“Where Am I?”: Unraveling Challenges in Smart City Data Cleaning to Establish a Ground Truth Framework

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***Abstract*—In the growing era of smart cities, data-driven decision-making is pivotal for urban planners and policymakers. Crowd-sourced data is a cost-effective means to collect this information, enabling more efficient urban management. However, ensuring data accuracy and establishing trustworthy “Ground Truth” in smart city sensor data presents unique challenges.**

Our study contributes by documenting the intricacies and obstacles associated with overcoming MAC randomization, sensor unpredictability, unreliable signal strength, and Wi-Fi probing inconsistencies in smart city data cleaning. We shed light on the practical difficulties faced during the “Ground Truth” establishment process.

By presenting our findings, we aim to facilitate a deeper understanding of the nuances involved in handling sensor data, ultimately paving the way for more accurate and meaningful data-driven decision-making in smart cities. Our experience underscores the importance of addressing MAC randomization and Wi-Fi probing challenges, emphasizing the need for innovative solutions in the realm of urban data management.

***Index Terms*—counting people, occupancy estimation, MAC randomization, Wi-Fi probing**

I. Introduction

Overcrowding is an issue in cities around the world, especially in towns that draw thousands or millions of tourists [1]. It is a safety hazard having too many people in one part of a city. Overcrowded, narrow streets or venues with limited points of entry or egress can lead to terrible tragedies like trampling, terrorist attacks, and lone gunman scenarios. The COVID-19 pandemic also made it essential that city planners consider how many people can safely remain together indoors or outdoors and at what distance. Additionally, overcrowding is an inconvenience for businesses that rely on a traffic flow, such as delivery services or taxis. When too many people crowd an area, it strains vital resources, like the availability of food or public transit.

Mitigating overcrowding situations requires a city to have a plan in place. It also requires that the city have a metric to distinguish overcrowding from normal crowd levels. To assess crowd level, a smart city may use sensor data to collect a real-time count of the number of people entering, leaving, or remaining an area. Many emerging smart cities use camera data. Yet, cameras may be more energy consumptive, more expensive to install, and require line of sight with a target area [2]. Not only that, but the installation of mounting hardware can damage historical buildings. Overall, there are mixed responses by the public in regards to surveillance by cameras, especially depending on context [3].

An affordable and easily installed alternative to cameras is using sensors to detect Wi-Fi probes, yet this area of research has not been standardized. Our contribution to this work is to create a framework for future researchers to use to conduct experiments that incorporate the relationship between the spatial layout of the city structures and the efficacy of the sensor in detecting the devices present in the area. This work is vital because of the recent spread of MAC Randomization technology and its impact on data quality.

II. Background

Smart City Bamberg in Bavaria, Germany, has installed several Flowtrack sensors in locations throughout the city in partnership with Safectory, a company based out of Bamberg. As part of the smart city project, the CrowdAnym Project at the University of Bamberg aims to collect and process anonymous data to assess crowd levels [4].

The Flowtrack[1] sensors work by receiving Wi-Fi probing signals from mobile devices in its range and performing anonymization of MAC Addresses by hashing the MAC Address with a daily randomly-generated SALT value. It then saves the hashed MAC in the CrowdAnym database so that people’s MAC Addresses are not exposed.

There are several major benefits of using Wi-Fi signals for counting people as an alternative to using cameras: cost-effectiveness, unobstructed counting, and more anonymity [5]. However, there are also many serious data quality issues.

A. MAC Randomization Effect on Data Quality

Media Access Control (MAC) is hard coded to a Wi-Fi capable device’s Network Interface Controller (NIC) by the manufacturer. A phone’s MAC address is a unique hexadecimal code that identifies a device on a network.

If MAC addresses are transmitted without encryption, they can be captured and potentially used to track a user’s location. In response to changes in data privacy laws, modern Android and iPhone devices protect users’ privacy by generating

[1]Information about Flowtrack sensors can be found on https://www.uni-bamberg.de/en/forschung/wissenschaftl-einrichtungen/forschungs-labs/smart-city-research-lab/translate-to-1-english-projektarchiv/translate-to-1-english-crowdanym/

a randomized MAC for each different Wi-Fi access point encountered, rather than sending out the MAC address that uniquely identifies that device. MAC addresses are randomized for whatever connections are made in order to keep the users anonymous and untraceable [6].

