Hybrid Participatory Sensing for Analyzing Group Dynamics in the Largest Annual Religious Gathering

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ABSTRACT
Understanding crowd dynamics of large-scale events is crucial to deliver a pleasant experience for the participants. In this paper, we propose a novel hybrid participatory sensing approach to capture large group dynamics. Specifically, our approach is based on distributing a large number of tiny, wearable Bluetooth Low Energy (BLE) tags and few smartphones among the group members. We start by identifying the best configuration; in terms of transmit power and beaconing interval; for detecting BLE tags in indoor and outdoor environments. Then, as a case study, we deploy the system during the six main days of the Hajj pilgrimage in 2014, which is the world's largest annual religious gathering. We used the proposed hybrid participatory approach to collect the mobility data of pilgrim groups based on GPS location and co-occurring BLE tag detections. Our system provided up to 80% group-wise detectability in a single scan event. Moreover, 98% cumulative unique tags detectability is achieved in the whole event, leading to 0.74 million records. Analysis of the group dynamics revealed unexpected behavior and interesting findings. In particular, regional variations are found among different groups in the entry or exit times, duration of stay, and group cohesion; which are attributed to congestion, improper arrangements, or the nature of activities. Furthermore, we show sub-community clusters could be identified revealing clear biases based on the demographic characteristics. Based on this case study, we also give suggestions on using the proposed system for other large-scale events.

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INTRODUCTION
Large scale events, such as sports galas, trade shows, and religious gatherings; present significant challenges in managing crowd dynamics, where the organizers of the events aspire to deliver a pleasant experience for the attendees. Transportation, housing, catering and healthcare services, all need to be managed efficiently to avoid chaos; essentially congestion, stampede and disease outbreak. This requires understanding the participating crowd behavior, their movement patterns and interactions, their needs and demands, throughout the event. For example, organizers need to know when and how people accumulate in different areas, how long they stay, how strictly they follow the event guidelines, and what the behavior of individuals or a group is. Answering such questions requires a mechanism to collect data about crowd movements. Hence, our primary motivation is to capture and understand the crowd mobility information in large-scale events.

We selected one of the world's largest and annually organized religious gathering, the Hajj pilgrimage [8], as a testbed to achieve our objective. Muslims from all over the world travel to the Holy city of Makkah, Saudi Arabia to perform the pilgrimage. Two million people performed Hajj in 2014 and this number is expected to increase significantly in coming years. Besides, the spatially and temporally distributed nature of Hajj activities makes the management of the event challenging for the authorities. In addition, the available statistics of visiting pilgrims and their activities are insufficient to assess the quality of Hajj experienced by them, making it difficult for the authorities to deliver the satisfactory level of services.

Crowd behavior studies suggest that large gatherings are usually composed of several groups, which has a significant impact on crowd dynamics [14, 15, 31]. In addition, crowd mobility is driven by the bonding of friends, families or people having common interest, for example tourists or spectators. Particularly, in our selected testbed of the Hajj event, pilgrims arrive from different countries in form of varying group sizes. Hence, we believe that collecting data about the groups dynamics and studying their mobility patterns would help us reveal on-the-ground realities and propose solutions for the better management of such massive scale event.

Participatory and opportunistic sensing has been extensively used to conduct various types of research studies. The utilization of smartphones in crowd dynamics studies [16,38,39,41] is limited by its dependence on a large user base, heterogeneity of mobile platforms, and difficulty of installation and deployment; particularly in huge events like Hajj. Usage of alternate crowd monitoring approaches, namely the RFID [35] and WISP tags [43] pose critical technological problems including range and interference issues as well as dependency on ***expensive*** specialized infrastructure-based readers.

In this paper, we introduce an innovative approach in our participatory sensing architecture that enables us to capture crowd mobility data by utilizing a few smartphones as readers. These few readers help to track large groups of people, carrying BLE [1, 5] proximity tags, coming in the vicinity. To realize this new design of hybrid sensing, we conducted a study to identify the best configurations for BLE tags and the scan durations for smartphones. Next, we configured the tags and distributed them within volunteer pilgrim groups from three different countries. Furthermore, we provided the smartphones, installed with a BLE scanning application running in the background, to the leaders of each group. The application was periodically transferring the scan-logs to our server for analysis. The seamless integration of BLE tags with smartphones, and smartphones with the server helped in collecting a rich set of data that allowed us to analyze the group dynamics during the six days mass gathering event. Specifically, we were able to get up to 80% group-wise unique tags detectability in a single scan event. Cumulatively, 98% of the tags were detected throughout the study period using all the smartphones provided to the groups. As a result, we received around 0.74 million detections of the 732 distributed tags.

Mining the collected data revealed interesting findings, which were never captured before, particularly for Hajj. In addition, clear and unexpected differences have been noticed among the groups with respect to entry or exit times and the duration of stay in each region. To better understand the behavior; a measure of group unity is proposed, calculated for pilgrims performing key activities, and compared region-wise to provide better insight of previously unknown behavior differences. Furthermore, we extract the community structure of each group to identify the sub-communities formation based on demographic characteristics. Our results reveal that there appear to be clear biases in sub-communities based on gender and age group of the pilgrims. Consequently, this analysis helped to identify key issues in the overall management of the Hajj event and suggests possible measures to tackle them accordingly.

In summary, our contributions are three-fold:

- Designing a novel scalable architecture, using a hybrid participatory sensing approach, by offloading the proximity sensing to BLE tags that can be carried by the attendees of an event in order to advertise their presence. These tags are detected by few smartphones located in the vicinity.
- Conducting one of the largest hybrid participatory sensing experiment, to collect group dynamics data from the world's largest annual religious gathering.
- Analyzing and visualizing the collected data to understand the captured crowd mobility and extract interesting spatiotemporal and behavior differences. We also reflect on how to use the proposed system in other large-scale events.

