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# An Improved Smartphone-based Non-Participatory Crowd Monitoring System in Smart Environments

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***Abstract*—Mobile Crowd Sensing and Computing (MCSC) is a replacement of static sensing infrastructure by user's mobile sensor-enhanced devices. MCSC collects user's local knowledge such as local information, ambient, and traffic conditions using sensor-enabled devices. The collected information is further aggregated and transferred to the cloud for detailed analysis. In this paper, we propose a Smartphone-based non-participatory crowd monitoring system, named *CrowdTrack*, to monitor the movement patterns of one or more persons (non-participatory) using unmodified Smartphones in a densely crowded environment. *CrowdTrack* uses the Smartphone as a sensing unit without any hardware modification to extract the MAC ids from the wireless probe requests emitted from the users' devices. MAC ids are stored and processed locally for short-term analysis and then the filtered data is uploaded to the server for better analysis and visualization. We have also developed a real-time testbed to identify mobility patterns in the data collected from our Institute campus and it is deployed to find the visiting sequences of students. Real-time experiments on a proof-of-concept prototype testbed with our dataset show the usability of our proposed system.**

***Keywords—MCSC; Mobile Crowd Sensing and Computing; 802.11 frame; Probe request; Human identification and location tracking***

## I. INTRODUCTION

In recent years, cities around the world are rapidly changing towards the resource-efficient, energy-efficient, and high level of living standards. Smart city management requires aggregation of urban informatics for well-organized and sustainable cities. Some conventional sensing techniques, such as sensor networks are used to gather real-world data [1]. Sensor network deployment is not an easy job because of high installation cost, insufficient space coverage, etc., [2][3]. Therefore, to handle the afore-mentioned problems, researchers have proposed a new large-scale sensing paradigm, Mobile Crowd Sensing and Computing (MCSC) [4] based on the power of user-companioned devices, such as Smartphones, smart vehicles, wearable devices, etc. MCSC collects user's local knowledge, such as local information, ambient context, noise level, and traffic conditions, etc., using their sensor-enabled devices. The collected information is further aggregated and transferred to the cloud for data processing. MCSC is a replacement of static sensing infrastructure by user's mobile sensor-enhanced devices. It can be used to find the mobility patterns, traffic analysis and planning, public safety, environment monitoring, mobile social recommendation, etc. In order to monitor and track the movement patterns of one or more people in a densely-crowded environment, the individuals must be uniquely identified. Human location tracking/monitoring can allow the authorities to find/identify a lost person among thousands in the crowd, to evacuate people during emergencies, to manage the crowd movements, to predict the crowd in the future and to plan the resources accordingly.

Existing wireless tracking based systems either use the packet analyzer software such as tcpdump [5], Wireshark [6], Kismet [7], etc., or extra hardware which incurs the high cost and makes the system complex. Some of the systems [8][9][10] require RFID/BLE/Bluetooth tags to be provided to each person which is quite challenging and significantly expensive. Moreover, it is not feasible to distribute tags in case of emergencies or disasters. Moreover, some systems use expensive tag readers [11], which limits the number of tag readers to be deployed in the area. Having more number of tag readers increases the area in which a tag can be detected, but it will also increase the infrastructure cost [11]. Some of the commercial tag readers or scanners, such as [12] and [13], use proprietary technology and software which makes it difficult to modify and integrate with other systems.

Recently, researchers have started utilizing sensor-enabled Smartphones as a tag for large scale human sensing [14]. As the usage of Smartphones is increasing in world, more persons can be tracked without providing any tag in future. Some of the Smartphone based location tracking systems [8][9][10] require an application to be installed on the client's Smartphone. The installed application obtains the location using GPS sensor of Smartphone and continuously updates the location to the remote server using Internet connection. However, it is rare that users in the large crowd and in remote locations will have the Internet connection all the time. There are many operating systems and versions for Smartphones, which makes the development and distribution of application a difficult task. In additions, at many indoor locations, GPS does not work. Most of the existing systems use two-step process [15][16][17][18][19] for intercepting the MAC id (first step is to capture the probes then second is to process them). Thus, there is a need to design a portable, low-cost and easy-to-deploy system for tracking a large

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number of people using wireless technologies. The proposed system should be able to find a person's current location as accurately as possible, as well as, upload the current position of a person with minimum delay, power, and network bandwidth.

To the best of our knowledge, we propose a first Smartphone-based non-participatory crowd monitoring system, named *CrowdTrack*, which scans the probe requests emitted from the user's wireless devices (non-participatory) using unmodified Smartphones and intercepts MAC ids from them. Smartphone (sensing unit) used to track the people does not require any extra hardware infrastructure to deploy as well as does not need any modification in hardware design at all. Moreover, *CrowdTrack* does not require any participation from the users and can track the significant number of individuals simultaneously.

Briefly, the main contributions of this paper are as follows.

