Estimating Crowd Distribution using Smart Bulbs

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***Abstract*—Many IoT applications require the knowledge of crowd distribution, particularly in indoor scenarios. To this end, we leverage the lighting grid infrastructure in buildings by using smart light bulbs, which can include variety of sensors, in these grids. The exponentially increasing adoption of smartphones and the Wi-Fi infrastructure has motivated us to tackle this problem using Wi-Fi. As we seek a solution that works in many buildings, relying on active user participation or installing apps is not an option. Therefore, we need a Wi-Fi based crowd distribution estimation technique that is non-participatory and non-intrusive, and works with very few Wi-Fi packets generated by users' smartphones sporadically.**

We approach the problem by analyzing the Wi-Fi packets for counting people (smartphones) and estimating their position within a pre-defined accuracy. To this end, extensive experiments are conducted in a real-world testbed with controlled settings as well as in test setups in office spaces with no control. We propose improvised counting techniques that results in people counts close to 75% of the ground truth. We further propose improvements to range-free localization techniques to refine the position estimation accuracy and reduce the execution time. Our algorithm estimates the location with an accuracy of 2m 74% of the time, when Wi-Fi sniffers are placed in bulbs every 4m in the grid.

I. Introduction

The knowledge of crowd distribution is important for various smart applications in the Internet of Things (IoT). Estimating crowd distribution opens up possibilities for various location based services. The estimation involves finding the number of people and their approximate location within a given area. In recent times, Wi-Fi based localization and counting methods have been popular due to ubiquity of Wi-Fi infrastructure and the increasing adoption of smartphones by people [1] has motivated us to design a non-intrusive system that can infer crowd distribution by tracking smartphones that people carry with them.

There has been significant development in the smart lighting domain for IoT. Many sensors can be embedded into bulbs because of the advancements in microelectronics. Thus our approach is to incorporate Wi-Fi sniffers into smart light bulbs as part of the lighting grid of a building such as an arena concourse or an auditorium in order to estimate the crowd distribution within a bounded area. Each light bulb sniffs for Wi-Fi signals in its vicinity. The data from a number of such sniffer bulbs is combined to estimate the overall crowd distribution of the area.

Specifically, we are interested in knowing the distribution of people within a bounded indoor space. As we seek a solution that works in many buildings, relying on active user participation or installing apps is not an option on the users' phones. Therefore, we work with Wi-Fi sniffing data obtained from smart light bulbs. In order to estimate crowd distribution

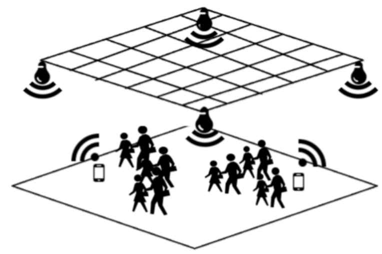


Fig. 1: Smart bulbs with Wi-Fi sniffers to estimate crowd distribution.

effectively with few packets, we need to design a system that can infer people count as well as their position within a given area. The area is divided into pre-defined square cells such as 3m×3m, 4m×4m or even larger cells. As the Wi-Fi sniffers will be part of lighting grids of the indoor space, several constraints apply on the system.

- Due to the passive nature of Wi-Fi sniffing, the number of packets received and the frequency at which packets arrive may not be consistent over time and the devices.
- As we wish to be non-intrusive and non-participatory, we do not attempt to increase packet generation rate from smartphones by injecting packets into the network.

We also deal with several challenges as we aim to estimate crowd distribution based on Wi-Fi sniffing data from unmodified smartphones.

- Due to an increase in the number of devices with Wi-Fi interface considerable errors will be introduced if we use the sniffed data without any filtering.
- As the Wi-Fi signal strength depends on several factors including the physical environment, counting and classifying people if they are within a small cell size precisely is challenging.
- The number of packets generated by a smartphone depends on its current configuration. Therefore, counting people and position information must be done with just a few frames, whose signal strength can vary vastly due to several unknowns in the system such as transmit power, orientation and antenna characteristics of the smartphone.
- Finally, the same solution must work in different buildings (i.e., different radio propagation environments).

In order to estimate crowd distribution using the passive Wi-Fi sniffers in the lighting infrastructure, we divide the problem into two: counting people (or unique smartphones) within the required cell sizes, and estimating their positions. As the deployment will be large areas, cost of the deployment is also a concern as bulbs with sensors are quite expensive. Therefore, we also look to minimize the deployment cost by minimizing the number of sniffers without sacrificing the accuracy. Specifically, our contributions are as follows.

