A distributed PIR-based approach for estimating people count in office environments

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***Abstract*—Office buildings are key energy consumers and thus require attention to achieve efficient operation. While individual office spaces are dynamically used, current building automation does not receive information on utilisation that could be used to adaptively adjust energy consumption. In this work, we propose an approach to estimate people count per office space using distributed strategically placed PIR sensors and algorithms that can process the distributed sensor information.**

We detail our sensing node and evaluate its performance in an office installation. A sensor model was subsequently used in a floor-wide simulation of realistic occupant behaviours to investigate two algorithms to estimate people count per office space. The occupant behaviour simulations confirmed that our estimation algorithms can accurately predict people count in different office use scenarios. The errors introduced by the PIR masking time after a detection can be partially compensated when using distributed sensor information. Our approach can be used for dynamic, occupancy-dependent lighting, climate, and appliances control of office spaces.

I. Introduction

Buildings contribute significantly to global CO_2 production and energy consumption, consuming more than 40% of produced energy in many world regions [4]. While current building automation integrates information from the smart grid, weather conditions, and seasonal changes in controlling energy-consuming building facilities, occupant activity is widely ignored. In particular, dynamic behaviour patterns of occupants in using office spaces, such as office rooms, pantry areas, etc., are hardly considered for energy saving beyond light-switching motion detectors. Nevertheless heating, ventilation and air conditioning (HVAC), lighting, and appliances could be adaptively and individually controlled per office space, using short-term (even hourly) changes in occupant usage patterns.

For office lighting control, studies have shown that adaptively controlled lighting through motion detectors indeed reduces power consumption [3]. Nevertheless, large office buildings could benefit from various further information to balance energy consumption and occupant needs: office space condition, such as temperature, air exchange, airflow, and ambient light level, depend on size and the number of people currently present in the space [2]. Thus, by estimating people count per individual office space, building control systems could adjust climate and building appliances. Estimating people count as occupants move between office spaces is however more challenging than estimating presence for light control only. Besides the concurrency of multi-user movement and large size of office spaces, installation and maintenance costs are critical design constraints. Thus, a sparse sensing concept is needed using inexpensive ambient sensors that moreover could be retrofitted into older office buildings. In contrast, current approaches to person tracking that could be used for people counting typically require a dense sensor infrastructure or require devices to be worn.

In this paper we present a sensing concept based on passive infrared (PIR) sensors to estimate people count per office space, such as a section or complete office desk room, hallway, etc. By positioning pairs of PIR sensors, we identify occupants' movement direction. Using a distributed sensor architecture, people count can be estimated per office space. To minimise installation and maintenance efforts, our prototyped PIR sensor nodes use solar energy harvesting. An intrinsic limitation of PIR sensors is the sensor masking time after a movement was detected. In this work, we leverage from the distributed sensing of office space passages to compensate for this limitation.

In particular, this work makes the following contributions:

1) We present a building-distributed sensing concept and system architecture using pairs of inexpensive PIR sensor nodes to estimate concurrent occupant movements and count people at office space gateways. We initially evaluate the sensor and sensing concept in an office prototype installation and determine the nodes' detection performance.
2) To validate our people counting approach and test different scenarios, a simulation environment is introduced. By using simulations, we could explore occupant behaviours at different sensor error conditions. For this purpose, PIR sensor model parameters have been derived from the performance measured in the office installation.
3) We propose two distributed algorithms to estimate people count. While the first algorithm considers the directional information obtained from PIR sensor pairs only, the second algorithm deals with PIR sensor masking time too. Based on office floor simulations, we illustrate the performance of both algorithms.

Previous energy consumption analyses confirmed that space use information is a key information source. For example, information from PIR sensors has been often used for controlling the office lights. Lelkens [5] used PIR sensors, Plugwise power meters, and light sensors for calculating energy consumption of lighting systems. Following measurements during a one year period, 31% of energy could be saved by using lights only when presence was detected. A similar approach was used in [3], where energy consumption was optimised based on human activity and ambient and artificial lighting conditions, where 58.6% of energy in open plan offices and up to 70.9% in corridors were saved by controlling lights only.

This paper is organised as follows: Section II describes related sensing and estimation approaches to the people counting problem. Section III introduces the distributed system architecture and people count estimation algorithms. In Section IV the design and evaluation of sensor node prototypes and an office door gateway installation are briefly described. Section V introduces the simulation environment and evaluations used to benchmark the people counting algorithms. Section VI concludes our work.

II. Related Work

Various in-building sensing concepts have been established to monitor presence and movement. Passive infrared (PIR) sensors are very popular as they are mass-produced at very low cost. Most commonly they have been used for in-building and homes applications to detect presence and movement in order to directly switch lights and appliances. In contrast to other sensors such as ultrasound rangers or infrared light distance sensors, PIRs have very low power consumption. Compared to surveillance cameras, PIR sensors need minimal maintenance for long-term use in large buildings.