- We propose a Smartphone-based non-participatory crowd monitoring system, named *CrowdTrack*, in which unmodified Smartphones simultaneously scan and track wireless devices (Wi-Fi/Bluetooth/BLE) of mobile clients (non-participatory) uniquely using the wireless probe requests. Smartphones (sensing unit) used to track the people does not require any extra hardware infrastructure to deploy as well as does not need any modifications in hardware design at all, which makes it cost-effective and easy to implement.
- We develop a real-time testbed to perform a spatio-temporal analysis of the real-time collected data in our Institute campus for a long-term deployment during working days. We study the students' behavior in the Computer Science department labs and exploit location analytics for improved campus operations and management without the active participation of people (non-participatory).
- Real-time experiments on a proof-of-concept prototype testbed with our dataset show the usability of our proposed system.

## II. BACKGROUND

Wireless probes are emitted from wireless devices to setup the connection with Access Points (APs). Probe requests can be the type of either 802.11 management, data or control frames [20]. The frame header contains relevant fields, like the frame type, subtype, transmitter address, receiver address, etc. However, probe counts per unit time can vary according to in-built hardware architecture of Smartphones used.

## III. RELATED WORK

Recently, Smartphones usages are increasing day-by-day across the globe. Consequently, researchers are concentrating on the development of Smartphone-based applications for both indoor and outdoor localization, human tracking and identification. In order to efficiently track individual locations, and to identify and monitor them, the proposed system should be highly scalable, accurate and should support high coverage. Some researchers have proposed systems in which sensor-embedded Smartphones can be used as a tag for human tracking and identification with additional requirements of particular hardware and software. E.g., PDX Bus [21] is a human tacking system which requires software and hardware installation on the client side with Internet connectivity all the time.

There are many research works focusing on single positioning/wireless technology, such as RFID [22], Wi-Fi enabled devices [23], Bluetooth (BT)/BLE tags [24], and Smartphone's GPS/General Packet Radio Service (GPRS) [25] to track human in indoor and outdoor environments.

RFID-based tracking and monitoring systems have significant performance issues, such as human body interference, expensive RFID readers and low coverage area when deployed at the heavily crowded places. Wi-Fi-based indoor localization, for instance, fingerprinting and ranging, both use Received Signal Strength Indicator (RSSI) measurements to estimate users' positions. However, fingerprinting methods are not robust to environment changes while range-based methods have significant localization errors due to the instability of Wi-Fi signals [21]. Wi-Fi-based indoor localization faces some challenges, e.g., signal multipath /interference caused by the interior setup and blocking signals, and requirement of additional hardware(s) [26].

*BT* is one more possible solution for Smartphone-based indoor localization [27] because of its low-cost and low-power consumption. The main issues of not using the *BT* to track the human at large crowd are its high discovery time and low range for scanning. Other *BT*-based indoor localization schemes use BLE tags based on RSSI measurements which have huge location errors due to non-uniform shadowing [21].

Another possible solution to track the clients' location in the large crowd is to use GPS sensor of Smartphone and continuously updates the location to the remote server(s) using the Internet. However, it is not feasible that all the clients in the large crowd will have the Internet connection. Also, GPS does not work well in the indoor, urban and dense area due to the multipath issues [28].

Furthermore, cellular-based positioning technologies are efficient if more base stations are present near to the localization area. Otherwise, location accuracy is limited. However, the localization scheme based on single wireless technology is not robust because of their trade-off among accuracy, power consumption, and coverage area as well as single point of failure [29].

To overcome the above-mentioned issues, multiple wireless technologies can be used together, like GPS-Wi-Fi-Cellular to increase localization coverage, and hybrid Global Navigation Satellite System (GNSS) signals along with other wireless/sensor technologies, such as *BT*, Near Field Communication (NFC), acoustic sensors, and inertial sensors to support high accuracy and low space/time complexity [30]. Some existing localization systems, like Wi-Fi-SLAM [31], Skyhook and Ekahau [32] are supporting fair location accuracy [33], while, they require extra hardware infrastructure to deploy, or they need the Internet all the time to locate the Smartphones [34][35].

We, on the other hand, can actually track, identify and monitor a client (indoor and/or outdoor) with no Internet connection in the densely-crowded places using client's Smartphone MAC ids (considering a person is associated/inalienable with his Smartphone) and raw location coordinates. Moreover, *CrowdTrack* employs Google location API [36], a combination of multiple positioning technologies, GPS-Wi-Fi-Cellular and sensor data to achieve the balance between accuracy and power consumption in both indoor and outdoor environments.

Furthermore, many research groups have considerable interest in exploring the usage of wireless probe requests emitted by user's wireless devices, such as Smartphones and BT/BLE tags. These tiny data packets can be leveraged for the analysis of the multitude of areas, such as social network, human behavior analysis, mobility pattern, traffic control, security, and privacy. Moreover, probe requests can be helpful in user tracking and monitoring as well as discovering nearby Wi-Fi networks. Luzio, et al. presented the idea to collect Wi-Fi probe requests from users' wireless devices, which can be helpful in determining device owner's nature, social information and de-anonymizing the origin of participants and events [37].

Rose, et al. proposed a wireless sensor network based approach for exploring the details of wireless access points, monitoring web browsing, Wi-Fi fingerprinting for user's past behavior analysis and Wi-Fi equipped vehicles tracking [15]. Cunche, et al. [16] analyzed the controlled dataset of Wi-Fi fingerprinting of user's wireless devices for predicting the social connectivity and behavior similarity. Moreover, authors leveraged the intersection among SSIDs of different wireless devices for estimating users' common trajectories, their interests and similarity metrics. Cheng, et al. [17] extended the previous approaches based on three dimensions: association history, physical closeness, and spatio-temporal behavior. Authors have taken the intersection of captured probe requests over a small sample dataset of users.