MAC randomization can cause problems for data quality as each time a sensor is logging a probe, even if it is from the same device, the MAC address is changing. It makes it seem as if there are more people than there are on the ground, leading to the problem of overestimation [7], see Fig. 1.

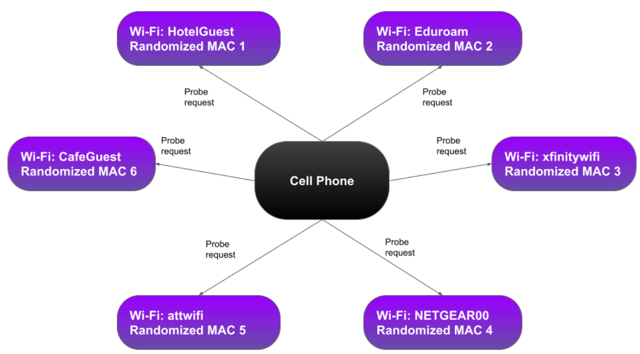

Fig. 1. Each device creates one randomized MAC address to send probe requests to all surrounding Wi-Fi Access Points

Due to this overestimation problem, we believe that it is imperative to set up a framework for researchers to use to track various aspects, such as how many Access Points exist in an area, what was the status of the device, and where each device was detected.

B. Wi-Fi Probing Issues

The goal is to count the number of people in an area, but when it comes to monitoring Wi-Fi probes, we cannot ensure that it is only a person that we are counting. There are bikes, scooters, cars, etc. A baby in a stroller may have a smart device for entertainment. Even dogs may have collars that send out Wi-Fi probes. Additionally, there are workers in the area who are there daily. There are also devices like routers, printers, etc. that are always in an area that need to be filtered out.

Once a person turns Wi-Fi on, a phone sends out a probe burst to its saved networks, also known as the Preferred Network List [6]. The null probe asks if any access points are in the area. It identifies all of the access points (available Wi-Fi networks) and populates the nearby networks list. Then the device asks if it can connect. The phone continually asks if the most recent network that it was connected to is still there. The frequency of probe transmissions varies by device brand, year, and OS version [6] [8].

In theory, one person can have as many hashed MACs (M) in the database as the number of Devices on their person (D) multiplied by the number of Saved Access Points (S) on each device, plus the number of Nearby Access Points (N) in the surrounding area that each device detects, plus one broadcast probe. As shown in Fig. 2, as a person walks along a street,

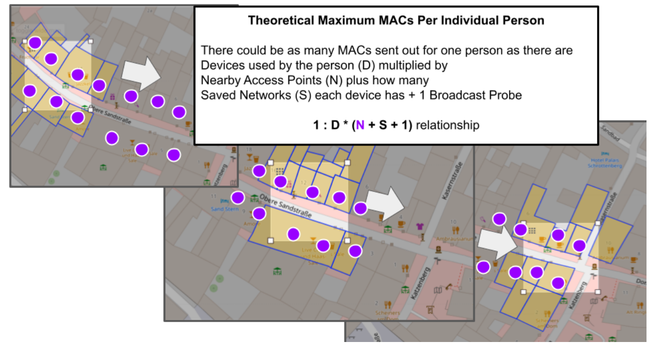

Fig. 2. Scenario where one person walks down the street and generates M entries in the database due to MAC randomization

the access points their device detects at the end of the street may be different access points than those the start of the street [9].

$$M = D * (S + N + 1) \tag{1}$$

There are several factors that go into how many access points are detected and probed: the range of the device, the battery level of the device, the type of device, the signal strength of the access points, the number of buildings and floors, the material that constructs the walls [5]. Therefore, carefully documenting the range of each sensor and the spatial layout of the area, along with details about the detected devices, will give much needed insights into the reliability of each sensor.

C. Related Work

Various methods have been applied to estimate indoor occupancy. One method involves using audio recordings via microphones to gauge room occupancy and automate HVAC operations in construction environments [10]. However, this method relies on the assumption that no significant audio sources like TVs or audio players are present and that sound from neighboring rooms is minimal. Another technique utilizes Ultra Wide Band (UWB)-based time-delay strategies for indoor human localization, assisting in determining human positions within indoor spaces [11]. Additionally, studies have explored the utilization of RFID technology to pinpoint occupants wearing tags in indoor environments [12]. While offering flexibility, it can be costly, and requires active user involvement and consent. Using Infrared technology or computer vision to recognize and count people are both costly and inconvenient. These methods suffer from the same problems that they both require line of sight, and both can lead to underestimation if there is any occlusion, overlapping of people, that blocks the detection [13]. RSSI or CSI-based methods utilize signals to estimate crowd density. However, comprehensive training and calibration for diverse environments are necessary for this approach. While many of these techniques work indoors, they cannot be applied to an outdoor environment where various variables cannot be controlled.