Agarwal et al. used PIR sensors in addition to reed contacts to determine the state of doors and controlled the HVAC system based on data derived from both sensors [1]. The PIR sensors were used as battery-operated presence detectors where no directional information was derived. Wren and Tapia presented an approach were PIR sensors were coupled into arrays forming a 27-node network [11]. The network was used for observing occupant movements in hallways and walkways. In their work it was feasible to detect turns and accurately determine occupant trajectories at the expense of a dense battery-powered sensor network installation. In contrast, our approach aims at estimating the number of occupants per office space using a sparse energy-harvesting PIR sensor nodes placed at key building locations to minimise installation cost and maintenance effort.

Directional information is challenging to derive from the PIR sensor output directly. In the past there have been efforts to modify off-the-shelf PIR sensors to derive direction. For example, Zappi et al. [13] modified the Fresnel lens that sits on a sensor so that the analog output of a sensor differs depending on the movement direction. With a modified lens the analog output showed two slopes with opposite polarity which depends on the direction of passing. Implementing this approach requires a custom adaptation (modification of the lenses) for a large number of sensors. Furthermore, following this approach would require to continuously sample the analog sensor output with a micro-controller, which is critical for a sensor node that is solely powered from solar harvesting. Therefore, we aimed to use the sensor's digital interface and unmodified off-the-shelf PIR sensor component.

Various probabilistic methods have been used for tracking. Among tracking algorithms that are able to maintain multiple simultaneous hypotheses, particle filtering has been considered. For example, in [12] particle filters were used to track selected individuals throughout building spaces. Tracked individuals were located by maximizing the similarity between a reference and a candidate window of a camera image. While the particle filters produce good results for continuous movement with a constant velocity, their performance is decreasing when the tracked subject takes turns or stands still. In contrast to the frequent tracking of individuals using probabilistic methods, people count estimation in our work requires simultaneous path estimates of all occupants within the monitored building space. Thus, in a multi-user setting, the state space of the particle modelling approach would drastically increase if directly applied.

In our approach, simulations of sensors and occupant behaviour is an essential tool to estimate the feasibility of tracking and people count estimation algorithms. Different pervasive system simulation environments exist already that investigate sensor placement and operations, but cannot be adapted for the our purpose. For example, the work presented by Poland et al. in [7] introduces a simulation environment that helps developers to determine the optimal sensor distribution. Their approach proposes a solution which is aiming at optimal sensor placement in smart homes to support the elderly. Poland et al. proposed a 3D virtual reality simulator using a computer games engine. The simulator emphasized visualisation and accurate representation of space in which a person moved. For the consideration in our work though, it was essential to build various floor maps and abstract space and time parameters for sensor and occupant behaviour models.

The work of Tabak [8] focused on tracking and counting people in buildings through simulation, to predict their next actions. The approach presented by the author used RFID-based solution to keep track of individuals' location. In contrast, our approach does not aim to recognize and track identified individuals. Instead, we aim at an anonymous path estimation in order to derive a people count per specific building space. Moreover, due to the public or semi-public nature of many office buildings, we target a monitoring solution that does not require occupants or visitors to wear batches or active tags.

III. In-building PIR-based people counting

For estimating people count in offices, key information can be obtained from occupant movement direction. Based on the detected movement direction at all gateways in a given building section, occupants can be counted. In our analysis, we considered one floor as a relevant building section. In this section we further detail our sensing and people count estimation approach, adapted for distributed operation in large-scale office buildings.

