Participatory Bluetooth Scans Serving as Urban Crowd Probes

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***Abstract*—We describe a system that leverages users voluntarily having their smartphones scan the environment for discoverable Bluetooth devices to analyze crowd conditions in urban environments. Our method goes beyond mere counting of discoverable devices towards a set of more complex, robust features. We also show how to extend the analysis from crowd density to crowd flow direction. We evaluate our methods on a data set consisting of nearly 200,000 discoveries from nearly 1000 scanning devices recorded during a three day city-wide festival in Zurich. The data set also includes as ground truth 23 million GPS location points from nearly 30,000 users.**

***Index Terms*—Crowd Sensing, Crowd Probing, Participatory Bluetooth Scanning.**

I. Introduction

CROWDS are an integral component of urban environments: from city festivals through sports events to rush hour in busy business or shopping districts. As a consequence monitoring, managing and planning for crowds is a key concern of civil protection and city authorities. Today the main instrument of crowd monitoring are CCTV cameras. While useful in many situations, they are, however, more suitable for intensive surveillance of constrained hot spots during well defined time periods than for long term monitoring of large areas. Alternatives (see related work) that have been considered range from airborne cameras through cell tower information to counting people at access control points (where possible).

As another alternative our group has been investigating smartphone based participatory approaches. The core idea is that smartphone apps are increasingly becoming basic tools of daily city life. This includes navigation, public transport (including online tickets), information about services and opening hours, tourism and special events. In particular, large events such as city festivals are today unthinkable without an own App. Our work leverages such apps asking users to voluntarily contribute data for crowd monitoring. Originally, we had focused on anonymized location information estimating crowd density distribution from the distribution of data points provided by the volunteers (see Figure 1). In a trivial approach one can simply count the number of people providing data from a certain location, assuming that they constitute a fixed percentage of the crowd, and then extrapolate to the number of people present. In reality, the procedure is more complex (as the percentage may be neither known nor constant), however, we have shown that, given enough participants, a good estimation of the crowd density as well as other parameters such as speed, flow direction is indeed possible [1]. A major concern that we have seen during this

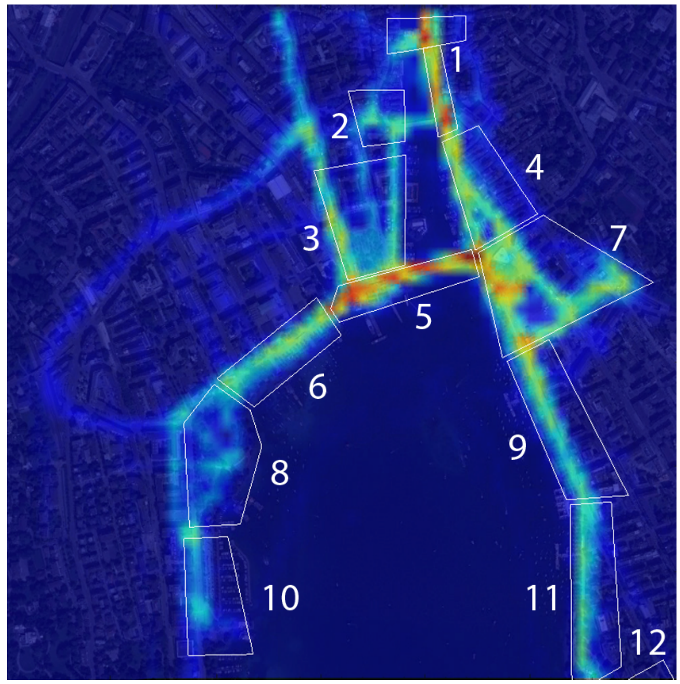

Fig. 1. Crowd density *heat map* snapshot at friday (05.07.2013, 9 p.m.) based on GPS location data transmitted to the server during 60 minutes. The main event areas at *Züri Fäscht* 2013 are shown as polygons with white borders.

work was how to achieve sufficient participation. Thus, for example, getting a few hundred to a thousand participants for large scale city events was not a problem (in fact, these could come from the organizers and civil protection forces). Getting tens of thousands participants is also possible as we had around 30,000 participants during a three day city wide event in Zurich (Switzerland) which is the foundation for this work. However, it requires an extremely well prepared, very intensive publicity campaign that is often not feasible.