HYBRID PARTICIPATORY SENSING FOR MEGA EVENTS

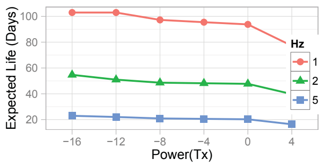
Previously, smartphones were used to understand the crowd behavior [16, 38, 39, 41]. There are certain design considerations that discourage us from relying on smartphones for capturing group dynamics data in the Hajj event:

- Not everyone in a particular group carries a smartphone during the event.
- Not everyone will be willing to install our data collection application, unless provided with a useful front-end application or other incentives.
- Preserving the smartphone battery is important, considering the scarcity of electricity points in the event area.

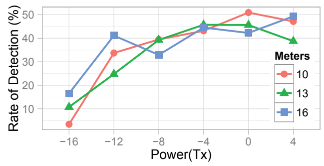
Based on these points, we introduce an innovative feature in our participatory sensing architecture that allows us to distribute a large number of BLE tags among the attendees, which are detected by few smartphones. A BLE tag continuously advertises its presence by broadcasting its MAC address within a closed range based on the transmit power setting. These advertisement beacons can be detected by the smartphones in the vicinity. To realize this new design of hybrid participatory sensing, we first need to assess the potential of BLE tags and smartphone readers in terms of battery life and detectability. In what follows, we present the feasibility analysis that helps us to identify the right configurations to be used in the actual field deployment, during Hajj.

BLE Tags Performance

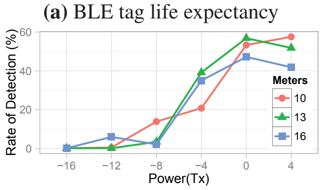
First, we need to identify the potential of BLE tags with respect to different transmit powers and beaconing intervals; and compare the detectability in both indoor and outdoor settings. Moreover, we must consider the factors which can affect the detectability of tags in dense deployment scenarios. In this section, we focus on identifying the best configurations for a BLE tag to be used in Hajj. To conduct this study, we selected off-the-shelf StickNFind [4] tags because of their advertised higher range and longer battery life. We further perform detailed performance analysis to confirm that they meet our design constraints before deployment in the field.



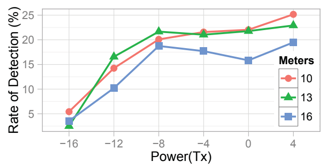
(a) BLE tag life expectancy



(b) Indoor detection @ 30 sec. scan



(c) Outdoor detection @ 30 sec. scan



(d) Indoor detection @ 15 sec. scan

Figure 1. (a) Expected life of a tag on varying transmit power and beaconing rate(Hz). (b)(c)(d) Detectability of a BLE tag @ 1Hz with varying transmit power and distances.

Energy Analysis

To measure the life expectancy, we attached wires to the battery terminals of a BLE tag and connected them to a FLUKE 289 TRUE RMS Multimeter. The Multimeter calculated the average current consumption of the tag based on the beaconing rate and the power with which the beacons are sent. The expected life of a tag (in days) is calculated by substituting the average current consumption (*Load Current*) in Equation 1:

$$\text{Battery Life} = \frac{\text{Battery Capacity (mAh)} \times 0.7}{\text{Load Current (mA)} \times 24} \tag{1}$$

where 0.7 is an approximate value to account for battery life reduction due to external conditions such as temperature, humidity and other environmental factors [3, 6].

Figure 1a shows the expected life of our chosen tags, with three different beaconing rates while increasing the transmission power setting from minimum to maximum. The tags were working on a 90mAh coin-sized battery. The figure shows that the expected life has a decreasing trend as we increase the transmit power. Moreover, it is evident that the expected life of a tag decreases significantly with the increase of beaconing rate.

Detectability of BLE Tags

To start, we explore the potential of BLE tags in ideal indoor and outdoor conditions, with different power settings, varying distances and a fixed beaconing rate of one beacon per second. We discuss the detectability of tags at large distances to cover the edge cases. Figure 1b and 1c show the rate of detection of ***individual*** BLE tags in a 30 seconds scan, at line of sight, using a Samsung ACE 4 smartphone — in indoor and outdoor settings respectively. The figure shows that decreasing the distance between the BLE tags and the reader and/or increasing the transmit power generally lead to increasing the tags detectability. Both indoor and outdoor settings have similar detectability for high transmit powers. However, for low transmit power, indoor environments have a better detectability. This can be due in part to the bouncing effect of signals caused by the indoor objects. Furthermore, we notice about 50% decrease in the detection rate as we reduce the scan duration from 30 seconds to 15 seconds (Figure 1d). We conclude that for detectability in outdoors, we need to configure the tags with high transmission power and long scan durations.

Next, we want to maintain adequate detection rate in a dense and dynamic deployment during Hajj; given that BLE signals can be attenuated by human bodies [37]. It is nearly impossible to orchestrate the Hajj-like dense and dynamic scenario for experimentation. Still, there are certain factors which motivated us to deploy the tags during Hajj event. Primarily, Hajj is a group-bound event and comprises a mix of indoor and outdoor activities. Pilgrims spend more than 60% of their time in Mina, staying in tents of sizes 10m $\times$ 20m or less [2]. Moreover, they travel in buses of length 16 meters or less. These conditions are similar to indoor like environment – where the bouncing effect of signals could increase the detectability. Besides, it is highly unlikely that the tags remain shielded behind the pilgrims all the time as people are mostly resting inside their camps due to the tiring activities of Hajj event. When outdoors, people tend to remain closer to each other [14], moving around or interacting with each other. In such cases, utilizing more readers, that is smartphones, could increase the coverage for attenuated signals and provide more chances of detections. Hence, we expect that careful selection of tag configurations and the usage of multiple readers in the vicinity could capture pilgrims' mobility in the dense and dynamic scenario of Hajj.

Selected Configurations

To deploy the BLE tags for crowd mobility and group dynamics study, we must consider the dynamic nature of the event; i.e. crowd density, level of mobility, and the nature of indoor or outdoor activities. The performance analysis of BLE tags in this section suggests that they could be used for detections during Hajj with carefully chosen configurations. Therefore, for field deployment, transmission of one beacon per second at 0dBm appears to be a reasonable choice that balances the tag lifetime requirement (enough to cover the setup and Hajj event duration) and high detectability.