Musa, et al. [18] presented a system for tracking Smartphone without installing any app. They use AP hardware with custom firmware as a Wi-Fi monitor to capture the frames transmitted from the Smartphones. Authors have presented several techniques for both passive and active tracking. Almost all the Wi-Fi frames contain their unique MAC address which is used for tracking a device. Barbera, et al. [19] collecting the probe requests for finding the social relationships among the Smartphone users. Bonne, et al. [37] proposed a mobile-phone and Raspberry-Pi based system for tracking the people at mass gatherings without user's active cooperation. In most of these approaches, extraction of MAC ids/SSIDs from probe requests requires a two-step process which makes the system complex w.r.to both time and space. One is to capture all probe requests and store them, and later, is to use sniffing tools/procedures to intercept MAC ids from stored probes. While, remaining systems require extra hardware for deployment (makes the system complex).

On the other hand, *CrowdTrack* does not require any additional hardware infrastructure to deploy as well as does not need any modification in hardware design (for sensing unit (Smartphone)) at all. Moreover, in *CrowdTrack*, a Smartphone used for identification and tracking users in mass gathering is enough to capture probe requests and user's location without their active cooperation.

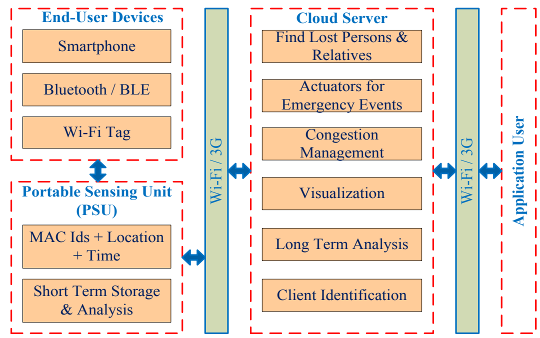



Fig. 1. System architecture

## IV. SYSTEM ARCHITECTURE

Fig. 1 shows the system architecture of the *CrowdTrack*. The proposed architecture is composed of three main modules: end-user devices and application users, Portable Sensing Unit (PSU), and cloud server (CSr).

End-user devices consist of either Smartwatch, BLE tags, *BT* or Wi-Fi enabled devices for movement monitoring. BLE and Bluetooth enabled tags or devices are energy and cost efficient. Hence, these are the best alternative solutions in case individuals do not have Smartphones with them. However, the range of *BT* is short as compared to Wi-Fi. When end user registers themselves to the *CSr*, they can get more services from the cloud, such as find last location of relatives during the lost, evacuation path planning, and actions priority during emergency, etc.

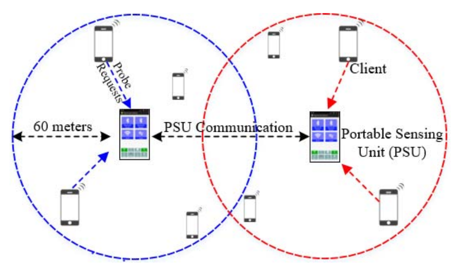



Fig. 2. Scanning of client's smart devices through PSUs

Fig. 2 shows the scanning of client's smart devices through *PSUs*. *PSU* is a primary functional layer of our proposed system. *PSU*, a Smartphone which identifies, tracks and monitors individuals in the large gathering using the MAC ids of client's wireless devices and uploads the data to the *CSr* for further processing and visualization. In *CrowdTrack*, probe requests are passively intercepted by Smartphone (working in a monitor mode) using external Wi-Fi adapter. The monitor mode allows *PSU* to capture all the probe requests send over the wireless medium, even the requests are not destined to it. The monitor mode does not require a user's device to be connected to a *PSU*, while it keeps all requests intact, i.e., without removing any frame header. The *PSU* consists of a Smartphone with GPS sensor, USB Wi-Fi Adapter, and Android app. After extracting MAC id, *PSU* appends current location obtained from Location Manager which uses Google location API. We have observed through experiments that the aggregate value of indoor location accuracy using pure GPS for the entire scanning period is 15.30 meters, while *CrowdTrack* system is having 7 meters of average location accuracy.

The current timestamp, the MAC address and current *PSU* locations are then sent to a temporary file. The data uploading task is handled by the background services, which uploads the file in the order they were created. After uploading a file successfully, it is deleted from the internal storage of the *PSU*. If uploading fails, it retries to upload the file when the network connection is available again.

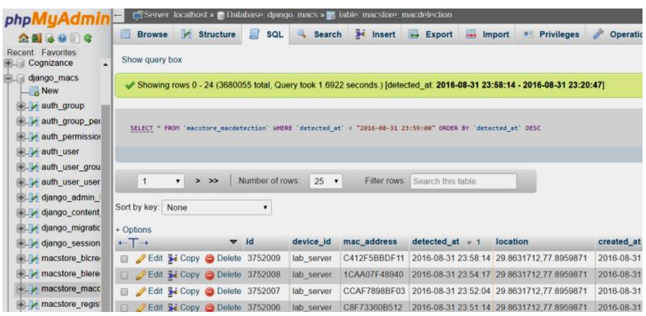



Fig. 3. MySQL Database at server side

*CSr* collects data from all *PSUs* and provides long-term analysis of the data and visualizes it for better understanding. The main components of the *CSr* are as follows: Django based server for data uploading and retrieving, MySQL database for storing the uploaded data and Apache web server (see Fig. 3).