- We propose an improved people counting algorithm with efficient filtering mechanisms to estimate people count within a given area, and avoid devices from adjacent cells.
- We adopt range-free localization techniques and propose enhancements to the localization algorithms in order to refine the position estimation accuracy and reduce the execution times.
- Extensive deployments and tests are done in office spaces and a real-world testbed (Wilab2 [2]), to show the effectiveness of our approach.

The rest of the paper is organized as follows. Section II briefly describes the related work. Section III describes the people counting method using Wi-Fi sniffing data and the results obtained. Section IV covers position estimation methodologies and proposed enhancements to improve the accuracy of localization and the extensive evaluation in testbeds. Section V presents the concluding remarks.

II. Related Work

Section II-A provides an overview of participatory techniques involving use of wearables and smartphone applications. Section II-B describes different techniques which do not require any participation from people in the crowd.

A. Participatory Techniques

These techniques require co-operation from people in the crowd in order to estimate the number of people in a given area. The participation can be in the form of wearing devices or installing a third-party application that allows them to be tracked.

Acer et al. [3] use battery powered wearable Wi-Fi badges and a set of Wi-Fi gateways deployed at various points across the location to capture signals from the badges. Note that the badges are distributed to a select set of the participants. Having a programmable Wi-Fi badge allows efficient detection as packets are sent at a constant rate. Cattani et al. [4] uses bracelets that emit RF beacons to estimate crowd dynamics at the Nemo Science museum in Amsterdam. The main drawback of this method is that it requires participation from people to be effective. Providing wearables to a large crowd can significantly impact the infrastructure cost. The authors of [5] make use of GPS equipped smartphones to infer crowd density information. In this system, pedestrians in the crowd share their location information voluntarily. Since only a fraction of the people in the crowd may share their location information, the crowd density is analyzed based on the walking speed of the pedestrians. It is assumed that the movement speed of pedestrians is proportional to the crowd buildup in a given area. This approach is suitable for large open spaces where GPS is available. If the gathering of people is relatively small such as an Auditorium where crowds might hardly move or a museum that may have multiple floors, this solution does not perform well.

B. Non-Participatory Techniques

These techniques do not require any form of co-operation from people in the crowd. Data is collected in a non-intrusive manner. This section provides a brief overview of the different technologies that have been developed to infer the crowd density using non-participatory approaches.

Image processing and computer vision algorithms have been used to count people using still images or live video streams. One of the most commonly used approach is to first identify an individual in a crowded scene and then feed this data to various classifiers to get the people count [6], [7], [8], [9]. Vision based techniques perform well as long as the features can be detected effectively. However, they suffer under severe occlusion in the crowd and under poor lighting conditions as the features may not be detected. Furthermore, these algorithms can be used in only a line-of-sight environment. The use of cameras also raise privacy concerns. Vision based systems are also known to increase the deployment costs and computational complexity of the system.

Xi et al. [10] have used Channel State Information (CSI) based approach to estimate the people count in a given area. They propose that CSI is highly sensitive to the environmental variations that might occur due to the presence of people in an area. A relationship is established between the number of moving people in an area and the CSI variations. Domenico et al. [11] also develop a CSI based crowd counting system that analyzes Doppler spectrum obtained through the gathered CSI data. Wi-Fi CSI based techniques are device free and does not require the users to even carry smartphones with them. However, the CSI information is not easily exposed on all Wi-Fi chipsets. Currently, only a select few variants of Atheros and Intel 5300 chips can expose the CSI information. These chips require modification of the underlying software stack [12]. This is the main drawbacks of this approach in our scenario as the commercial-off-the-shelf (COTS) chipsets cannot be directly used in the deployment. Another drawback with respect to our scenario is that CSI based techniques do not work well when deployed on the ceiling.

RF based device free passive techniques have the ability to localize individuals and does not require them to carry any radio devices with them. These techniques consider the disturbance pattern of radio waves by the users and derive their location. Wilson et al. [13] proposed a Radio Tomographic Imaging (RTI) which aims at localizing multiple individuals relative to radio links Line of Sight (LoS). Depatla et al. [14] try to count the number of people solely by measuring signal strength variation between a pair of stationary transmitter and receiver antennas.