Smartphone Performance

Although, smartphones come with improved battery rating and optimized Operating Systems (OS) to conserve energy, the battery life can be highly affected by the design of the data collection application. Our primary objective is to perform BLE and GPS scanning, which can drain the battery within few hours if performed continuously. Earlier, we identified that the 30-second BLE scan is the suitable setting for our experiment to provide sufficient BLE detection rate. Subsequently, we need to identify the smartphone battery consumption based on the frequency of BLE scan and GPS query, with a high number of tags present in the surrounding.

Our lab experiments show significant variations in the detectability of BLE tags on different smartphone models, including Samsung Galaxy 4, Samsung ACE 4, HTC One M8, Nexus 4 and Motorola Moto G. This difference in detectability could be due to the specific BLE scanning hardware used or the optimization of OS version by the vendor. Our tests, with 100 tags in the vicinity and with a 5 minutes delay in

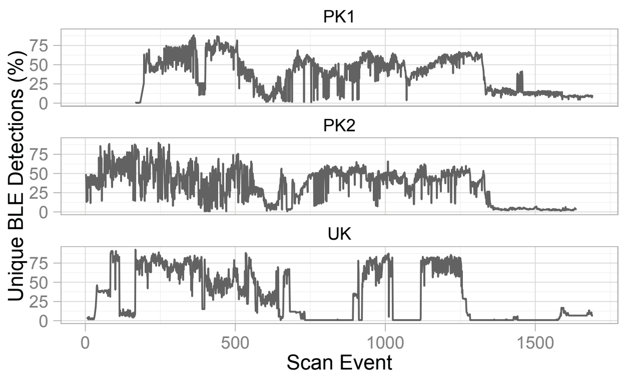


Figure 2. Unique BLE detections (%) of three groups in 30-second scan events occurring every 5 minutes.

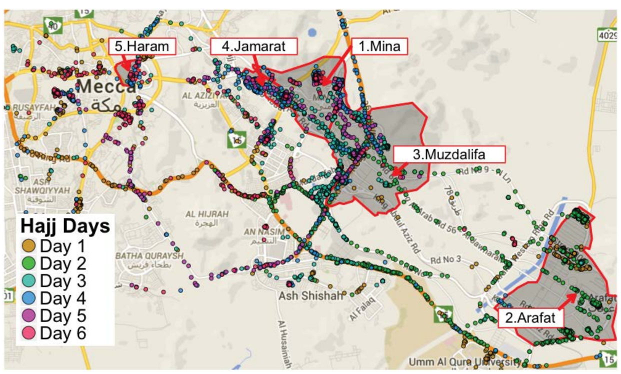


Figure 3. Data distribution across regions and days important for Hajj. The regions are labeled with respective names and colored dots are representing the locations where BLE tags were detected on different days.

consecutive scan cycles; reveal that the Samsung ACE 4 battery of 1500mAh could last for approximately 2.5 days. In each scan cycle, we ran the BLE scanner for 30 seconds and simultaneously acquired the GPS location. The 5 minutes delay between scan cycles is acceptable considering the nature of activities performed during Hajj. To cover the whole duration of Hajj, power banks were provided with the phones to at least double the battery life. Hence, we utilized the Samsung ACE 4 phone – due to its higher BLE tag detectability, longer battery life and low price – as our primary smartphone reader device during the Hajj event.

Preliminary Analysis

To understand the impact of chosen configurations, this section provides high-level statistics from the data collected during the Hajj event. Figure 2 shows the unique BLE tags detections within three pilgrim groups. Clearly, the detectability has reached up to 80% for each group at certain intervals, and remained at 50% in most of the scan events. We also discovered that each phone detected at least 94% unique tags within the designated group during the whole event. This confirms that group members usually remain closer to each other, while staying within the coverage area of the smartphones. Furthermore, Figure 3 shows that the collected data is well distributed across important regions and dates of Hajj. To sum up, the preliminary analysis validates the choice of selected

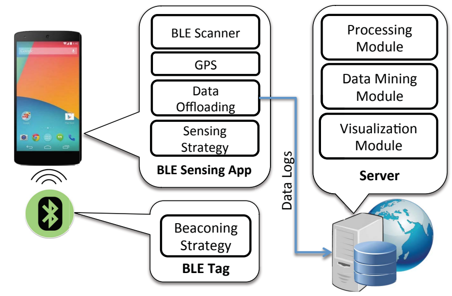


Figure 4. Hybrid Participatory Sensing Architecture comprised of coin-sized BLE tags, standard smartphones, and a server with storage.

Activity	Region	Duration
Prayer activity	Mina	Day 1 00:00 - Day 2 06:00
Stand in vigil*	Arafat	Day 2 06:00 - Day 2 18:00
Night stay*	Muzdalifa	Day 2 18:00 - Day 3 06:00
Devil stoning*	Jamarat	Day 3 06:00 - Day 5
Prayer activity	Mina	Day 3 - Day 6

Table 1. Hajj activities performed from 2nd till 7th of October 2014 (Day 1 to Day 6). Activities could be performed during the specified approximate durations. Obligatory activities are marked with '*'.

tag configurations and scanning strategy on the smartphones, which provide good detectability and coverage throughout the event.

EXPERIMENT DESIGN

In this section, we discuss the architecture design of the proposed system and elaborate on the overall design decisions including the deployment scenario, selection of groups and distribution of devices.

System Architecture

To achieve our new design of hybrid participatory sensing experiment, we propose an architecture which incorporates three essential components (Figure 4):

- **BLE tag** is required to support a proximity profile, smaller in size, easily wearable and have a long battery life.
- **Smartphone** as reader must support Bluetooth v4.0, a GPS receiver and runs on Android 4.3+.
- **Server** machine for data mining.

Every 5 min a leader's smartphone triggers a scanning process that detects nearby BLE tags in a 30 second scan cycle. After scanning, the list of tags are annotated with GPS coordinates and logged with timestamp. The data logs are opportunistically transferred to the back-end server when a WiFi connection is available.