Other work has estimated outdoor occupancy [14], but the work in that area is limited due to the volatility of outdoor environments. In a city environment, it makes most sense to measure indoor and outdoor occupancy, as overcrowding can be an issue both at the street level and inside of popular buildings.

Past studies on Wi-Fi occupancy estimation typically involve headcounting to establish a ground truth count of people. Some researchers utilize mobile applications to track people entering and exiting an area [6], offering precise second or millisecond granularity, yet lacking categorization, such as pedestrian, car, or bike, which could be used for future filtering. Recognizing the significance of documenting researchers' coordinates and experiment spatial layout, our emphasis lies in creating maps for each experiment type outlined in our *Methods* section.

III. Methods

We performed three types of experiments: Counting Experiments, Proximity Experiments, and Sensor Range Experiments.

A. Dataset

In our database, a hashed MAC is saved with an event type of either "Status" or "Leave" along with a timestamp. "Status" indicates that the device has been detected by the sensor and is somewhere within range. If within 15 seconds the database does not receive another ping from the device, the hashed MAC is marked as "Leave", with its corresponding timestamp.

Along with collecting the timestamp of these "Status" or "Leave" events, the database also collects the zone identifier of the sensor as well as an Received Signal Strength Indicator (RSSI). The RSSI value serves as a metric for gauging a device's proximity to the sensor, spanning a range from -256 to 0 dBM (decibel-milliwatts). A reading of 0 signifies close proximity to the sensor, while -256 indicates the maximum distance a person can be from the sensor.

We proposed the addition of the daily SALT value storage in the database. This strategic addition allowed us to hash MAC addresses from our own devices, enabling a precise search for our devices within the dataset.

Furthermore, we made additional database tables to track our experiments and provide a framework for future researchers to continue our work, which is further discussed in Section III-E.

B. Counting Experiments

Counting experiments were conducted at sensor locations, comparing real-time observations with sensor-recorded data. Each experiment documented sensor location, collection coordinates, time window, pedestrian count, 'other' count (encompassing cars, bikes, etc.), and pedestrian direction (in or out of range). Different time intervals (1, 5, and 10 minutes) and collector positions (latitude and longitude) were tested.

Various methods, including positioning researchers at street ends and tracking people coming in and going out, were explored, as shown in Fig. 3. A mobile app for counting was considered but deemed prone to human error. In cases of an uneven number of collectors, one person was placed directly in front of the sensor to tally people passing without considering direction, as shown in Fig. 4.

Tallying on paper was used for experiments, with data manually transferred to the database. Initially categorizing people, bikes, and cars proved challenging with large groups, prompting a focus on pedestrians and 'other.'

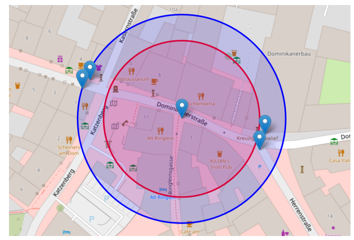

Fig. 3. This sample Counting Experiment map shows four data collectors were positioned at a set radius away from the sensor. The sensor is the central map marker in this example. Red is a distance of 30 meters; blue is a distance of 40 meters from the sensor.

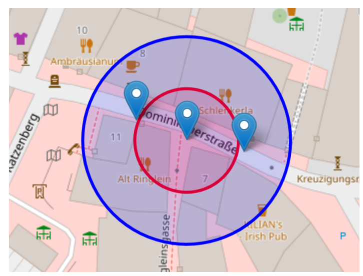

Fig. 4. This sample Counting Experiment map shows three data collectors were positioned. Two at a set radius and one at the sensor location. Red is a distance of 10 meters; blue is a distance of 20 meters from the sensor.