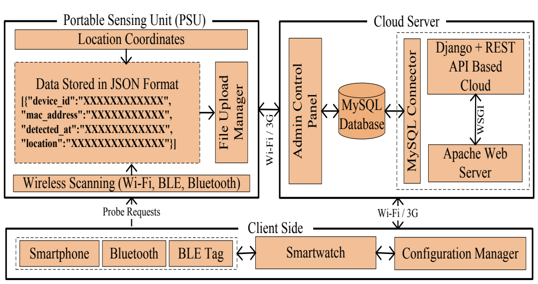



Fig. 4. Automated methodology framework of *CrowdTrack*

## V. Prototype Implementation and Testing

Fig. 4 shows the automated methodology framework of our proposed system *CrowdTrack*. In this section, we discuss the implementation of *PSU* and *CSr*. we shall also introduce our testbed and dataset used to test and evaluate the *CrowdTrack* system.

### *A. PSU*

We have used Android as the platform for developing the *PSU's* application. In Android, it is not possible for the user application to access a Smartphone's built-in Wi-Fi to discover nearby Wi-Fi devices without changing the authorization (rooted) and the driver of device. Therefore, it is better to use external Wi-Fi adapter with the Smartphone as per the need of applications, such as cost-effective, power-efficient and high receiver range. We have used Tenda and Alfa Wi-Fi adapters to support the monitor mode. The range of Tenda and Alpha adapters are approximately 10-12 meters and 50-60 meters, respectively. The Android app for the *PSU* is developed in Java 7 using Android Studio IDE on Windows.

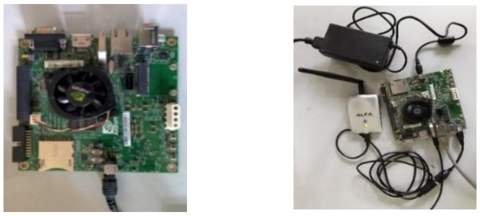
Every Smart device's MAC address is cached in a HashMap. HashMap contains a key-value pair, where the key is MAC address and value is the time when the MAC address is detected. Whenever a new MAC address is detected, it is added to the HashMap and also logged in a temporary file along with current time and location. If MAC address is already present in HashMap, then only its time is updated after a certain fixed interval to minimize the detection of duplicate MAC addresses. To make the *PSU* memory-efficient, the entries in the HashMap are deleted periodically. There are two possible cases for removing the entries. First is, when the number of entries in HashMap reaches a certain limit. Second is, at the pre-specified time interval. Data collection process is continuous and round-the-clock. Data is uploaded to the *CSr* when the number of records in the temporary file reaches more than the pre-specified threshold to make the system energy and network efficient.

### *B. Cloud Server*

The *CSr* uses the Django RESTful API to upload and retrieve data from/to *PSUs* and clients' devices. The Django REST framework provides a web browsable API with pagination support. Fig. 4 shows the interaction between various components on Cloud. To use MySQL with Django, a connector "mysql-connector-python" is required. Django uses Python Web Server Gateway Interface (WSGI) to provide connectivity between web servers and Python web applications or frameworks and portability across different web servers. Briefly, this module implements a WSGI compliant interface for hosting Python based web applications on the top of Apache web server.

### *C. Prototype Testbed Setup*

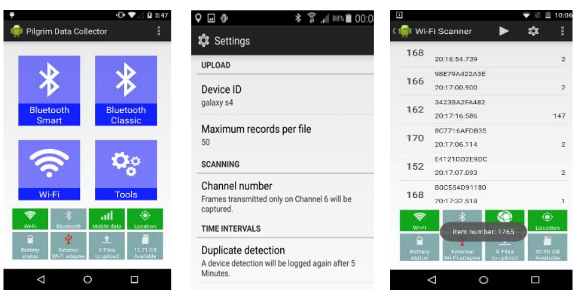
We perform extensive experiments for identifying and tracking individuals and show the working of *CrowdTrack* in and around the UGPC lab and IS lab of the CSE department at Indian Institute of Technology (IIT), Roorkee, India.



(a) NVIDIA Jetson TK1 developer kit (b) Jetson TK1 as a sensing unit

Fig. 5. Setup of NVIDIA Jetson TK1 developer kit (optional as sensing unit)

In most of the experiments, we need either to capture or to transmit Wi-Fi frames. We have used two portable NVIDIA Jetson TK1 (2) [39] (see Fig. 5 a & b) and five Android-based Smartphones (*Dell Venue 8* (2), *Samsung Galaxy S4* (2), *Nexus5* (1)) as *PSUs* to capture the frames transmitted from nearby client's devices. These *PSUs* are capable of scanning around the radius of 60 meters and can process 5000 frames/second (tested in real-time). Android app developed for sensing the client presence is shown in Fig. 6. *PSU's* Android app has different activities such as main activity, settings activity and Wi-Fi scanner activity as shown in Fig. 6 a, b, and c respectively. We have also used BLE, BT tags and Smartwatches (BLE/BT embedded) as the client devices as shown in Fig. 7. Fig. 8 shows the setup of a client node (*Samsung S4*) and a *PSU* (*Dell Venue 8* with Android app).