Deployment Scenario

The Hajj activities lasted for six days, that is from 2nd till 7th of October 2014. However, the pilgrims gradually populate the city of Makkah a month before the Hajj event and leave a month after. More than two million people gathered to perform Hajj. We used 732 pilgrims as volunteers to take part in

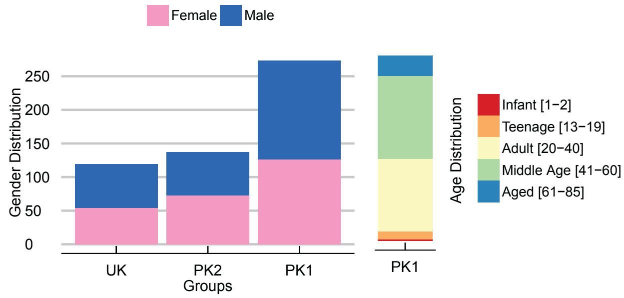


Figure 5. Tags distribution by gender and age. Only 3 groups provided gender details and one group provided age details of the pilgrims.

Group	Country	BLE Tags	Phones
PK1	Pakistan	273	7
MAL	Malaysia	200	7
PK2	Pakistan	140	3
UK	Britain	119	3
RND	-	-	4
Total		732	24

Table 2. Devices distribution per group. RND is for random pilgrims (not part of any group) carrying only smartphone readers.

our experiment. Generally, all the pilgrims perform the same set of activities in a similar sequence; hence we expect our selected sample to be a representative of the whole population with respect to the flow of activities being performed.

The space-time bound activities (Table 1) performed during Hajj include 1) the obligatory activities without which the Hajj will not be considered valid 2) the optional activities, which can be skipped depending on the health and time constraints. The regions and their approximate boundaries where these activities are performed are shown in Figure 3.

Groups Selection

Due to the intrinsic hierarchical grouping of the pilgrims, we targeted whole groups instead of individuals. This strategy helped us to focus on group dynamics, and also eased the coordination, distribution, and collecting back the tags as compared to targeting individual pilgrims. Basically, the selection criteria of the volunteer groups was based on two factors 1) Target groups from different ethnicities, as we hypothesize that people from different ethnicities could have behavioral differences 2) Target groups which plan to stay at locations different from each other, as we hypothesize that different stay locations could have an impact on route selections, travelling times, and activity delays. Thus, the groups were selected from three different countries, that is two groups from Pakistan, one from Britain and seven smaller groups from Malaysia. Figure 5 provides distribution of pilgrims based on demographic information. Only three groups provided the gender data and just one group provided the age information.

Tags and Smartphones Distribution

Our idea was to target moderate-sized groups and distribute tags among all the pilgrims within each group. Moreover, we

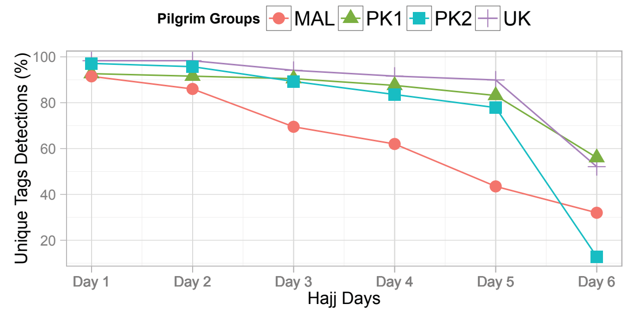


Figure 6. Group-wise unique detections of BLE tags per day

wanted the group leaders to carry the smartphone devices. While traveling, the groups were expected to commute in multiple buses, which are at least 40 persons per bus. Therefore, this traveling condition influenced our decision to decide the number of smartphones provided to each group. Table 2 provides counts of the distributed devices to each group. The Malaysian pilgrims were part of seven isolated groups; hence they received one smartphone per group. Generally, the distribution of more smartphones to a large group provides more coverage and increased chances of detections.

DATA ANALYSIS

In following subsections, we provide insights of the collected data and analyze various aspects of the pilgrims' activities in terms of space-time and highlight inter-group differences. We also explain other aspects of group dynamics in terms of cohesion, inter-group encounters and intra-group formation of sub-communities.

Spatiotemporal Analysis

In large-scale events of massive crowd gatherings, there exist certain risks, like stampedes or severe congestion, which might pose life-threatening situations or cause unpleasant experiences for the attendees. Such situations mostly occur due to the unexpected movement of the crowd with respect to both space and time. To avoid such situations, it becomes important to answer specific questions in the post-event analysis, which might demand fine granularity in the data. In this analysis we particularly focus on such questions, for example, 1) How long people stay together in a group? 2) When do they accumulate in different areas, and how long do they stay there? 3) How strictly people follow the event guidelines? 4) Do the groups divide into subgroups? When and Why? and 5) Are there any specific times for crowd congestion?

It is important to analyze the groups' mobility data with respect to space and time, in order to answer the posed questions. Hajj is defined as a sequence of daily activities being performed in different regions, at particular times, and in a specific order. The nature of activities, or other circumstances, could force the pilgrims to detach from the group. To answer **Question 1**, we analyze the daily trend of group-bound activity, by counting the unique tag detections of a group on each day, as shown in Figure 6. It can be seen that the detections were highest in the beginning and then start decreasing for all the groups. This observation reveals that the