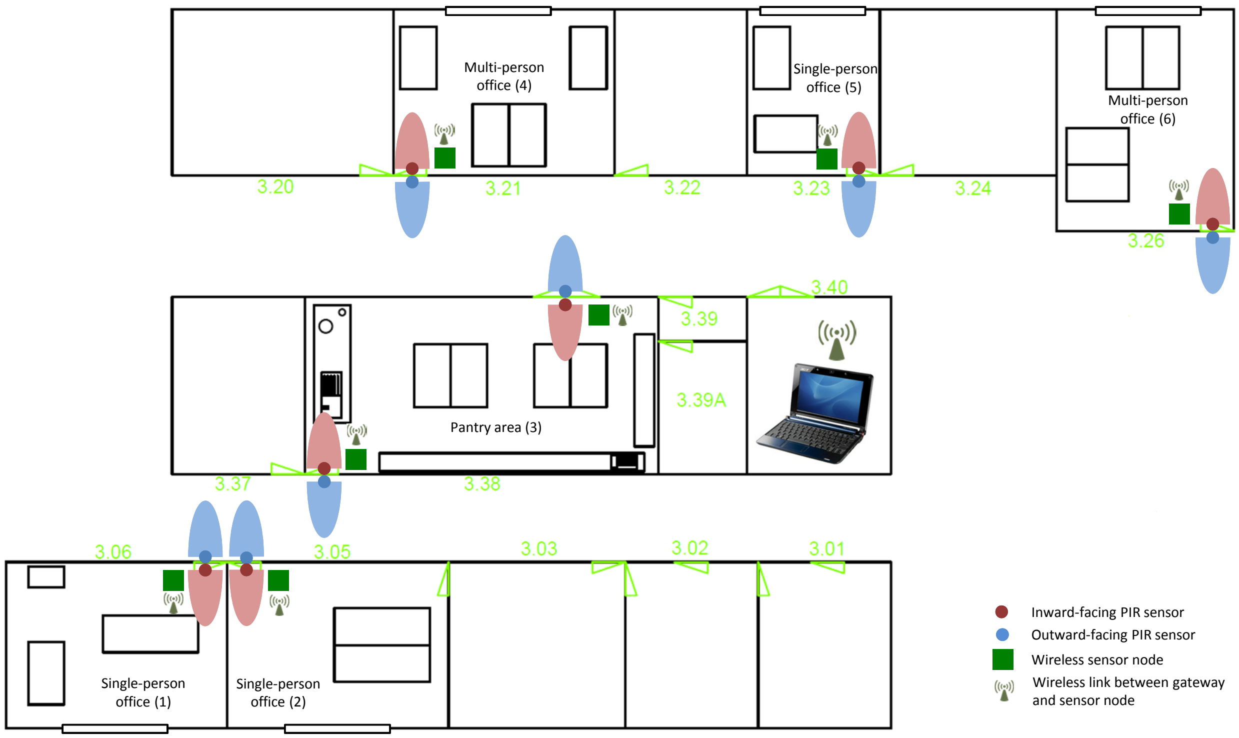

Figure 1. Illustration of the distributed PIR sensor configuration used for estimating people count in office buildings. To minimise installation and maintenance costs, we considered wireless self-powered sensor nodes mounted in pairs at physical and virtual gateways, such as doors or hallway sections. The example floor shown here was used to evaluate our approach in simulations of occupant movement patterns.

A. Sensing principle to detect movement direction

To count people per office space, we consider a sparsely distributed network of inexpensive PIR sensor nodes, installed in pairs. When located at gateways within building structures, the sensor pairs can be used to detect movement direction. Gateways are typically established according to building requirements related to HVAC control and other building services, including doors, passages, and hallway sections interconnecting stretches of office rooms. Besides physical gateways, our approach supports virtual gateways, e.g. sections in open office spaces or dividers in larger hallways, as explained below.

We use pairs of uni-directional PIR sensor nodes in order to observe the two passage areas around a gateway. Hence, people passing through the gateway would enter into both PIRs' fields of view in sequence. Based on the timing of motion events reported by the PIR pair, movement direction can be discriminated.

In our architecture, two PIR sensors can be distinguished based on their location: sensors facing corridors or hallways can often capture occupant movement activity between office spaces. We refer to these PIR sensor nodes as outward-facing. In contrast, inward-facing nodes are pointed towards the inner side of an office space. An office space with multiple gateways, such as a pantry area with more than one door, will be equipped with sensor pairs for each of its gateways. All nodes form a distributed network for movement direction monitoring. The motion events of each PIR sensor node are wirelessly transmitted to an access point for processing. In this work, we consider a building with regular office room structure at each floor for our evaluation. Figure 1 illustrates an example floor, in which the sensing architecture is depicted.

Standard commercial PIR sensors that contain Fresnel lenses can provide a wide viewing angle. Nevertheless, uni-directional operation - as it is needed for our approach - can be realised by mounting nodes at the top of door frames. Hence, the door frame constrains the sensor's view. Similarly, virtual gateways can be implemented, e.g. by mounting omni-directional PIR pairs with ceiling deflectors in between, using PIRs without lenses, or PIRs with narrow field of view.

B. Directional movement modelling approach

Based on their operation principle however, PIR sensors can incur errors in movement detection. PIR sensor errors include event insertions, e.g. due to heat fluctuations at windows and installed heating. Thus, insertions often correspond to random errors in PIR sensors. In addition, motion events could be deleted, e.g. due to missed movements or wireless transmission failures. Deletions could be regarded as resulting from systematic errors mostly, e.g. due to sensor design, selection, and deployment issues. Moreover, PIR sensors have a masking effect after registering a heat change/movement. During this masking time, the sensor cannot detect further movements, which could result in motion event deletions, e.g. if more than one person passes through a building gateway.