(a) Android App at PSU for Sensing the clients' devices (b) Settings activity for file size, channel number and duplicate detection (c) Wi-Fi Scanner activity at PSU

Fig. 6. Android app for PSU

(a) BLE and Bluetooth Tags (optional) (b) BLE/Bluetooth embedded Smartwatches (optional)

Fig. 7. Client devices in case Smartphones are not available to the users


Fig. 8. Smartphone working as a client and PSU

We use the Wi-Fi traces as a source of data to find when a given MAC address (encrypted) visits the location. In this work, we assume that the person carries their mobile devices with them all the time. The client's presence will be detected only when the Wi-Fi mode is enabled on mobile devices and the devices actively sends Wi-Fi packets. The frequency of receiving packets depends on how frequently a person uses his/her mobile to access the Internet. If the individual is not using his/her mobile to access the Internet but if the Wi-Fi is enabled, it will send probe request packets after some duration which in turn depends on some number of factors. Moreover, even if the device is sending packets, the Wi-Fi adapter should be able to capture it. The adapter is more likely to capture a packet from a device which is in direct line of sight to Wi-Fi adapter.

For the period of 16 months (April, 2015 – Aug., 2016), we have collected 36,78,613 records with more than 74,165 unique MAC ids using *CrowdTrack* system.

Fig. 9. Locations of individuals in IITR using PSU

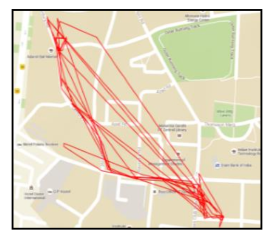


Fig. 10. Locations tracking of an individual person in IITR using PSU

### D. Case Study

Fig. 9 shows the location coordinates of the *PSUs* on a map where scanning was performed and Fig. 10 illustrates the tracking of an individual person in the IITR campus on 30-Aug.-2016. Every location has a semantic meaning associated with activity. The presence of a student in a semantic location implies that the student is performing that activity. For example, canteen implies eating, lecture hall implies attending lectures, and library implies self-study. Most of the time, there is a certain frequency, periodicity and order in which a student visits these locations. This contains information that can be used to build powerful predictors of future behavior. Any change or deviation from this normal behavior is an anomaly.

We performed some basic analytics on the data like the number of days people visit that location and the average amount of time a person spends in that vicinity daily or the primary periodicity of a person's visits. Fig. 11 and 12 illustrate the cumulative fraction of the total number of individuals visited the UGPC and IS labs, respectively for the given number of days. In Fig. 13, Google-Heatmap shows the utilization of UGPC and IS labs. Fig. 14 exhibits the average visiting sequence of individuals for the period of 16 months. Highest visiting frequencies detected during the time (24 hours' time period) interval of 8-12 and 12-16 are 52,608 and 49,959, respectively including duplicate detections. The lowest visiting frequency in and around the lab is during the time 0-4. Fig. 15 depicts the total number of individuals visited in and around the lab for the entire time span of 16 months. Aug., 2015 – Nov., 2015 and Apr., 2016 – July, 2016 are the peak months when detection of individuals' MAC addresses is high in compared to other months. Fig. 14 and 15 can also be used to find the lab utilization during the given time span. Most visited individuals in and around the lab (CSE building) and their time spent for the particular time duration are shown in Fig. 16. To show that *CrowdTrack* system can identify and track individuals, we carried out an experiment as shown in Fig. 17. It shows the visiting frequency sequences of an individual in and around the lab for the fixed time interval. Fig. 17 also shows the working behavior/pattern and hours spent in the department. The identified person is spending more time during the day hours of 8 to 16 and 20 to 24.

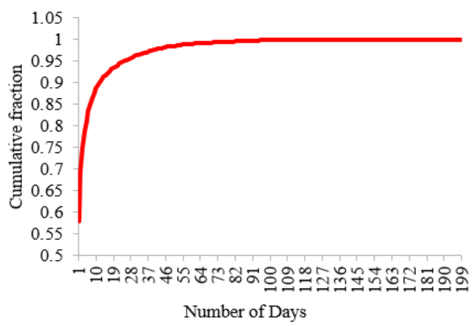



Fig. 11. Fraction of total number of individuals that visit for less than given number of days at UGPC lab, IIT Roorkee

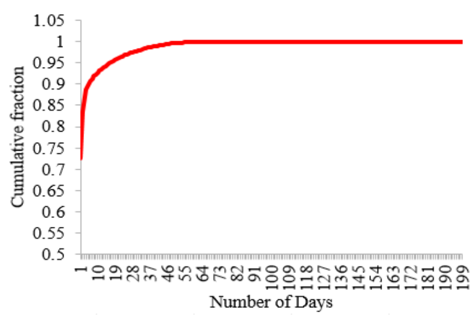



Fig. 12. Fraction of total number of individuals that visit for less than given number of days at IS lab, IIT Roorkee