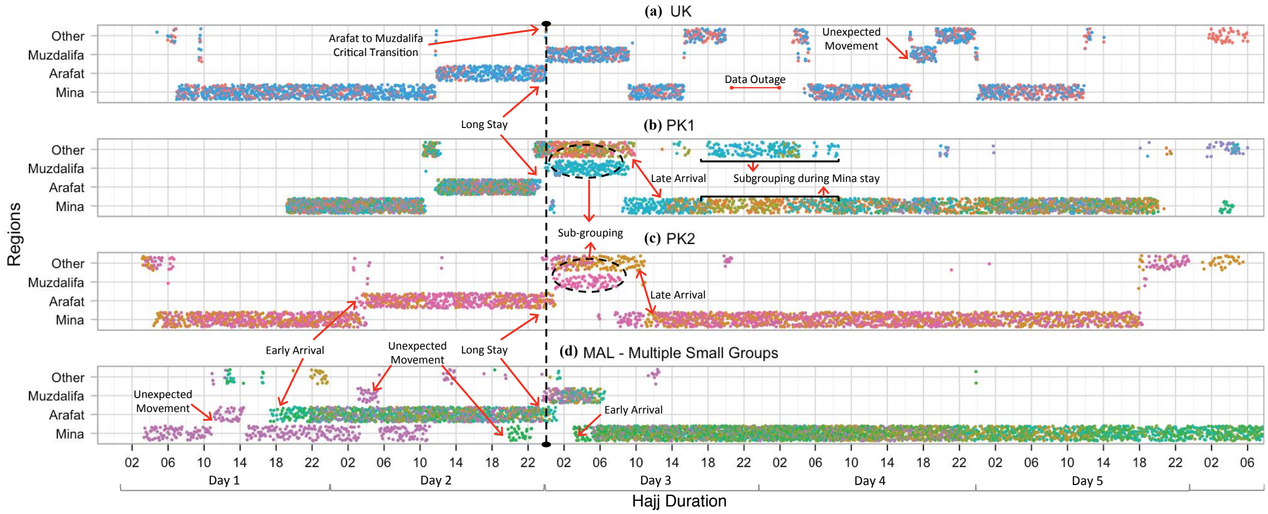


Figure 7. Entry, exit and stay durations of groups in different regions. Colored dots represent data coming from a unique smartphone.

Hajj event starts with highly group-bound activities, where pilgrims tend to stay together in their respective groups during the main activities in initial days; gradually they start to disperse as the event approaches towards its end. To look at the changes of group unity while performing different activities, we present a detailed group cohesion analysis in the next section.

Figure 7 shows the movement and stay of groups in different regions in chronological order. The annotations in the figure point towards the differences in each group's activities, in relation to the actual plan of Hajj activities presented in Table 1. In the following, we discuss some interesting findings, which answer the questions raised above:

- To answer **Questions 2 and 3** we analyzed the overall activity flow of the groups which appear to be in line with the Hajj schedule, but with some exceptions. The Arafat stay began earlier for the PK2 group and the MAL subgroups. Moreover, it lasted longer for all the groups, which effected the arrival time in Muzdalifa. The transition from Muzdalifa to Mina was also delayed for some of the participants. These exceptions of late or early arrivals and longer stay durations point towards either the congestion problems or management issues, for instance, unavailability of transport or not following the Hajj schedule.

- To answer **Question 4**, we analyzed the subgrouping behavior of the groups. We notice that pilgrims were split into subgroups – highlighted in black circles – which mainly happened when they are making region transitions and stuck in traffic in different buses. Such instances could cause critical delays in the overall group movement while waiting for subgroups to re-accumulate at the desired meeting point.

- All groups transitioned from Arafat region to Muzdalifa region nearly during the same time interval – shown with a black dotted line in the figure. Noticing this behavior, it became evident that this transition is the most critical time for the crowd flow (answer to **Question 5**). This mainly happened due to the limited time span for Muzdalifa activities, where everybody wants to enter the region as early as possible.

- The Malaysian pilgrims were divided into seven different subgroups, each one represented by a different color (see Figure 7d). Each group was traveling on its own schedule. For some of the subgroups we noticed an overall trend to remain ahead of all the other groups. Taking this approach would save on travelling times by skipping the rush hours, but it might lead the pilgrims to compromise on some of the Hajj activities. We also encountered a high number of unexpected movements among them, which is a sign of deviating from the general Hajj schedule.

Observations and Recommendations: The observations in this analysis highlight some crucial issues, which require immediate attention of the authorities. The early arrivals and longer stays disrupts the overall Hajj activities, hence demands enforcement of Hajj guidelines and event schedules from the Hajj ministry. Moreover, critical durations of mass crowd movement result in severe congestion and divisions of groups into subgroups. To address this issue, immediate measures are required, such as a mass transit system or strict schedules for region transitions. All these measures are critical to control such massive crowd dynamics in order to minimize the associated risks, for example, congestion and stampede. This study also calls on the domain experts and research community to introduce better methods which can be implemented in the field to monitor, control, and organize the events of such massive scale, happening all over the world.

Group Cohesion Analysis

To identify the level of organization in different groups and to find reasons for the lost people during an event, it becomes important to understand the cohesion among the individuals of each group. To understand the cohesion characteristic of the groups, we divide the data in ***n*** number of time-windows,

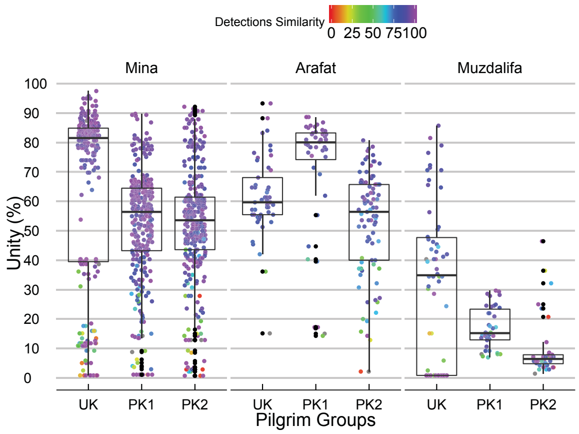


Figure 8. Group unity analysis per region in each time window. The color of dots depicts the similarity level in detections. The box-plot shows the distribution with Q1 (25%), Q2 (50%) and Q3 (75%) quartiles.

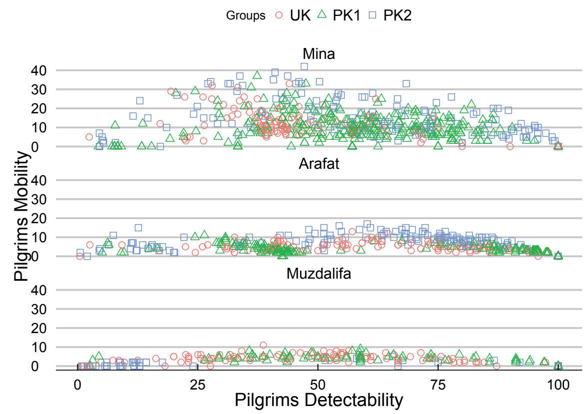


Figure 9. Detectability VS Mobility of individual pilgrims of different groups in separate regions.

which allows us to control the temporal granularity of cohesion, for instance in 1 minute intervals. Further, we calculate the levels of unity by identifying the detection rate of unique BLE tags over designated time-windows for each group separately. More formally, for a specific group, the unity level can be computed as:

$$\text{Unity}_{\text{n}}(\text{Group}_{\text{m}}) = \frac{|\text{Unique Detections Set}_{\text{nm}}|}{|\text{Total Tags}_{\text{m}}|} \qquad (2)$$

where **n** is the index of time-window, **m** is the group identifier, **Unique Detections Set$_{\mathbf{nm}}$** represents a set of unique detections by all the smartphones of group **m** in the **n**$^{\text{th}}$ time window and **Total Tags$_{\mathbf{m}}$** represents the set of all the tags given to the group **m**.

