auxiliary information is defined as occupancy-pattern information that the adversary has about the individual. An example of a piece of auxiliary information is a travel schedule of the individual from which the adversary can infer that the individual was not in the building for a given time interval. Such information is often public information that can easily be obtained from social network sites including LinkedIn¹, where postings may include an individual receiving an award or giving a presentation at a conference. Such information would indicate that the individual was not present in the building on the days when this was posted.

For each auxiliary information $a_i^{[t_0, t_f]} \in \mathcal{A}_i$, we denote $a_i^{[t_0, t_f]} = 1$ if the individual i was known to be in the building during the time interval $[t_0, t_f]$ and $a_i^{[t_0, t_f]} = 0$ if the individual i was known to be absent from the building during the time interval $[t_0, t_f]$.

4 PROPOSED ATTACK

In this section, we propose an attack in which the adversary infers the sensor ID of the targeted individual i with high probability by combining the auxiliary information with the queried occupancy patterns. The main idea of the attack is to exploit the fact that the sensor s_j has to satisfy all the conditions presented by the auxiliary information $\mathcal{A}_i$. An illustration of the proposed attack is shown in Figure 2.

Without loss of generality, we index the set $\mathcal{A}_i$ as

$$\mathcal{A}_i = \{a_i^{[t_0, t_1]}, \dots, a_i^{[t_{n-1}, t_n]}\} \quad (1)$$

$\mathcal{A}_i$ represents the set of auxiliary information obtained by the adversary for individual i . For each item of auxiliary information $a_i^{[t_{m-1}, t_m]} \in \mathcal{A}_i$, define the set $S_m^i \subset S$ as

$$S_m^i = \{s_j : o_j^{[t_{m-1}, t_m]} = a_i^{[t_{m-1}, t_m]}\} \quad (2)$$

In other words, the set S_m^i is the set of sensors such that the corresponding occupancy patterns are consistent with the auxiliary information $a_i^{[t_{m-1}, t_m]}$. Given n auxiliary information, the adversary can construct n such sets, and the sensor s_i has to be in all of the sets $S_1^i, \dots, S_n^i$. Assuming the adversary does not have any a priori

¹<https://www.linkedin.com/>

information regarding s_i , the probability of correctly guessing s_i given $\mathcal{A}_i$ is written as

$$P(\hat{s}_i = s_i | \mathcal{A}_i) = \frac{1}{|\bigcap_{m=1}^n \mathcal{S}_m^i|} \quad (3)$$

where $\hat{s}_i$ is the adversary's estimate of s_i .

Figure 2: Figure illustrating the proposed attack.

5 EXPERIMENTAL STUDY

We conducted an experimental study using real-world occupancy sensor data from an office building.

We selected one zone of the office building for the experimental study which contained 1663 motion detectors. Each motion detector records a binary value of 1 if it senses presence via motion and 0 otherwise. The presence value is recorded every 5 seconds and transmitted to a centralized database. The auxiliary information we considered was daily travel schedules of individuals. The travel schedules used for this study were obtained either with user consent or through public data from LinkedIn. The set of auxiliary information was gathered within the period of 5 months.

For each day, we assumed that an individual was present in the building if person stayed in his or her primary location for more than an hour, which is equivalent to having more than 720 number of 1's in the presence data for one day. The assumption was made to account for triggering of the motion detector by bypassing people or patrolling security guards at night time. If the presence data for a sensor contained less than 720 number of 1's for one day, then we assume that the area covered by the sensor was unoccupied for that day. We conducted our experiment on four employees. For the first case, we used three pieces of auxiliary information.

- (1) The person traveled for two days during weekdays and therefore was not present in the building during the travel.
- (2) The person has not worked during the weekends for a particular month.
- (3) The person returned to work after two days of travel and was present in the building on the third day.

Without any additional information, the probability of correctly guessing the sensor ID that is located at the person's primary location is $\frac{1}{1663}$. After identifying the set $\mathcal{S}_1$ that satisfied the first auxiliary information 1), the cardinality of the set was reduced to 14 from 1663. In addition, after obtaining the intersection $\mathcal{S}_1 \cap \mathcal{S}_2 \cap \mathcal{S}_3$, where $\mathcal{S}_2$ and $\mathcal{S}_3$ are the sets that satisfied the auxiliary information

2) and 3) respectively, the cardinality of the new set was reduced to 9 from 1663. We have verified that the person's primary location (an office space) was indeed one of the nine candidate locations that we identified.