To achieve accurate people count estimates, both error types must be compensated. Here we investigate two different algorithms that use motion events from distributed PIR sensor as input, to dynamically estimate people count per office space. In our approach, PIR sensor nodes are permanently installed in an office building and node locations are known. Our algorithms use sensor location details, such as the nodes' distance to compensate for errors in motion event reporting and moreover to deal with concurrent activities.

We consider the set of sensor nodes and arrangement by the superset $\mathcal{X}_F = \{\mathcal{X}^{(1)}, \mathcal{X}^{(2)}, \ldots, \mathcal{X}^{(N)}\}$, where $\mathcal{X}_F$ is the set of nodes in the considered building, or building section, such as a floor. The sets $\mathcal{X}^\star$ contains all sensor nodes within an office space, e.g. a desks room. An office space may be assigned a set of k node pairs $\mathcal{X}^\star = \{\{x_1^\star, x_2^\star\}, \{x_3^\star, x_4^\star\}, \ldots, \{x^\star_{(2k_\star-1)}, x^\star_{(2k_\star)}\}\}$. The total number of sensor nodes in $\mathcal{X}_F$ is $N_S = \sum_{i=1}^{N} k_i$.

A basic concept of our counting process is to determine occupant movement direction at gateways. To this end, we used the PIR sensor node setup, where pairs of inward-facing and outward-facing nodes are deployed. Figure 1 illustrates this approach for the office building considered in this work, where $k^\star \geq 1$ for any considered office space. Furthermore, each PIR sensor node was assigned to exactly one office space using a constant assignment vector R with size $N_S \times 1$.

To investigate different algorithms, we obtain a continuous observation sequence of motion events $x(t)$ in the temporal interval $[t_i, t_n]$ with $i \leq n$ from $\mathcal{X}_F$, as shown in Eq. 1. For simplicity, we denote each motion event by $x(t)$ and omit the office space annotation. Our algorithms however consider the office space to which a node is associated using the assignment vector R. This allows us to determine people count per office space.

$$s = \{x_i(t_i), x_{i+1}(t_{i+1}), x_{i+2}(t_{i+2}), \ldots, x_n(t_n)\} \quad (1)$$

The operation of our people counting algorithms can be separated into three subsequent online tasks: *segmentation*, *path estimation*, and *people count update*. Segmentation is used to partition the continuous stream of motion events (from Eq. 1) for further processing. Based on segments obtained, the path estimation task identifies occupant movements between office spaces. Eventually, people count per office space is updated based on the estimated path. Our people counting approach is illustrated in Figure 2.

C. Direction-based algorithm

Using the directional information obtained from inward and outward PIR sensor node pairs directly is a trivial option to count people per office space. Our approach in direction-based counting follows from the firm positioning of nodes at gateways (as illustrated in Fig. 1). In this configuration the timing sequence of a PIR sensor node pair reveals movement direction. Following from the detected movement direction, the people count of affected office spaces is updated. This approach was used as a baseline in our evaluations to determine the performance benefit of further people counting algorithms.

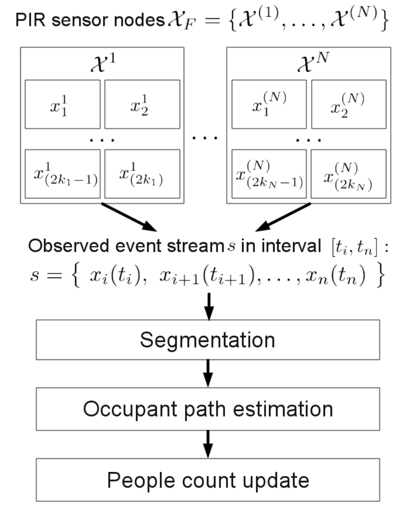

Figure 2. Concept of distributed PIR-based people counting. We consider sets of PIR sensor nodes $\{\mathcal{X}^{(1)}, \ldots, \mathcal{X}^{(N)}\}$ per office spaces, such as office desk rooms. In this work, two algorithms are described for motion event stream segmentation, occupant path estimation, and estimating people count.

Segmentation and path estimation. In the direction-based counting approach, motion event stream segmentation and path estimation can be performed simultaneously. Here a path is considered as an atomic movement between two adjacent office spaces via a gateway, e.g. from an office room to a hallway. The segmentation is implemented by searching for motion event pairs in s such that for $i \neq j$:

$$s_{i,j} = \{\ x_i(t_c),\ x_j(|t - t_c| \leq \Delta t)\ \}\ . \quad (2)$$

Here, t_c marks the segment start, which is followed by a second motion event of another node within time span Δt. Δt determines the search window of the segmentation. For practical implementation, we considered small Δt settings below 2 s since the PIR sensor node pairs were considered to be located in adjacent positions around a gateway.