Generally, the Hajj pilgrimage is assumed to be a group-bound event and group-wise unity is expected while staying in different regions. However, occasional low unity intervals are also expected, which may occur due to the movement of pilgrims or smartphone carriers. To detect these instances of low unity, we define a similarity measure that captures the overlap of MAC addresses (tags) in two consecutive time-windows. Low similarity means a new set of pilgrims is detected in each scan due to their high mobility. On the other hand, high similarity means the same set of pilgrims are detected in each scan. Figure 8 presents the computed unity levels for all the groups in different regions. We selected a 15 minutes temporal granularity for this analysis to compensate for short-term detachments of the pilgrims for personal needs. It is evident that the unity levels were varying in different regions. Additionally, it is interesting to see the variability in colors when the unity is below 40%, which suggests that the low unity is mainly associated with the mobility of either the pilgrims or smartphone carriers, and not because of pilgrims' isolation from the main group. Moreover, the dots in Mina region are denser as more time has been spent in this region. Surprisingly, for some groups, the average unity levels are higher in Arafat, where only one-sixth of the time has been spent as compared to Mina. The reason for less unity in Mina is probably due to the types of activities performed there, which are usually carried out in smaller subgroups depending on the personal ease of the pilgrims.

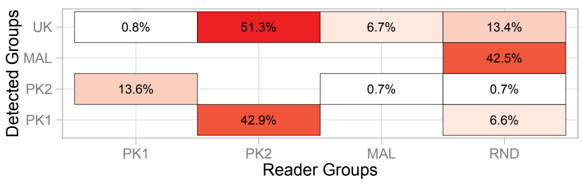
We hypothesize that the mobility of ***individual*** pilgrim will effect its detectability, hence effecting the overall group unity. To understand this effect we calculated the region-wise mobility and detectability for each pilgrim (tag) as follows:

- **Detectability** is computed for each tag by finding its rate of detection in the total number of time windows.

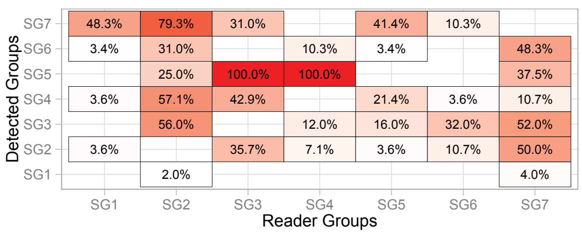
- **Mobility** is computed for each tag by incrementing a counter if the tag is not detectable in a specific time-window; given that it was detectable in the preceding time-window.

Figure 9 shows the mobility of individual pilgrims in each region. The pilgrims appear to be more mobile in Mina region as compared to the other regions, which explains the reason of less unity in Mina. In contrast, the mobility of pilgrims is low in Muzdalifa but the unity also remains low in this region. This is due to the subgrouping of pilgrims during Arafat to Muzdalifa transition, as discussed in the previous section. Some people reached Muzdalifa early while others were stuck in traffic for a long duration. Other possible reason is the lack of proper arrangements to spend a night in Muzdalifa. These factors may hinder the pilgrims to stay together with the group.

Observations and Recommendations: The observations in this analysis point toward a number of key issues. The outages in data or the instances of very low unity imply that either the group members were dispersed or the leaders did not remain with the respective groups all the time. A closer look revealed that the organizers of one group left the pilgrims unattended at different time intervals, which may be a sign of poor management. Further, we observed a significant decline in the unity levels in Muzdalifa region, which may lead to a higher number of lost pilgrims in this particular region, causing panic and frustration. This could be happening



(a) Main groups interaction



(b) Multiple Malaysian (MAL) groups interaction

Figure 10. Cross-group interactions. (a) shows the groups from different countries detecting each other. (b) shows multiple Malaysian groups detecting each other.

due to the lack of proper arrangements for the groups to stay together. Hence, the authorities and the group organizers may need to take appropriate actions to make the stay more secure and comfortable for the pilgrims.

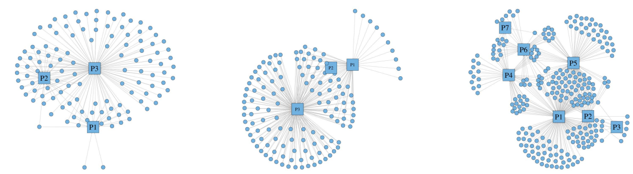
Cross-group Interactions

In this study, we selected the groups that are located far from each other. We did not expect them to cross their paths and detect each other. To our surprise, we discovered many interactions between the participating groups in different regions. Figure 10a shows the interactions of different groups during the whole Hajj event. This inter-group detectability was high for some of the groups. For instance, the PK2 group detected more than 40% pilgrims of the PK1 and UK groups. This could be the effect of high mobility or social behavior of the pilgrims and smartphone carriers, or due to crossing each other while transitioning between the regions.

Similarly, Malaysian pilgrims were divided in multiple smaller groups, staying in different camps and outside the coverage area of each other. However, their camps were located around the same road. As a result, their inter-group detections were much higher (see Figure 10b), where each group was able to detect pilgrims from at least four other groups. They detected each other while performing Hajj rituals in different regions.

To explore the chances of opportunistic sensing in such large gatherings, we employed four random mobile readers (RND) who were performing the Hajj pilgrimage and volunteered to carry our smartphones. Despite being less in number, those four random readers were still able to detect other pilgrims, as shown in Figure 10a.