Figure 3 shows how probabilities of correctly identifying primary locations (Equation (3)) change with auxiliary information for all four cases. The horizontal axis is the relative time of the year when the auxiliary information was gathered within the period of five months. For cases 2,3, and 4, the *off* label shown in Figure 3 indicates that the person was not present in the building during weekdays and the *on* label indicates that the person was present in the building. In all four cases, we observed that with two to three pieces of auxiliary information, the cardinalities of candidate sets will reduce to approximately 10, resulting in significant increase of probabilities of correctly identifying the primary locations for all four individuals to approximately 0.1 from $\frac{1}{1663}$.

Figure 3: Figure illustrating the increase of probability of correctly identifying the primary locations given auxiliary information.

In all four cases, it was observed that a person's absence in the building during weekdays significantly reduces the size of the candidate set initially. This is due to two reasons. First, identifying the candidate set of locations that are occupied during weekdays will eliminate almost all sensors that are located in hallways, which are usually occupied during weekdays. Second, since the building chosen for this study does not allow working from home, being absent during weekdays is a rare event.

6 MITIGATION STRATEGY

In this section, we propose a set of potential mitigation strategies against the proposed attack.

6.1 Principle of Least Privilege for Privacy

Principle of least privilege has been widely accepted as one of the governing principles in designing mitigation strategies in security. The principle of least privilege states that the minimum amount of information and resources should be given to a subject in order for the subject to perform required duties. The same principle can be used for privacy enhancement as stated in [11].

For building applications, we need to ensure that only the minimum, necessary level of occupancy information is disclosed. For example, for occupancy-driven HVAC control, the controller only requires occupancy information at the zone level, but does not require the information at the individual sensor level [12].

The adversary could still potentially perform the attack using the zone level occupancy information to at least identify which zone includes the targeted individual's primary location. On the days when the individual is not present in the building, the adversary would expect to observe a decrease in the number of occupants in the zone. However, unlike the attack performed on the individual sensor level, the behaviors of other occupants in the zone would affect the accuracy of the identified sets in (3). It is possible that the decrease in the number of occupants could be due to other individuals not present in the building when the targeted individual is present. Similarly, even when the targeted individual is not present in the building, other individuals that were not previously in the zone could be present, resulting in no change or even an increase in the number of occupants in the zone. Moreover, even if the adversary were able to correctly identify the zone where the targeted individual resides in, k -anonymity [13] will be provided where k is the number of sensors in the zone.

6.2 Differential Privacy

When the occupancy information at the zone level is released, it is possible to implement additional privacy enhancing mechanisms that will provide differential privacy. In this setting, probabilistic noise is added to the released occupancy information to ensure that answers to queries regarding the occupancy level in a zone would be statistically similar even when a single individual is present or not present in the zone [14].

We have implemented PeGaSus [9] on the collected occupancy data to examine how the utility of the occupancy data would change as we vary the parameter ϵ . However, initial results suggest that even for a relatively large value of ϵ , the utility of the gathered occupancy data decreases significantly. Finding the optimal trade-off between the utility and privacy for the differential privacy based mitigation would be part of future work.

6.3 Deletion of Past Information

The proposed attack does not rely on the particular times when the presence data are collected. Whether the presence data was collected in the past or present, any data that matches the auxiliary information would be equally valuable in narrowing down the set of candidate sensor IDs of the targeted individual.

While the past data could be valuable in many applications that rely on predicting future occupancy levels as well as energy consumptions through machine learning techniques, keeping a large amount of past data will provide additional opportunities for the adversary. Setting an expiration time on the gathered occupancy data and either deleting or encrypting it automatically at the time of expiration will provide additional privacy against the proposed attack by eliminating the occupancy data that correspond to auxiliary information in the past.

7 CONCLUSIONS

In this paper, we studied privacy implications of occupancy sensors in smart buildings. We have proposed a privacy breaching attack in which the adversary combines the gathered occupancy data with auxiliary information, and identifies the sensor ID that is installed at the primary location of the targeted individual. We have

validated the feasibility of the proposed attack using real-world data where we have demonstrated that even a small amount of auxiliary information is sufficient to greatly reduce the set of sensors that the targeted individual's sensor ID is located in.

We have also proposed mitigation strategies against the proposed attack. The principle of least privilege can be used as a governing principle in providing the right level of information to various applications. Differential privacy and deletion of past occupancy data could also be used to enhance the privacy of the building occupants. However, the exact details of implementing the mitigation strategies will differ from application to application. A systematic approach of determining the exact parameters of the mitigation strategies will be part of future work.

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