C. Proximity Experiments

We assessed the RSSI value's reliability in detecting proximity to the sensor, testing the hypothesis that it changes as a person moves closer or further away. To create a pattern, we intentionally toggled Wi-Fi, generating "Status" and "Leave" timestamps. Experiments involved three to six individuals, starting close to the sensor with Wi-Fi off, activating it collectively, moving away, and repeating until beyond the sensor with Wi-Fi off, activating it collectively, moving away, and repeating until beyond the sensor's coverage. To assess the sensor's effective range systematically, we moved outward from the base, adhering to the street layout constraints. Mobile devices were brought to the sensor's base with Wi-Fi off, then activated for a minute, deactivated, moved away, and reactivated in a cyclic sequence. This deliberate pattern developed easy to follow irregularities in the database as devices distanced themselves from the sensor.

D. Sensor Range Experiments

As we initiated proximity experiments using sensors with an expected range of 50-60 meters, inconsistencies arose in device detection, prompting us to modify sensor ranges while meticulously documenting detected device specifics. This naturalistic experiment focuses on tracking detected device information such as manufacturer, model, OS, MAC Randomization, power-saving mode, battery level, and access point details without intentionally toggling Wi-Fi.

Our aim is to create a citywide point cloud of detected devices, capturing real-life movement patterns indoors and outdoors, simulating various individuals (tourists, workers, residents) near sensor locations both inside and outside buildings. The data recorded from these experiments, including device and experiment details, can be found in the ”Device Table” and ”Experiment Table” in Section III-E.

E. Implementation

The objective of this study was to establish a framework that enables fellow researchers to leverage our initial data and assessments for the refinement of a precise ground truth algorithm. As part of our visualization tools, we developed a real-time query-enabled density map using OpenStreetMap and Leaflet. This tool allows users to filter data based on date and time, providing a visual representation of people density across the city.

Additionally, we constructed several essential database tables within the database to serve as a framework for forthcoming experiments. These tables include:

- **Experiment Table:** This table stores comprehensive details about specific experiments, encompassing experiment type, date, attendees, devices used (referenced from the Device Table), and sensor zones (indicating sensor locations).
- **Device Table:** Recognizing the significance of tracking devices used in experiments, this table captures data on device type, manufacturer, model, operating system, Bluetooth settings, MAC randomization, battery-saving mode, and battery percentage. All these parameters are meticulously recorded within this table to analyze their impact on the sensor-captured data.
- **Data Collection Table:** Dedicated to tracking data collected during each Counting Experiment, this table documents start and end times, participant details, participant coordinates, sensor location, pedestrian counts per time interval, ’other’ counts, and additional notes.
- **Event Table:** To investigate potential correlations between city events and fluctuations in people density, this table records event type, name, dates, sensor zones associated with the event, and start and end times. Simultaneously, this table can be utilized for tracking planned attacks on the system.

We named generated maps using the format “date-location-type” to facilitate tracking, aiding future researchers in visualizing experiments and refining data collector positioning relative to the surroundings. It is crucial to consider spatial layout due to the sensors’ line-of-sight nature; their coverage area forms a polygon, not a circular shape. Varying geographic locations, with differences, like narrow streets or open spaces, affect sensor effectiveness. To address potential crowding disparities across regions of the city, we suggest the following definitions:

- **Frequency:** The number of unique MAC Addresses in a (1, 5, 10 or 30 minute, adjustable) time window.
- **Occupied Space:** Each person has a certain surface area that they occupy. We choose a set value of 1 square meter per person.
- **Adjusted Frequency:** Filtered version of frequency (our estimate of how many people we think are there).

We have also developed a formula to estimate the percent of “Crowdedness” in an area, where C represents Crowdedness, O represents Occupied Space, F is Frequency, and A is Surface Area.

$$C = (O * F)/A \qquad (2)$$

IV. Results

Results exhibited significant variability. One prominent issue arose when, at seemingly arbitrary time windows, the sensor failed to detect any traffic. Despite the presence of individuals during counting experiments, the sensor occasionally recorded zero traffic for multiple 5 and 10-minute time windows. Possible explanations include individuals not carrying Wi-Fi-enabled devices, having Wi-Fi turned off, moving at a rapid pace, an object obstructing the sensor’s range, an overload of data burdening the sensor, or many devices not actively sending out probe requests at that moment.