To identify complementing sensor pairs assigned to the same office space, a sensor node pairing matrix S was used. S has size $N_S \times N_S$ and contains count increments/decrement values $1, -1$ that were needed to update the total count per office space. For example, $S_{1,2} = 1$ and $S_{2,1} = -1$, if $x_1^{(r)}$ and $x_2^{(r)}$ belong to the same office space r. In contrast $S_{a,b} = 0$, if x_a and x_b have not been assigned to the same office space.

People count update. Using matrix S, the relative count update can be determined. In addition, the count is assigned using the vector R.

D. Probabilistic distance-based algorithm

Most occupant movements in office buildings aim to transfer from one room to another. Hence, movement paths could be regarded as initiating and concluding in particular office spaces. When counting people, these defined start and conclusion criteria could help to compensate for erroneous motion events reported by PIR sensor nodes.

In the probabilistic distance-based algorithm, we consider movements as paths that start and end in office spaces. When an occupant's movement extends across multiple office spaces that each satisfies our path conclusion criteria, the path is segmented into two subsequent paths. Since we aim at tracking movement of multiple occupants concurrently, parallel paths need to be started and maintained open by the algorithm until the path conclusion criteria is met.

In order to match motion events related to path starts and ends, we consider a distance metric describing the spatial relation of sensors. The sensor distance can be interpreted as follows: if a PIR sensor pair that is spatially close to an open path transmits a corresponding direction event, the new events may conclude an open path. If several open paths with short distance co-occur, this concept may not suffice. Thus, we use the spatial distance only to initially filter relevant paths. While being spatially close, paths still have different relevance, where some paths are used more frequently than others. Thus, path probabilities are used to eventually select a path's start and end. For example, a secretary office room may be visited from certain desk areas pertained to work-related interactions of occupants, while the pantry area may be visited by many occupants at similar frequencies. Finally, we include a check for PIR masking-induced deletion errors in the probabilistic distance-based algorithm before estimating people count.

Segmentation. Path starting and conclusion is determined by inward-facing sensors of office spaces, thus we use a vector S_{Seg} of size $N_S \times 1$ to denote the set of possible start and end sensor nodes. To segment a path s_P, we require that for $t_i < t_n$ the following conditions hold:

$$\begin{aligned} \text{Path start:} \quad & s_P : \quad S_{Seg}(x(t_i)) = 1 \quad \text{and} \\ \text{Path conclusion:} \quad & s_P : \quad S_{Seg}(x(t_n)) = 1\ . \end{aligned} \tag{3}$$

Path estimation. To derive a movement path online, all paths are filtered at segmenting events. Since there is a physical lower bound on how much time is needed to walk from one PIR sensor to another, a temporal distance map T of size $N_S \times N_S$ is used to filter relevant paths for a considered path conclusion. To select relevant open paths for $x_j(t_j)$, we search all open paths for those paths $s_T(x)$, which achieve the minimum distance with regard the the latest concluding motion event pair $S_{Seg}(x(t_x))$:

$$s_T(x) : (t_x - t_i) \geq \Big[T(S_{Seg}(x(t_i)), S_{Seg}(x(t_x)))\Big]. \tag{4}$$

To select the best matching path s_P, the path with the highest probability is chosen from $s_T(x)$:

$$s_P : \max_{s_T} \Big[p\big(\ S_{Seg}(x(t_i)), S_{Seg}(x(t_n))\ \big)\Big], t_i < t_n\ .$$

The path is eventually concluded by observing $x(t_n)$. In a practical setting the conclusion criteria may be never met, if a concluding motion event was lost due to an error. We used a timeout to close paths that were maintained open for extended time periods. The setting used here is described in Section V-A.

```
if length(cList) == 1 then
    k ← cList(1, 1)
    noUses(k) + +
    noUses(length(noUses)) + +
else if length(cList) > 1 then
    minUses ← ∞
    minUsesId ← 0
    maxProb ← −∞
    maxProbId ← 0
    for k = 1 → length(cList) do
        if cList(k, 3) ≤ minUses then
            minUses ← cList(k, 3)
            minUsesId ← cList(k, 1)
        end if
        if cList(k, 2) ≥ maxProb then
            maxProb ← cList(k, 2)
            maxProbId ← cList(k, 1)
        end if
    end for
    if noUses(maxProbId) == 0 then
        k = maxProbId
        noUses(k) + +
        noUses(length(noUses)) + +
    else if noUses(maxProbId) > 0 then
        maxProb2 ← −∞
        maxProb2Id ← 0
        for k = 1 → length(cList) do
            if cList(k, 3) == minUses ∧ cList(k, 2) ≥ maxProb2 then
                maxProb2 ← cList(k, 2)
                maxProb2Id ← cList(k, 1)
            end if
        end for
        k = maxProb2Id
        noUses(k) + +
        noUses(length(noUses)) + +
        if noUses(maxProb2Id) > 1 then
            roomId ← SRmap(idToTrigger(k))
            rooms(roomId) − −
        end if
    end if
end if
```

Algorithm 1: Pseudo code of the path revision step used in the probabilistic distance-based algorithm to compensate for PIR masking-induced deletion errors.