Observations and Recommendations: The discovery of inter-group interactions suggests that our method may provide nearby participants' mobility data with opportunistic encounters in the massive gatherings. Also, it can help in identifying the hotspots of crowd accumulation, which is one of



(a) UK Group **(b)** PK2 Group **(c)** PK1 Group

Figure 11. Base community structures for three groups. The squares are depicting smartphones while circles represent BLE tags (pilgrims).

the reasons for disasters like crowd congestion or stampedes. Hence, further targeted experiments are required to reveal the true potential of this hybrid participatory sensing using BLE tags and smartphones for opportunistic scalable monitoring of large-scale events.

Community Analysis

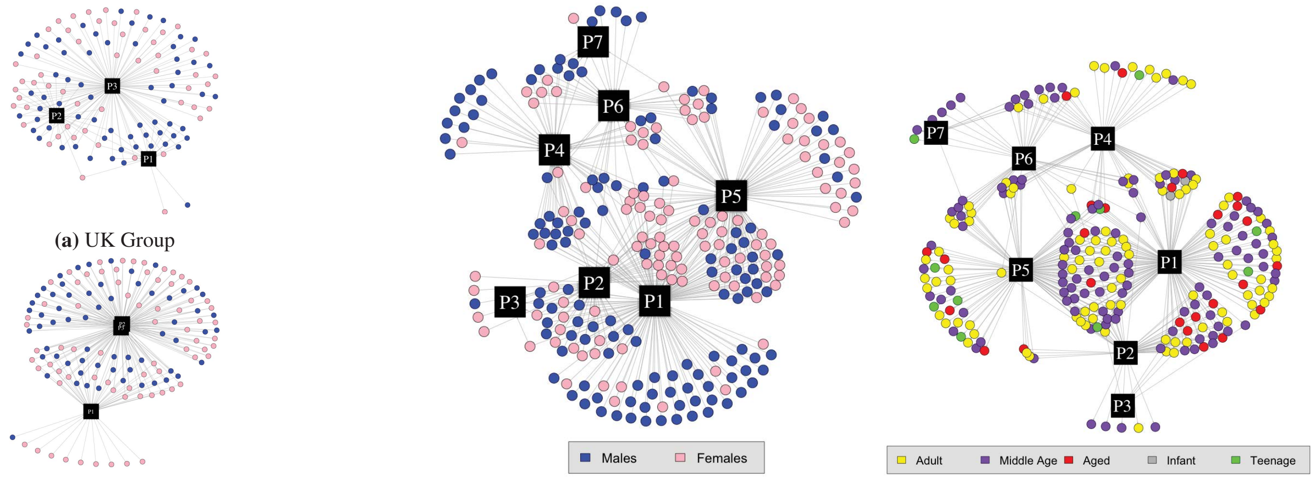
To fully understand the crowd dynamics it is important to understand the behavior of individuals who are part of different communities. Typically, Social Network Analysis (SNA) is used to understand the social links in organizations or outdoor environments. This requires data either from online Social Network Platforms [17, 18] or offline Bluetooth, ANT+ [7] and GPS co-location based proximity networks [21–23, 32, 33]. In the following subsections, we focus on extracting link-based communities within each group, using the BLE proximity tag detections, and represent them with respect to demographic characteristics of the pilgrims. Our objective is to identify how people bond with each other during the time they spend together throughout the Hajj event.

Community Extraction

In this section, we present our method to extract the base community structure using the BLE tag detections data. For this reason, we measured the Tag-Smartphone affinity between each tag and a phone, by calculating their relation strength based on the percentage of detections. Next, we generated bipartite graphs using the calculated Tag-Smartphone affinity. To reveal the affiliation network in each graph, we kept the top K strongest links (relations), where K is decided based on the node loss ratio. We kept around 50%, 75% and 25% of the strongest links for the UK, PK2 and PK1 groups respectively, with approximately 1.5% or less node loss. Figure 11 shows the base community structures for the three groups that provided the demographic information. The PK1 group was the largest group and carried a large number of phones, which were well distributed among the pilgrims. Consequently, it recorded a high number of detections, which revealed a large number of sub-communities.

Gender-based Communities

We applied the gender information on previously extracted base community structures. Figures 12a, 12b and 12c show differing gender based community structures for the three groups. Generally, we can see three types of communities in each group 1) small clusters of isolated pilgrims 2) larger pilgrim clusters 3) overlapping pilgrims in multiple clusters. We were expecting two large clusters, one for each gender with



(a) UK Group

(b) PK2 Group

(c) PK1 Group

(d) PK1 Group

Figure 12. (a)(b)(c) Gender based community exploration for three groups. The black squares represent smartphones, while blue and pink nodes are depicting males and females respectively. (d) Age-based sub-communities for the PK1 group. The black squares represent smartphones, while colored nodes represent different age groups.

some possible overlaps, because the men and women are usually segregated in separate camps during Hajj. We see this behavior only for the PK1 group where P1 and P5 smartphones captured male and female dominated sub-communities. In contrast, we see one large community of mixed genders in the UK and PK2 groups. The reasons for these mixed communities could be 1) the high interaction of males with their female family members 2) the movement of group leaders, carrying smartphones, back and forth between the male and female camps for organization purpose; or 3) adjacent location of the male and female camps. We see many smaller sub-communities emerged in the PK1 group, which could be a result of other demographic properties as we do not see a clear bias there in terms of gender. We will explore this possibility in the next subsection.

Age-based Communities

We applied the age information on the previously extracted base community structures. Figure 12d shows differing age-based clusters for the PK1 group, the only group that provided the age information. In the previous section, we already categorized the larger clusters, i.e. P1 and P5 for being male and female dominated clusters respectively. At first glance, the Adult and Middle-Aged pilgrims look equally distributed across the whole group. Closer examination reveals that some of the smaller clusters provide clear divisions based on pilgrims' age group. The P4 cluster mainly contains Adult pilgrims, whereas P6, P7 and P2 contain mostly Middle-Aged pilgrims. Multiple clusters of the same age group suggest that there may be other demographic properties, common interests or existing relationships forming these separate sub-communities. Moreover, the Teenagers and Aged pilgrims were mainly distributed in two larger communities, around P1 and P5 smartphones depending on their gender. This may have happened because they were less mobile due to the age factor or health conditions. Additionally, the overlapping detections of some pilgrims in multiple sub-communities could be due to their more mobile nature as compared to the other pilgrims. Interestingly, more than 80% of the total pilgrims hold strong affinity with only two smartphones, that is P1 and P5, which suggests that the coverage is achieved using smaller number of phones but more phones help in detecting a large number of sub-communities.