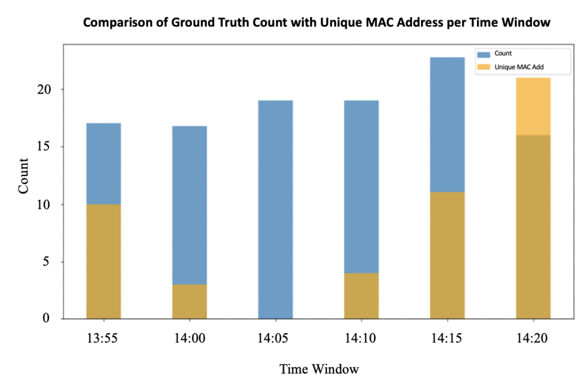

Fig. 5. Blue represents the ground truth count of the number of people entering the sensor range. Yellow represents the number of unique MAC Addresses detected for each 5-minute window. This coincides with Fig. 3

Furthermore, the sensor’s range displayed considerable fluctuations. Sensor range experiments revealed instances where the sensor could capture traffic at a range exceeding the specified maximum of 60 meters. Conversely, there were times when the sensor’s data collection range was limited to only 40 meters in radius. The variability in sensor range appeared somewhat arbitrary.

A noteworthy observation is that RSSI exhibited no discernible correlation with a person’s distance from the sensor. Our experiments indicated that, regardless of proximity, RSSI values demonstrated complete randomness, adding a layer of complexity to the interpretation of distance-related data.

As mentioned earlier, the presence of MAC randomization significantly distorts the outcomes. With each probe logged by a sensor, even if originating from the same device, the MAC address undergoes a change due to automatic MAC randomization. This behavior can create a misleading impression of higher foot traffic in an area than what is genuinely present.

To address the challenge posed by devices that may be consistently situated at a sensor location, such as routers, printers, scooters, etc., we opted to gather data during the early morning hours, specifically from 3 am to 4 am on consecutive days. The rationale behind this approach was that during these early hours, fewer people are typically in transit, offering a baseline for devices that persistently occupy the location throughout the day. However, despite mitigating some discrepancies, the collected data proved to be inconsistent. The sensor registered varying probe counts, ranging from over 100 on certain days to fewer than 10 or even none on others.

Sensor range experiments revealed how environmental constraints significantly affect sensor data. Thick building walls emerged as a major hindrance, obstructing Wi-Fi probes from reaching the sensor and limiting its effective range to more line-of-sight transmission. This partially addresses the issue of stable devices inside buildings, like printers and routers, potentially distorting results. However, further exploration and research are essential to fully understand this aspect.

V. Discussion

A. Limitations and Future Work

Below, we outline ways in which our experimental methods could be enhanced:

1) Counting Time Window: Using larger time windows, such as 20 or 30 minutes, could offer a promising direction for further research. If smaller window times have not shown strong correlation with the data, it would not be worthwhile to keep reducing window sizes. Given that no probes were detected within several 5-minute windows, using a larger time window might yield more accurate results.

2) Counting Area: Our counting experiments were conducted in a 5-meter wide street that had only two points of entrance or exit, but there are other areas in the city where the sensors cover a large pedestrian mall area. Further research needs to be done into how to set up counting experiments for those areas.

3) Proximity: Another way to enhance proximity experiments involves reversing the approach: moving toward the sensor instead of away. The rationale is that a person's body positioned between the device and the sensor might act as a barrier, hindering the probes' ability to reach the sensor.

4) Sensor Range: Due to time limitations, we were unable to fully execute this idea. Within a Sensor Range map, detected devices could have been illustrated using color-coded map markers, each color indicative of a distinct manufacturer. Such representation aids in visualizing sensor range patterns concerning specific device types. Furthermore, extending the mapping to three dimensions would have provided even greater detail, offering insights into the varying reach of sensors across different floors of adjacent buildings.

5) Additional Limitations: Below, we list additional limitations to the existing system and in the following section, we provide recommendations to potentially mitigate some of these issues.