People count update. The people counting per office space is updated based on the identified path and its start and concluding motion events x_i and x_n using the space assignment vector R. To deal with PIR masking-induced deletion errors and obtain correct people count estimates when masking errors occur, an additional path revision step is performed. In this revision step, we show how the algorithm can correct masking-induced errors originating from more than one person leaving a room simultaneously. Paths estimates that do not have individual starting segmentation points are corrected if path obtained similarly high probabilities. Algorithm 1 shows a the revision step in pseudo code.

By considering PIR sensor location in occupant movement paths, the probabilistic distance-based algorithm can deal more robustly with event errors compared to the simpler direction-based counting approach. For example, if an the motion event of an outward-oriented sensor node is not detected, the direction-based counting algorithm would fail to derive the direction and cannot update the people count. Moreover, paths that occur concurrently and in close spatial relation could be identified as path probabilities were considered. The path probabilities could be obtained by observation. Finally, by considering paths from start to end, the algorithm maintains a global view when selecting the minimum distance and maximum probability.

IV. Self-powered sensor node design and evaluation

An essential feature of our approach is that PIR motion sensors can be inexpensive and easily installed in buildings using wireless operation and energy harvesting. To confirm that the directional movement detection and people counting can be realised under these constraints, we designed a sensor node prototype and evaluated its operation. This section reports the node design and evaluation results.

A. Sensing principle and node architecture

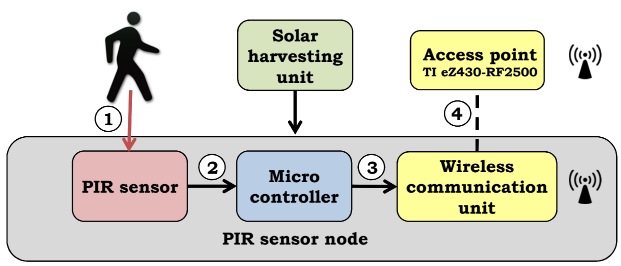

Figure 3. Block scheme of the PIR sensor node and energy harvesting unit design and operation principle. When a person passes the PIR sensor's field of view (1) a trigger is received by a micro-controller (2), forwarded as PIR motion event to the wireless unit (3), and eventually transmitted to a remote access point (4).

Figure 3 shows the sensor node architecture including key components. Each time that a person passes the sensor's field of view, a trigger is expected (1) due to emitted body heat in the infrared light spectrum. The toggling PIR sensor component triggers a wakeup of the micro-controller (2). The micro-controller composes a data packet and forwards it to the wireless communication module (3) for subsequent transmission. The wireless communication unit sends the message through the wireless channel to a remote access point (4). After completing the transmission, the micro-controller and wireless module will go to sleep mode again. A detailed description and evaluation of the sensor node has been shown in [9].

PIR sensor node selection. PIR sensors use a pyroelectric sensor to measure infrared radiation [6]. When passing through the sensor's field of view, a person's emitted body heat causes the sensor to trigger. The main characteristics of PIR sensors are angle, shape, and radius of the field of view, power consumption, as well as their masking time after triggering. For the approach targeted in this work, we considered ultra-low power PIR sensing components, which trigger for motion in the direct sensor vicinity (within 5 meters). We used the EKMB1101112 from Panasonic in this work, which has a current consumption of $\approx 1\mu A$ when operating in stand-by.

Processing and wireless communication. We used a TI MSP430 F2274 micro-controller in the prototype node. For wireless communication a eZ430-RF2500 module was used that provides the TI CC2500, operating in the 2.4 GHz ISM band. The used PIR sensor provides a digital output, which allowed us to trigger a micro-controller interrupt if a person is detected. While waiting for an interrupt the micro-controller was put into sleep mode.

Energy harvesting design. Solar energy harvesting has been found suitable for energy scavenging in office environments [10]. While office desk rooms are well lit spaces, the harvesting in corridors is frequently limited due to dimmed artificial lights. We used a separate solar energy harvesting unit connected with a power cord to the PIR sensor node. One harvesting unit could be used to power pairs of PIR sensor nodes simultaneously, while being effectively positioned facing lighting sources. For the prototype design, we used a harvesting unit from CYMBET. We experimentally confirmed that our prototype could process and transmit 361 triggers without recharging. We found this number sufficient for continuous operation solely relying on solar harvesting as under normal working conditions it is possible to harvest from sunlight or artificial light.