Considering our scenario wherein we incorporate crowd analytics as a part of the ceiling-mounted smart lighting grids, we find that device free approaches such as RTI with multiple sensors [13] or link based approach [14] cannot be used as these require a Line of Sight between a TX-RX pair and the subjects to be tracked.

Passive Wi-Fi techniques make use of Wi-Fi scanning to infer the occupancy estimation at a given location [15], [16], [17]. Wi-Fi scanners are deployed in the area of interest to capture signals from smartphones that people might be carrying with them. Scanning is done in a non-intrusive manner without

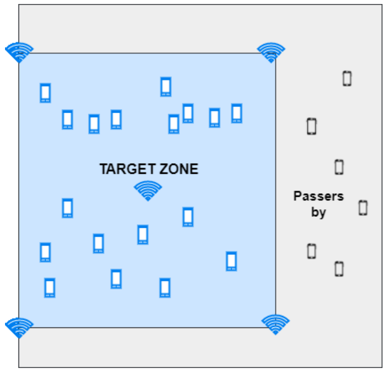


Fig. 2: Stray devices outside the area of interest

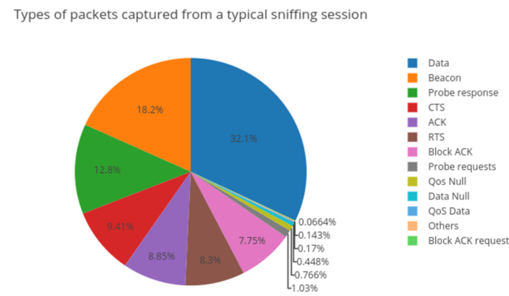


Fig. 3: Type of Wi-Fi packets seen during Wi-Fi sniffing

the need to modify any software or install any application on the smartphone. Although a plethora of work exists on Wi-Fi based localization, the application constraints mentioned in Section I are satisfied by passive sniffing techniques, thereby invalidating the other methods. However the existing passive Wi-Fi methods do not tackle the problem of fine grained counting and localization within a bounded indoor space.

Thus, we select passive Wi-Fi sniffing as it can be easily implemented on COTS Wi-Fi hardware and does not require any active participation from the users. Due to growing adoption of smartphones, we can expect most of the people to carry a smartphone with them all the time. The sniffers can be incorporated in the light bulbs and mounted on the ceiling.

III. People Counting

Our approach for estimating crowd distribution is to count the number of smartphones and estimate the approximate position of the smartphone using localization algorithms. We look at the first part, i.e., counting people, in this section.

A. Challenges

- **Increasing number of Wi-Fi devices :** The number of devices with a Wi-Fi interface has increased significantly over the years and this number is predicted to increase further. When we try to sniff for Wi-Fi packets in such a scenario, we see a large number of devices that get discovered in our vicinity. Generally the number of Wi-Fi devices is much more than the number of people in a given area. This is due to the presence of many devices other than smartphones including laptops, tablet computers, routers, Wi-Fi repeaters, and other smart devices with Wi-Fi capabilities.
- **Devices outside Target zone :** Since Wi-Fi sniffers have a large range (around 100m), the sniffers will be able to detect even devices which are outside the target zone. These may include people who are just passing by around the target area. Consider a situation shown in Figure 2. It is important to ignore the passer by devices as it may impact the count severely depending on how many devices are outside the area of interest.
- **RSSI Approach:** Since we choose Wi-Fi sniffing as our preferred approach to gather data, the only information that is available about an unknown node is the timestamped RSSI values from multiple sniffers. We are restricted to use only RSSI based localization approaches as no other fine grained information such as TDoA, AoA are available to us. RSSI is known to be prone to large and small scale variations due to multipath and reflection of signals. It may also vary depending on the orientation and position of the smartphone. This may lead to inaccuracies in location estimation.
- **Time resolution and Frequency of Packets:** As our approach is non-intrusive in nature, we do not possess any control over how many packets might be sent from a smartphone at any given time. We conducted several experiments with several smartphones (in one case upto 3000 devices) and we conclude that the majority of the smartphones send a packet every 30 - 60 seconds. The number of packets transmitted heavily depends on the configuration a smartphone is in; a large number of packets can be expected during data transfer where as fewer packets during idle or low battery mode. Having more number of packets gives us the ability to mitigate the effects of RSSI variation by applying appropriate filtering and smoothing mechanisms. However, a large number of packets cannot be assumed to generated from each smartphone all the time. Due to these factors, the accuracy of localization might be non-uniform among the discovered smartphones.