- **Sensor Sensitivity:** The sensor's sensitivity lacks consistent tuning, resulting in varying probe detection capabilities. It fluctuates between covering wider ranges and narrowing down, leading to potential inconsistencies in detecting probes. Additionally, there are instances where the sensor fails to detect probes despite the presence of individuals during various time windows.
- **Limited Probe Type:** The current sensor configuration is limited to detecting Wi-Fi probes exclusively, neglecting the potential detection of other probe types, such as Bluetooth. This limitation restricts the system's ability to capture a comprehensive spectrum of signals, potentially overlooking crucial data.
- **Static Positioning:** The system's setup remains stationary with sensors placed in fixed locations. This static positioning hinders complete coverage, as highlighted by issues like the line-of-sight problem. Consequently, certain areas might be inadequately monitored or missed entirely due to this limited setup.
- **Barriers:** There are many barriers impacting the sensor range. Some sensors are positioned behind windows within buildings while others are mounted at significantly elevated heights on buildings. This inconsistent line-of-sight placement will affect the capabilities of each sensor.
- **RSSI Unpredictability:** RSSI proves to be an unreliable measure for determining proximity to a sensor. Variability in RSSI measurements could lead to inaccuracies in assessing distance or proximity, compromising the reliability of the system's proximity estimations.

B. Recommendations

Expanding sensor capabilities beyond Wi-Fi to detect additional probe types like Bluetooth would enrich the system's dataset, capturing a wider spectrum of signals and behaviors from various devices. This diversification not only offers insights into user behaviors and interactions but also enhances the system's adaptability and analytical capacity, potentially revealing hidden patterns for more informed decision-making.

Positioning sensors in diverse settings, such as behind windows or at varying heights on buildings, introduces inconsistency in the gathered data across sensors. Establishing standardized guidelines for sensor placement regarding both height and positioning could significantly enhance data uniformity. This standardization would serve as a baseline, fostering more precise and comparable results across sensors. For the time being the database could store information on sensor positioning. This could encompass essential details like proximity to walls, elevation from ground level, indoor or outdoor placement, and other pertinent positioning specifics.

Addressing the line-of-sight issue might involve deploying multiple sensors in one location with different orientations. Aggregating data from these diverse sensor placements could potentially mitigate the line-of-sight problem, enhancing the overall accuracy of data collection. However, implementing this approach may increase costs due to the deployment of multiple sensors.

The unreliability of random RSSI values and its lack of correlation with proximity raise doubts about the value of collecting this metric. Instead, leveraging Channel State Information (CSI) could address these concerns. CSI offers an in-depth understanding of the wireless channel between a transmitter and receiver in networks like Wi-Fi or cellular systems, going beyond basic signal strength measurements [15] [16]. While the system might not require such intricate details, understanding CSI could prove beneficial. However, harnessing meaningful insights from CSI demands specialized hardware and intricate signal processing techniques, surpassing the complexity of metrics like RSSI. If it is not practical to collect CSI data, then it may be possible to calibrate RSSI or to discretize the RSSI values into ranges [17].

Many researchers validate Wi-Fi data against ground truth by deploying diverse sensors like cameras, list sensors, pressure sensors, and audio-processing tools to automatically collect comprehensive measurements [2]. Recently, the City of Bamberg integrated a camera into a new sensor location. However, our observation revealed weaker correlations between our counting experiments and database results when the data collection team operated within a confined radius around the sensor. This discrepancy raises concerns about the accuracy of mounting cameras at the exact sensor point. To ensure precision, we propose conducting experiments with overlapping sensors positioned at least 20 meters apart.

VI. Conclusion

In navigating the complexities arising from MAC Randomization and inconsistencies in Wi-Fi probing, researchers face the imperative of gathering comprehensive environmental data. This data is crucial for refining estimates related to overcrowding. Beyond the reliance on Wi-Fi data alone, documenting the spatial layout of sensor locations becomes pivotal due to the variable surface area coverage associated with these sensors, as highlighted by numerous factors.

To address these challenges, we advocate for a structured framework allowing researchers to gather extensive data, map out experiments meticulously, and gain deeper insights into each sensor's capabilities. Focusing on counting experiments, proximity assessments, and sensor range analyses at individual locations enables the discernment of behavioral patterns unique to each sensor. This data, instrumental in decision-making processes like optimal sensor placement and network expansion, establishes a framework for comprehensive analysis.

Introducing defined metrics such as Frequency, Occupied Space, Adjusted Frequency, and Crowdedness offers a standardized approach, facilitating cohesive analysis. Implementing consistent counting techniques and database structuring for sensor range mapping ensures the establishment of a robust foundation for ongoing smart city research endeavors. By meticulously considering spatial factors, researchers can construct more trustworthy models and predictions concerning crowd density, ultimately advancing the efficacy of a smart city planning and management.

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