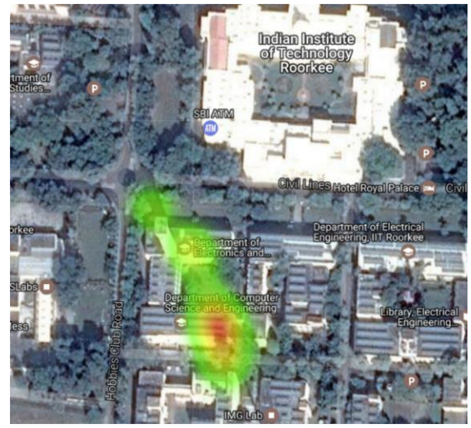



Fig. 13. Heatmap to show the lab utilization of CSE building at IIT Roorkee

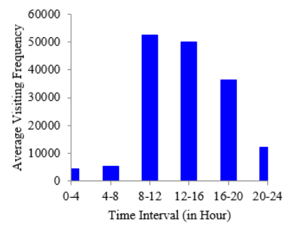



Fig. 14. Average visiting frequency of individuals in UGPC lab for the time interval (in hour)

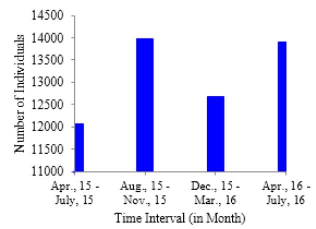



Fig. 15. Total number of individuals detected in UGPC lab during the time interval (in months)

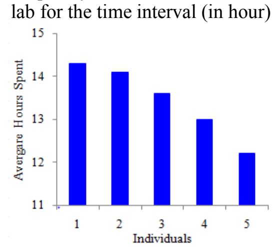



Fig. 16. Top 5 individuals for spending maximum average time per a day in UGPC lab

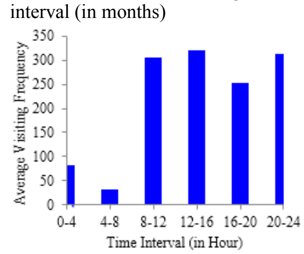



Fig. 17. Average visiting frequency of a highly visited individual in UGPC lab

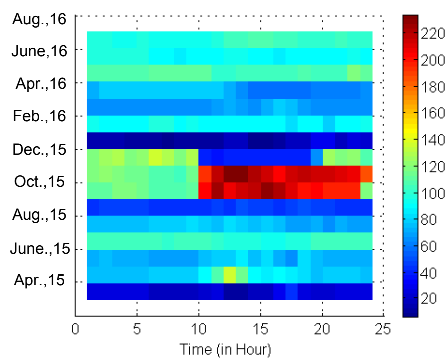



Fig. 18. Month/Hour wise visiting frequency of a highly visited individual in UGPC lab

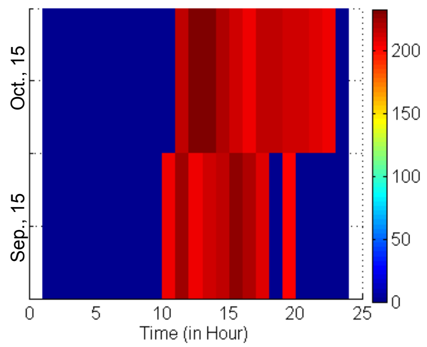



Fig. 19. Month/Hour wise visiting frequency sequence of top 20 individuals in UGPC lab

To further analyze the individual working pattern, we plot the month/hour wise Heatmap of an individual's visiting frequency in the lab (see Fig. 18). The analysis shows that the individual was highly active in his/her work during the period of Sep., 15 to Nov., 15. To find the working pattern of the CSE building, we extract top 20 most frequently visited individuals from the database as shown in Fig. 19. This result also shows the time spent by those individuals in the month of Sep., and Oct., 2015.

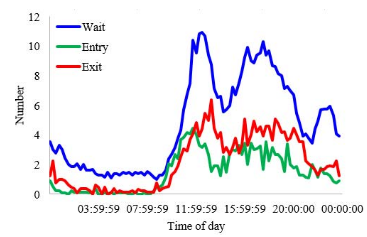



Fig. 20. Average Day for a frequent visitor in the month of Aug. 2016 at UGPC lab

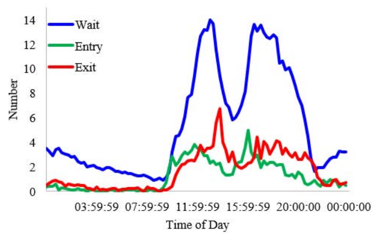



Fig. 21. Average Day for a frequent visitor in the month of July 2016 at UGPC lab

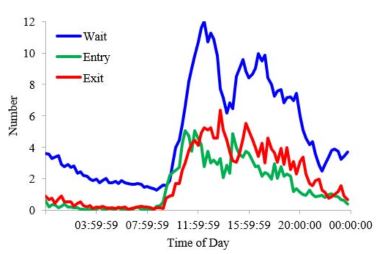



Fig. 22. Average Day for a frequent visitor in the month of June 2016 at UGPC lab

We also analyze the month-wise average visiting frequency pattern for frequent visitors near the UGPC lab at CSE department. MAC addresses can be categorized into 3 sub-groups as frequent visitors who are frequently visiting in the vicinity of tracker devices and detected in the time span of last week, non-frequent visitor, if the person has not been detected in the last week, new visitor, if the person has been detected for first time on a particular day. These are mostly outsiders who usually visit during some special event. For each time segment of 15 minutes, we further divide each subgroup into whether the visitor has arrived at the venue during the given slot (enter), left the venue (exit) or has stayed (wait) at the location before, during and after the slot. For this analysis, we need to track the object's MAC addresses' presence for *N* time slots before and *N* time slots after the current time slot.