B. Filtering Mechanisms

The Wi-Fi data collected from smart bulbs are subjected to a number of filtering and post-processing steps to infer the people count in the target zone. This section describes the steps we propose in order to avoid counting unwanted devices in and around the area of interest.

Filtering based on Wi-Fi Packet type: Figure 3 shows a pie chart of the different types of Wi-Fi packets encountered during a sniffing session that collected close to 2 million packets. A majority of the packets are *Data* packets constituting around **32%** followed by *Beacon* frames and *Probe Response* packets which constitute roughly **18%** and **12%** respectively. The *Beacon* frames and *Probe Response* packets are transmitted by Wi-Fi routers, hence can be ignored. Removing these would reduce the size of data set by **31%**.

Filtering based on Proximity: To avoid detection of the devices that are far away from the target zone, we propose to set an RSSI threshold for each sniffer. The threshold is chosen such that we avoid detection of very weak signals which probably might originate either from a far away device

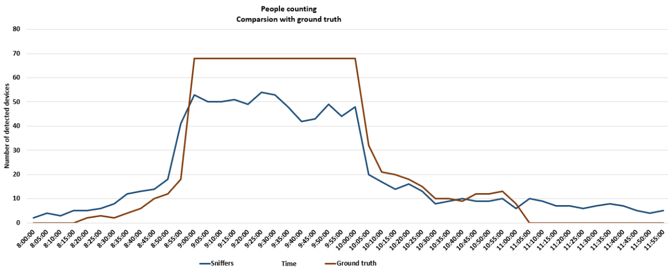


Fig. 4: Comparison of count results obtained at an auditorium with the ground truth from manual counting

Fig. 5: Wilab2 testbed setup showing static Wi-Fi nodes on the left and mobile robots to the right

or a device which might be on the other side of a thick wall. The area of interest is surveyed and measurements are taken both inside and outside the target zone in order to select an optimal threshold. This can be done during the lighting grid installation phase.

Filtering based on Manufacturer Identities: Many static devices within the target zone such as routers, smart television, printers can be blacklisted based on such manufacturer identities. To further reduce the dataset and remove static devices, we use a time-based blacklisting approach. Each day a blacklist file is built up containing newly detected OUIs. A time is chosen such that no activity from people is seen, for instance every night between 2AM to 4AM would be a probable time where Wi-Fi activity will be mostly because of static devices in the area and not from people in the vicinity. All these devices are put in a blacklist and ignored when they are detected the next time.

Avoiding Stray Devices: After various levels of filtering as discussed in the previous sections, there might still be false positives due to passers by and devices just outside the target area. In order to reduce the number of false positives we try to estimate the dwell time of each device. It represents the length of time a device was visible during a sniffing session. Devices which just passed by will be detected for a very short interval resulting in lower values of dwell time. To further reduce the number of false positives, we only take into account devices which were detected by multiple sniffers after applying an RSSI threshold as mentioned before.

C. Counting Results

In order to evaluate the algorithm in real word scenarios, we deployed Wi-Fi sniffers at an event involving people at an auditorium and a coffee corner in an office building.

Auditorium: The space is 10m $\times$ 14m with a capacity of approximately 120 people. We deployed 3 sniffers in the room and gathered Wi-Fi sniffing data during an event. The people count obtained after post processing is shown in Figure 4. The ground truth was collected by manual counting. We see in Figure 4 that the algorithm closely follows the ground truth. However during peak times, the estimated people count is much less than the actual count. Upon surveying people, two reasons were found. A number of people who attended the event never brought their smartphones with them (many left their phones on the desk). Several people also switched their Wi-Fi off as they were paranoid about privacy reasons.

IV. Position Estimation

In order to efficiently analyze the viability of localization algorithms, we make use of a Wi-Fi testbed, Wilab2 testbed [2], where we can recreate scenario with a large area. Wilab2 is a generic, heterogeneous wireless testbed of size 61m $\times$ 22m and consists of over 120 fixed Wi-Fi nodes mounted close to the ceiling and 16 mobile robots that can be remotely operated. This setup closely mimics spaces such as an arena concourse or an auditorium. Since the robots also have Wi-Fi nodes mounted on them they can be used to mimic the people moving or emulate crowd buildup at different locations. The data collected from the experiments are analyzed using different localization algorithms.