Observations and Recommendations: The analysis revealed smaller sub-communities based on gender and age group. These early results suggest there are interesting opportunities for the research community and domain experts. In further studies, BLE tags could serve as a community exploration tool with more demographic data for deeper understanding. Particularly, event organizers can use this information to better understand the divisions in crowd and, for instance, deliver interest-based services or do target marketing.

LIMITATIONS AND DISCUSSION

Our results show that the proposed framework for data collection is successful in gathering a large number of detections, revealing interesting findings about group dynamics in the Hajj event. In this section, we discuss some of the limitations of our work and propose enhancements for future deployments. *First*, our feasibility study of BLE tags performance can be extended to understand the coverage and detectability of tags in varying densities, area sizes, and structures. This could also help in identifying an accurate number of the required smartphone readers to cover a certain density of BLE tags. *Second*, it was not possible in our deployment to restrict the location of smartphones within the groups. The proper distribution of smartphones within a group, with respect to group-size and demographic characteristics, can provide more detections with enriched sub-community structures. *Third*, although we were able to collect specific demographic information from some groups, collecting more data from all participants could reveal more insights about their behavior. *Fourth*, we noticed outages in location updates, which happens mostly in covered areas where there is no visibility of GPS satellites. Accordingly, utilizing some alternate outdoor [10, 24–26, 46] or indoor [11, 13, 19, 30, 34, 44, 45] localization techniques could be helpful in covered places. Similarly, installing a few fixed readers in such important areas could provide better coverage and finer-granularity of the detected activities.

Adaptive sampling on the smartphone, based on battery level and activity information, could significantly increase the battery life. Transportation modes and activity information could also help to better understand the behavior changes with respect to the current activity of the group.

During data analysis, we observed cross group detections and also detections by random readers, which point towards the possibility to deploy this system on a much larger scale. To deploy the beacons on such large scale, the Hajj ministry can introduce new identity cards for the pilgrims, which are equipped with BLE beacons. A useful front-end functionality can be provided as an incentive, to encourage the use of data collection application.

RELATED WORK

Crowdsensing has emerged as a powerful mean to collect data using participatory and opportunistic sensing. Researchers have leveraged the abundance of smartphones to perform crowdsensing experiments, which mostly recruit a large number of participants carrying smartphones. Each study utilizes different sensing modalities [9, 12, 20, 36] or focus on specific events, such as [16] or [41], which collects participant's smartphone location data to understand crowd dynamics in a large-scale event. Similarly, we also aim to collect data about large events but our focus is on understanding group dynamics, which pose certain limitations, such as 1) in multicultural and group-based events, like Hajj, we cannot guarantee the smartphone penetration rate within a particular group, 2) not everyone would install our data collection app without an incentive, and 3) keeping the mobile phones functional is critical during the massive gathering events, but there could be scarcity of electricity points in the event area to keep them charged. Additionally, deploying and maintaining the data collection application for a large number of participants introduces more challenges, including the heterogeneity of mobile platforms, extra burden to install the application, and increased network demands for data transfer. Other known challenges are extensively discussed in the literature [42].

Different studies have focused on tracking people using RFID tags [35] or WISP tags with fixed readers [43]. Specialized scanners must be installed at key locations of the study-area to capture crowd dynamics, which leads to excessive deployment and maintenance costs. In addition, the authors in [35] have highlighted problems of range and interference issues. Many studies [38–40] utilize Bluetooth sensing and GPS data to understand crowd mobility and density estimates to highlight, for example, popular shows in an event. The usage of Bluetooth fixed readers [29] for crowd dynamics relies heavily on attendees carrying Bluetooth-enabled smartphones, which is not always the case. Other infrastructure based approaches, like CCTV cameras [14,28] have also been used but they have their own limitations, which restrict their usage in massive gatherings, such as the inability to identify specific individual/group, 360° coverage, and high computation requirements for analysis.

Our work builds upon the past studies, which utilized smartphones for Bluetooth sensing and GPS data collection. However, our approach of distributing tiny wearable BLE tags to the participants and detecting them using few smartphones releases the burden of utilizing a large smartphone-carrying user base for collecting data pertaining to group dynamics. This way, we made sure that everybody in the group is being monitored all the time and also provided data at a fine granularity to understand group dynamics in detail.

Finally, this work is an extension of a pilot study conducted in Hajj 2013 [27]. In this extension, we conducted a feasibility study for using BLE tags, greatly improved the experiment design, and performed detailed analysis of the collected data including spatiotemporal analysis, group cohesion analysis, cross-group detections and community exploration.

CONCLUSION

We explored the potential of using smartphone-detectable BLE proximity tags for group dynamics study. The experiment was performed during the six days event of Hajj pilgrimage in 2014. To start off, we conducted a feasibility study to understand the potential of BLE proximity tags in terms of battery life, and detectability in both indoor and outdoor settings. Next, we distributed 732 BLE tags and 24 smartphones among the pilgrims from three different countries. As a result, we were able to get a maximum of 80% group-wise detectability in a single scan event, with a 98% cumulative unique tags detectability during the whole event, resulting in 0.74 million records. Further data analysis provided interesting insights about the group dynamics, including differences in regions' entry and exit timings, the critical time-slot for crowd movement, the subgrouping behavior, and traffic congestion problems. We also analyzed groups' cohesion over time, which revealed important aspects of group dynamics in Hajj that was never studied before in such manner. The study of community structures revealed underlying subcommunities based on demographic properties. Further analysis, like inspecting transportation modes, travel durations, congestion points, could help authorities to understand the ground-realities and provide better services to the pilgrims.

We conclude that using BLE tags we can understand an important aspect of mass gatherings, i.e. group dynamics. Similar in-depth studies could help explore interesting opportunities and allow the organizers to better manage the mega events and make it a memorable experience for the attendees.

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