- If the difference between the previous time of detection of MAC address before the given time slot and the following time of detection including the given slot is less than *N*, then the MAC address is a staying at that location (wait).
- If the MAC address has not been detected in the *N* time slots before the given time slot but detected during the given time slot and in any of the *N* time slot after the given slot, then the MAC address has arrived (entry) at the location.
- If the MAC address has been detected in some of the *N* time slots before the given time slot and also detected during the given time slot but not in any of the *N* time slot after the given slot, then the MAC address has left (exit) the location.

We applied feature engineering on Wi-Fi Logs for understanding the semantics of a location. Fig. 20, 21 and 22 show the month wise average day pattern for frequent visitors at UGPC Lab.

## VI. CONCLUSION

MCSC has received considerable attention as a replacement of WSN with the user companioned devices. The data collected using MCSC can be used for analyzing the traffic conditions, environment monitoring, surveillance, etc. In this paper, we made a first attempt to develop a Smartphone-based non-participatory crowd monitoring system, named *CrowdTrack*, to monitor the movement patterns of one or more persons (non-participatory) in a densely crowded environment. *CrowdTrack* uses the Smartphone without any hardware modification as a sensing unit to extract the MAC ids from the wireless probe requests emitted from the users' devices. These MAC ids are associated with the timestamp in which they are detected and location of the sensing unit. Further, they are processed and stored in the cloud for finding the users' working patterns and their location coordinates within a time span. Our case study and extensive experimental results show the usability of *CrowdTrack* system. As part of our future work, we will deploy *CrowdTrack* system for large scale environments, such as those occurring in disaster management scenarios.

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## VIII. REFERENCES


[1] F. L. Lewis. “Wireless Sensor Networks.” John Wiley and Sons, pp. 11–46, 2005.

[2] J. Burke, D. Estrin, M. Hansen, A. Parker, N. Ramanthan, S. Reddy, and M. B. Srivastava. “Participatory sensing.” In Proceedings of the World Sensor Web Workshop, ACM Sensys, 1–5, 2006.

[3] Y. Liu, Y. He, M. Li, J. Wang, K. Liu, and X. Li. “Does Wireless Sensor Network Scale? A Measurement Study on GreenOrbs.” IEEE Transactions on Parallel and Distributed Systems, 2013.

[4] B. Guo, Z. Yu, X. Zhou, and D. Zhang. “From participatory sensing to Mobile Crowd Sensing.” In Proceedings of PERCOM Workshops, 593–598, 2014.

[5] "TCPDUMP and LIBPCAP," [Online]. Available: http://www.tcpdump.org/. [Accessed 10-Sep-2016].

[6] “Wireshark packet analyzer,” [Online]. Available: https://www.wireshark.org/. [Accessed 12-Sep-2016].

[7] “Kismet: wireless network detector, sniffer, and intrusion detection system,” [Online]. Available: https://www.kismetwireless.net/. [Accessed 12-Sep-2016].

[8] M. Mohandes. “Pilgrim tracking and identification using the mobile phone.” in International Symposium on Consumer Electronics (ISCE), 2011.

[9] M. Mohandes, M. A. Haleem, A. Abul-Hussain, and K. Balakrishnan. “Pilgrims Tracking Using Wireless Sensor Network.” in International Conference on Advanced Information Networking and Applications (WAINA), Biopolis, 2011.

[10] M. Yamin and Y. Ades. “Crowd Management with RFID & Wireless Technologies.” in First International Conference on Networks & Communications, 2009.

[11] M. Bolic, R. Majed, and M. D. Petar. “Proximity Detection with RFID: A Step Toward the Internet of Things.” IEEE Pervasive Computing, vol. 2, pp. 70-76, 2015.

[12] “Libelium, Smartphone Detection.” [Online]. Available: http://www.libelium.com/products/meshlium/smartphone-detection/ [Accessed 11-Sep-2016].

[13] “Cisco Wireless Location Appliance.” [Online]. Available: http://www.cisco.com/c/en/us/products/collateral/wireless/wireless-location-appliance/product_data_sheet0900aecd80293728.html. [Accessed 6-Sep-2016].

[14] W. Z. Khan, Y. Xiang, M. Y. Aalsalem, and Q. Arshad. “Mobile phone sensing systems: A survey.” Communications Surveys & Tutorials, vol. 15, no. 1, 2013, pp. 402-427.

[15] Rose, Ian, and M. Welsh. “Mapping the urban wireless landscape with Argos.” Proceedings of the 8th ACM Conference on Embedded Networked Sensor Systems. ACM, 2010.