We describe the localization algorithms which were used to deduce the location of an unknown node. We propose enhancements to improve localization accuracy and its dependency on various factors.

Centroid Based: Weighted Centroid Localization (WCL) has been used to determine the location of nodes in Wireless Sensor Networks (WSN) [18]. The algorithm has low execution time and computational complexity. WCL determines the position of a target node to be localized by averaging the locations of known reference points also known as anchor nodes. In WCL, the weights are adjusted such that the anchor nodes closest to an unknown node gets more weight compared to the nodes that are farther away from the unknown node. This increases the location estimation accuracy.

Traditionally WCL algorithms are typically used in large scale WSN deployments; it takes into account only the anchor points in range of the target node to estimate the position. In our scenario, all the deployed sniffers will be located close to each other as they are part of the lighting grid. This combined with long range of Wi-Fi a majority of them are always within the range at any given time. Hence errors will be introduced in position estimation if we take into account all the sniffers in the area. Hence, we take only S sniffers out of the total N that receive the strongest RSSI values.

Constraint Matching: Ecolocation (ECL) algorithm proposed by Kiran et al. [19] is a range free localization algorithm. The algorithm has a low complexity and a reasonable accuracy. The localization area is partitioned based on distance constraints. These constraints form a unique signature for different regions in the localization area. The location which has the maximum number of satisfied constraints is then determined to be the best estimate of the target node's location. The ECL algorithm

Algorithm	Average Execution time (ms)
Naive ECL	1200
Modified ECL	168

TABLE I: Execution times for naive and modified approach

estimates the position by doing an exhaustive search on all possible points in the localization area. This can be highly time consuming if the area is large with high number of anchor points. In order to reduce the computation time, we need to perform constraint matching only in selective regions instead of doing it for the complete space.

We propose a bounded polygon method (BPM) to reduce the execution time and improve estimation accuracy. BPM involves finding the approximate zone of localization based on signals from the first S strongest sniffers. A bounded polygon is then formed based on lowest and highest dimensions of the strongest sniffers. The constraint matching is then applied within the bounded polygon. Choosing an appropriate value of S determines the area of the resulting polygon area. If $(S = N)$ then complete localization space is considered. Table I shows the improvement in execution time. Having an approximate pre-localization stage before actual localization can reduce the execution time by almost 8 times. Let (Sniffer$_i.x$,Sniffer$_i.y$) be the location of i^{th} sniffer. Let Sniffer$_i$.RSSI represent received signal strength of the i^{th} sniffer. The algorithm to construct the bounded polygon is shown in Algorithm 1.

Algorithm 1: Algorithm for constructing a bounded polygon

max_sniffers = **get_4_highest_RSSI_sniffers** (Sniffer$_i$.RSSI) $\forall i \in S$
x_min = min(max_sniffers$_j.x$) $\forall j \in \{1, 2, 3, 4\}$
y_min = min(max_sniffers$_j.y$) $\forall j \in \{1, 2, 3, 4\}$
x_max = max(max_sniffers$_j.x$) $\forall j \in \{1, 2, 3, 4\}$
y_max = max(max_sniffers$_j.y$) $\forall j \in \{1, 2, 3, 4\}$
Bounded_Polygon = **bound**(x_min,y_min,x_max,y_max)
ConstraintMatching(Bounded_Polygon)

A. Results

The discussed range free algorithms were compared against popular localization techniques such as Multilateration with Linear Least Squares (LLS) approach and Non-Linear Least Squares (NLLS) approach [20]. Figure 6 shows the comparison between the localization algorithms. It can be observed that range free localization methods such as Constraint matching and Weighted Centroid Localization (WCL) perform better than range based methods like Multilateration. Multilateration suffers as it requires estimation of the distance based on path loss models where even small errors in distance estimation introduces errors in position estimates. Figure 7 shows the reduction in error when we consider only S strongest sniffers out of the total N using Weighted Centroid localization. Figure 8(a) shows the CDF of errors for the naive algorithm that considers every possible location in the localization space. Figure 8(b) shows CDF of errors based on bounded polygon approach. It can be observed that bounded polygon method results in higher accuracy even when the distance between