B. Per-space system evaluation

In order to verify the sensing approach an experiment was conducted. Over a period of two days, a pair of PIR sensors was mounted at the gateway to an office used by three people. To derive ground truth, the gateway area was monitored using a video surveillance camera. This experiment was designed to determine characteristics of the selected PIR sensor and the motion event insertion and deletion rates for a realistic number of occupants as these are important parameters for the simulations.

Video recordings were reviewed to determine entry, exit and passing movements. In total, 369 entry and exit movements were observed. In a preliminary study where a PIR sensor connected to a counter was mounted to the ceiling in order to estimate how many triggers could be expected in one workday, we measured 388 triggers per day on average. Insertions and deletions were reported per time unit and having a duration of one second as they are independent from the number of movements. The results showed $\approx 0.67\%$ insertions and no deletions which indicates that the PIR sensor node prototype can robustly identify movement in a real setting and could be used for people counting.

V. People counting simulations

To explore the different algorithmic approaches for estimating the people count per office space, we implemented a simulation environment. We performed simulations for an office building floor containing several office rooms, as well as other spaces under known sensor error rate conditions. The sensor model was derived from the PIR sensor node characteristics derived from measurements, as described in Section IV. In this section, we detail the simulation environment, the simulated occupant activities considered, and the people count estimation performance.

A. Simulation environment

We found that simulations of office spaces are an affordable and fast method to compare different people counting algorithms and investigate the impact of sensor errors. In our approach, the simulation environment allows us to configure a floor map reflecting an actual office environment. In this map, sensors and occupants can be placed during initialisation. We realised the concurrent behaviour pattern of occupants through dedicated batch scripts, denoting an individuals movement pattern. While moving through the virtual office environment, a person will trigger PIR sensors when passing their field of view. If a sensor was triggered, the motion event information is stored in a log file together with a time stamp.

We observed in the sensor study described in Section IV that PIR sensors incurred insertion errors and had a masking time behaviour. We captured these properties in a sensor simulation model. We assumed a masking time of $\sim$2 s.

We plotted the floor maps with sensors and occupants during the simulations for illustration and investigating particular algorithm behaviour. Figure 4 shows this visualisation for the initial state of our simulated office scenario. The floor plan was configured corresponding to the dimensions of office building floor plan described in Sec. III.

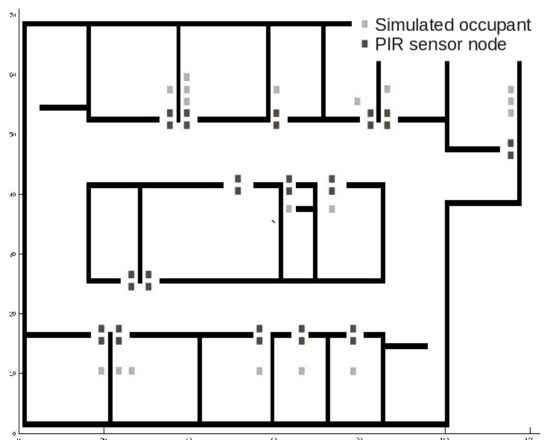

Figure 4. Initial state of the simulation.

B. Simulated occupant activities

For our simulation, we incorporated a variety of typical office situations, such as single persons visiting each others and a meeting of several occupants. Table I summarises the situations considered in the simulation.

C. Performance analysis

In order to obtain performance figures for both algorithms, the scenarios described in Table I were simulated for different motion event insertion probabilities (from 0% to 5% in steps of 1%). Motion event deletions have not been considered. This behaviour can be considered realistic, given the PIR sensors used in our prototype design. For each step in insertion probability the simulation was repeated 100 times to average across random error occurrences. For each of these simulations, the number of false decisions was derived and summed up for all repetitions. Figure 5 illustrates the results of the simulations.

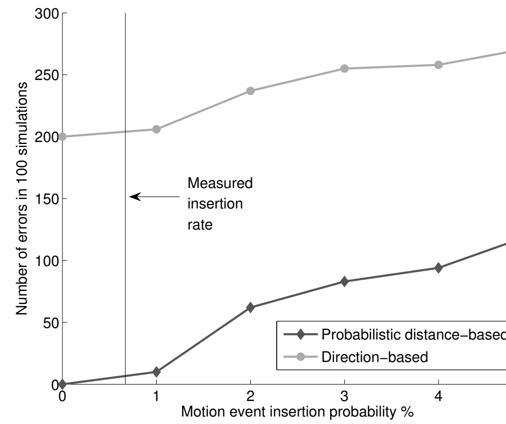

Figure 5. Simulation results for both algorithms. The results show that the probabilistic distance-based algorithm outperforms the direction-based algorithm for all error probabilities. The insertion probability observed in the evaluation using our prototype hardware is shown as vertical line.