[16] Cunche, Mathieu, M. A. Kaafar, and R. Boreli. “I know who you will meet this evening! linking wireless devices using wi-fi probe requests.” IEEE WoWMoM, 2012.

[17] Cheng, Ningning, P. Mohapatra, M. Cunche, M. A. Kaafar, R. Boreli, and S. Krishnamurthy. “Inferring user relationship from hidden information in wlans.” IEEE MILCOM, 2012.

[18] A. B. M. Musa, and Jakob Eriksson. “Tracking unmodified smartphones using wi-fi monitors.” Proceedings of the 10th ACM conference on embedded network sensor systems, 2012.

[19] Barbera, A. Epasto, A. Mei, Perta, and J. Stefa. “Signals from the crowd: uncovering social relationships through smartphone probes.” Proceedings of the conference on Internet measurement conference. ACM, 2013.

[20] IEEE 802 LAN/MAN Standards Committee. “Wireless LAN medium access control (MAC) and physical layer (PHY) specifications.” IEEE Standard 802.11 (1999).

[21] H.S. Maghdid, I.A. Lami, K.Z. Ghafoor, and J. Lloret. “Seamless Outdoors-Indoors Localization Solutions on Smartphones: Implementation and Challenges.” ACM Computing Surveys (CSUR) 48(4), 2016.

[22] L.M. Ni, D. Zhang, and M.R. Souryal. “RFID-based localization and tracking technologies.” Wireless Communications, 18(2), 2011, pp. 45-51.

[23] C. Yang, and H.R. Shao. “WiFi-based indoor positioning.” IEEE Communications Magazine, 53(3), 2015, pp. 150-157.

[24] P.C. Deepesh, R. Rath, A. Tiwary, V.N. Rao, and N. Kanakalata. “Experiences with using iBeacons for Indoor Positioning.” in the Proceedings of the 9th ACM Conference on Software Engineering, 2016.

[25] D. Angelis, Guido, G. Baruffa, and S. Cacopardi. “GNSS/Cellular hybrid positioning system for mobile users in urban scenarios.” IEEE Transactions on Intelligent Transportation Systems, 14(1), 313– 321, 2013.

[26] R. Mautz. “The challenges of indoor environments and specification on some alternative positioning systems.” in the Proceedings of the WPNC, 29–36. 2009.

[27] F. Subhan, H. Hasbullah, A. Rozyyev, and S.T. Bakhsh. “Indoor positioning in Bluetooth networks using fingerprinting and lateration approach.” in Proc. of the International Conference on Information Science and Applications, 2011.

[28] Waadt, Andreas, G.H. Bruck, and P. Jung. “An overview of positioning systems and technologies.” in 2nd International Symposium on Applied Sciences in Biomedical and Communication Technologies, 2009, pp. 1–5.

[29] A. Boukerche, H.A. Oliveira, E.F. Nakamura, and A.A. Loureiro. “Secure localization algorithms for wireless sensor networks.” IEEE Communications Magazine, 46(4), 96–101. 2008.

[30] J. Partyka. “A look at small indoor location competitors. GPS world.” Available at: http://gpsworld.com/ wirelesslook-small-indoor-location-competitors-13229/ [Accessed 31-Jan-2016].

[31] J. Huang, D. Millman, M. Quigley, D. Stavens, S. Thrun, and A. Aggarwal. “Efficient, generalized indoor WiFi GRAPHSLAM.” in Proceeding of the IEEE International Conference on Robotics and Automation (ICRA), 1038–1043, 2011.

[32] T. Gallagher, B. Li, A. Kealy, and A.G. Dempster. “Trials of commercial Wi-Fi positioning systems for indoor and urban canyons.” in Proceedings of the symposium on GPS/GNSS (IGNSS), 2009.

[33] R. Faragher and R. Harle. “SmartSLAM–an efficient smartphone indoor positioning system exploiting machine learning and opportunistic sensing.” in Proceedings of ION GNSS, 2013.

[34] Sensewhere LTD, 2011. Geo-fence technology and applications. Indoor Location Technology Leaders. Available at: http://www.sensewhere.com/images/geowhereDatasheet_compressed.pdf [Last access January 31, 2016].

[35] P. Zandbergen. “Accuracy of iPhone locations: A comparison of assisted GPS, WiFi and cellular positioning.” Transactions in GIS, 13(s1), 2009.

[36] “Making Your App Location-Aware, Android Developers.” [Online]. Available: https://developer.android.com/training/location/index.html. [Accessed Nov. 20, 2015].

[37] Di Luzio, Adriano, A. Mei, and J. Stefa. “Mind your probes: De-anonymization of large crowds through smartphone WiFi probe requests.” Computer Communications, IEEE INFOCOM, 2016.

[38] B. Bonne, A. Barzan, P. Quax, and W. Lamotte. “WiFiPi: Involuntary tracking of visitors at mass events.” IEEE WoWMoM, 2013.

[39] “The NVIDIA Jetson TK1 developer kit.” [Online]. Available: http://www.nvidia.com/object/jetson-tk1-embedded-dev-kit.html. [Accessed 12-Sep-2016].