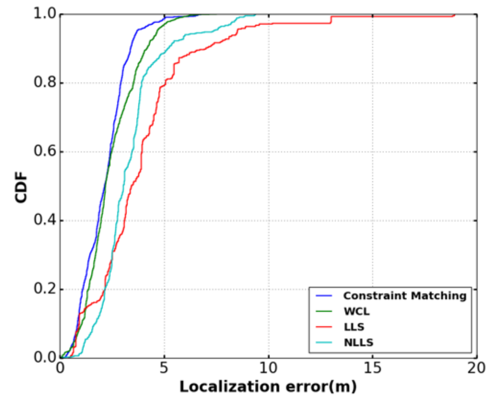


Fig. 6: Comparison of CDF of errors for different localization algorithms

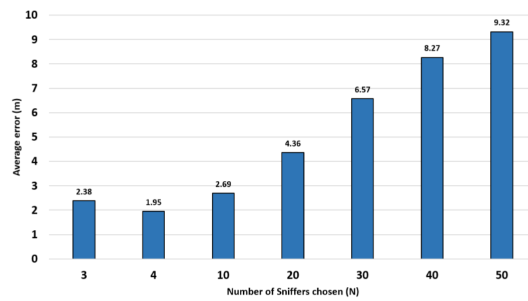


Fig. 7: Average localization error for a node as the value of S approaches N

sniffers is high compared to the naive approach. The naive algorithm provides as estimation accuracy within 4m only 30% of the time where as with bounded polygon method the accuracy is within 4m close to 80% of the time.

We define the term *sniffer density* as the distance between adjacent sniffers in the grid. The results are summarized in Table II for a select few values and the number of smart bulbs required to achieve the denoted accuracy.

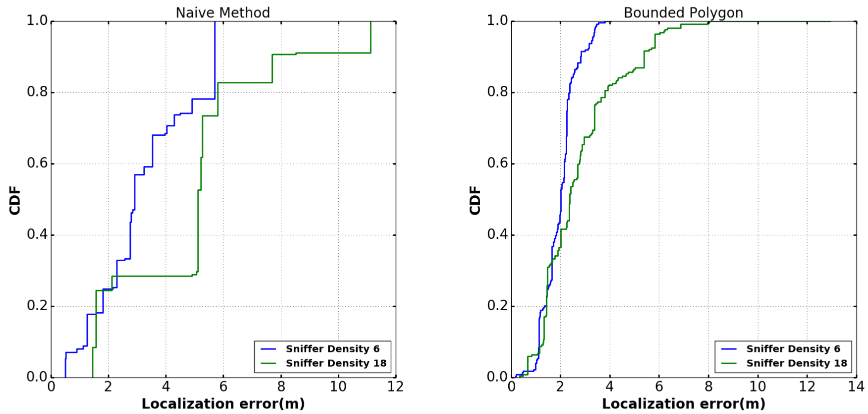
Sniffer Density	Accuracy <2m	Accuracy <2.5m
3	80%	95%
4	74%	82%
5	52%	70%
6	55%	55%

TABLE II: Sniffer densities and associated localization accuracy with number of smart bulbs required

V. Conclusion and Future Work

We looked at leveraging existing lighting grids for estimating crowd distribution with Wi-Fi sniffers for smart IoT applications. We were constrained to developing a non-intrusive and non-participatory crowd density estimation technique, which led us to use passive Wi-Fi based methods.

We split the problem of estimating crowd distribution into people counting and localization. For people counting, we



(a)

(b)

Fig. 8: Improvement in position estimation using bounded polygon

proposed several filtering and post processing mechanisms. When evaluated in live office setups and testbeds, we got to 75% of the ground truth despite people's behavior. For localization, our bounded polygon algorithm gives accuracy within 2m $\geq$ 80% of the time with sniffer density of 3m. We tested our algorithms in a real-world testbed, wherein mobile robots with Wi-Fi interface were used to mimic movement of people.

Some of the directions for future research are as follows

- The accuracy of counting by Wi-Fi sniffing can be influenced the demography of the crowd. A future research can take into account heuristics and statistics of smartphone usage among different age groups to further refine the count.
- Analyzing social interactions among the people in the crowd is another interesting area of research. The remembered SSID information in the sniffed probe request frames can be used an input for this.

ACKNOWLEDGMENT

SCOTT (www.scott-project.eu) has received funding from the Electronic Component Systems for European Leadership Joint Undertaking under grant agreement No 737422. This Joint Undertaking receives support from the European Unions Horizon 2020 research and innovation programme and Austria, Spain, Finland, Ireland, Sweden, Germany, Poland, Portugal, Netherlands, Belgium, Norway.

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