The results show that the probabilistic distance-based algorithm outperforms the direction-based algorithm at all insertion rates. This result is mainly influenced by the meeting scenario, where the direction-based algorithm incurs errors for persons returning from the meeting due to the masking time of the sensor. These errors are shown as offset of 200 wrong decisions at 0% motion event insertion probability for the direction-based algorithm. In contrast, the probabilistic distance-based algorithm does not take wrong decisions at 0%. At 5% motion event insertion rate, the direction-based approach makes 272 wrong decisions, while the probabilistic distance-based approach makes 121 wrong decisions. This result indicates that the latter algorithm still performs twice as accurate compared to the direction-based approach.

Figure 5 also shows that the probabilistic distance-based approach gains wrong decisions faster than the direction-based approach for increasing insertion probability. This result can be interpreted since the probabilistic distance-based algorithm tries to correct masking-induced errors of the sensors. Therefore, if an insertion completes a motion event pair this algorithm would more likely make wrong decisions, resulting in less robust performances than the direction-based approach. However, our experimental measurements confirmed that the insertion rates achieved with our prototype hardware were very low ($\approx$ 0.67%). At these low insertion probabilities, the probabilistic distance-based algorithm performed stably.

VI. Discussion and Conclusion

In this work we introduced an approach to estimate people count per office space, which is a key information to adaptively control large office buildings. To our knowledge, this investigation is pioneering in estimating people count using a sparse, unmodified PIR sensor installation.

Scenario 1: Mixed tasks (accounting for $\approx 47\%$ of the total simulation time)			
Person No.	**Simulated activity**	**Sequence of visited offices**	**Correct PIR motion event sequence**
1	Getting coffee	1-3-1	1-2-14-13-13-14-2-1
2	Visiting secretary, passing through pantry area	11-7-2-7-11	23-24-16-15-13-14-4-3-3-4-14-13-15-16-24-23
3	Visiting supervisor	15-13-15	31-32-28-27-27-28-32-31
4	Getting coffee	15-7-15	31-32-30-28-26-24-22-2-4-14-13-15-16-32-31
Scenario 2: Chatting without entering a room (accounting for $\approx 28\%$ of the total simulation time)			
Person No.	**Simulated activity**	**Sequence of visited offices**	**Correct PIR motion event sequence**
1	Getting coffee	1-3-1	1-2-14-13-13-14-2-1
2	Visiting secretary, passing through pantry area	11-7-2-7-11	23-24-16-15-13-14-4-3-3-4-14-13-15-16-24-23
4	Chatting with supervisor without entering the room	15-15	31-32-28-28-28-28-28-28-28-32-31
Scenario 3: Meeting of 5 persons (accounting for $\approx 25\%$ of the total simulation time)			
Person No.	**Simulated activity**	**Sequence of visited offices**	**Correct PIR motion event sequence**
1	Getting coffee	1-7-1	1-2-14-13-13-14-2-1
2	Attending meeting	11-13-11	23-24-26-28-27-27-28-26-24-23
3	Attending meeting	15-13-15	31-32-28-27-27-28-32-31
4	Attending meeting	15-13-15	31-32-28-27-27-28-32-31
6	Attending meeting	11-13-11	23-24-26-28-27-27-28-26-24-23

Table I
OVERVIEW OF SIMULATION SCENARIOS CONSIDERED.

By using a real-life test deployment in an office building, we obtained performance figures for our sensor prototypes. The results confirmed our approach to direction detection and thus the potential for people counting per office space. Subsequently we used empirically obtained PIR sensor characteristics to explore the performance of two people count estimation algorithms in an office floor simulation. Our simulations confirmed that the probabilistic distance-based algorithm can outperform a more simple direction-based counting.

The simulations helped to confirm the robustness of our algorithms. For deletion and masking time errors, the direction-based algorithm makes one error for each deletion while the probabilistic distance-based algorithm compensates these error types. For insertion errors above 1%, both algorithms incur errors. However, we consider that these large error ratios do not appear in real systems as confirmed by our measurements in Section IV-B: For both algorithms, inserted triggers would have to arrive in a temporal sequence to result in wrongly detected paths. Furthermore, for our probabilistic distance-based algorithm, insertions would have to happen on two gateways to satisfy the temporal distance criteria.

We found that the simulation provides helpful insights into the algorithms' performance under varying concurrent occupant movement scenarios, which would be challenging to explore otherwise. The PIR masking effect appeared as the most prominent error source, which can be compensated at the insertion error ranges expected for this setup.

Our people counting approach could be applied in any (office) building including larger open office spaces, where subspaces can be defined using virtual gateways. The estimated people count per building space is a key information to dynamically control building systems related to HVAC and lighting.

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