A. Motivation and Problem Definition

In summary, the question is how participatory crowd monitoring can be extended to situations where the number of participants is too low to represent the crowd distribution and motion in a statistically significant way from their GPS traces alone (in other words the participants are too sparsely distributed within the crowd to accurately reflect its structure and motion). The proposed solution is based on the following observations:

1) Many users leave their smart phone bluetooth subsystem in discoverable mode "per default" e.g. for the conve-

nience of just getting into the car and being automatically connected to the speakerphone (see Figure 2).
2) Scanning for discoverable Bluetooth devices is a standard functionality in most smartphones so that participants' devices can be made to transmit not only their GPS data but also information on discoverable devices that are within their reception range.
3) In general Bluetooth range is limited to significantly less then 100m (often $\leq 10m$). This means that adding information about discoverable devices in reception range to participants' GPS data is equivalent to providing location information not only about the participant but also about the owners of the discovered devices. This effectively increases the size of the sample that can be used for crowd density and motion estimation.

Initial studies by our group (see related work [2]), with students as participants carrying scanning smartphones

- at small scale events (thousands of people in an area of about 200 x 200 m),
- following well defined walking patterns

have confirmed the basic feasibility of using such an approach to accurately estimate crowd density. However they have also shown that the actual number of discoverable devices can vary strongly in space and time for a given crowd density so that only very rough estimates are possible when using the absolute number of discovered devices as a feature. Motion patterns of the scanning devices have significant influence on the performance. Thus, the core scientific questions addressed in this paper are defined by the following aspects.

1) *How does such an approach perform in unconstrained city scale environments where participants* **are not** *students following well defined motion patterns but "normal people going about their business"?*
2) *What does it take to improve the system performance under such conditions, in particular in terms of choosing and designing features that go beyond a mere device count?*
3) *Is it possible to go beyond density estimation towards the recognition of motion patterns even through the owners of the discovered devices (who do not actively participate in the data collection and do not provide GPS data) from whose have the approximate location but have no motion information?*

B. Paper Contributions

Towards answering the above questions the paper makes the following contributions:

1) A large, real life data set with nearly 1000 devices (subsequently called *Bluetooth scanner* or *scanner*) providing Bluetooth scans (nearly 200,000 discoveries) annotated with location information over a period of three days during a city-wide festival in Zurich. The data set also contains the ground truth for the density and motion analysis that is based on around 30,000 users providing their GPS coordinates.
2) Use of the data set to evaluate the naive crowd density estimation method (extrapolating from the number of seen devices) against the GPS based ground truth.
3) A more advanced method that goes beyond absolute numbers towards relative features that are more robust against statistical variations of the number of devices present at a given density. The method is evaluated on the same data set and compared to the naive method.
4) A method for the estimation of the crowd flow direction, again with evaluation on the data set against the GPS based ground truth.

C. Related Work

Our work deals with (1) participative (2) crowd state analysis estimation using (3) Bluetooth scanning. The relevant state of the art research in the three areas can be described as follows.

1) Participatory Sensing: Among others Campbell et al. [3] and Burke et al. [4] introduced the general concept of people-centric sensing and participatory sensing. Since then a lot of work has been done in this area including sound pollution [5], air pollution [6] or road and traffic conditions [7]. Closest to our work [8] have studied temporal patterns of crowd behavior indirectly speculated from a massive number of collected Twitter messages. In our previous work [1] we demonstrated how participatory collection of GPS traces can be used to monitor crowd condition (this is being used as ground truth for the Bluetooth methods described in this paper).

2) Crowd Monitoring: Video based crowd analysis became popular in the 1990s with the increased use of CCTV cameras and availability of sufficient computing power (e.g. [9]). Since then extensive research has been done and a comprehensive overview goes beyond the scope of this paper (see. e.g. [10]). Examples of specific work range from detection of anomalies in crowd behavior [11], through work related to privacy preserving analysis [12] (not tracking or identifying individuals) to various multi-camera systems [13]. Significant attention has also been given to tracking individuals in crowds [14] including large area tracking with multiple cameras [15]. Overall the video monitoring work must be seen as complementary rather then an alternative to our research of long term large area participatory analysis being complemented by punctual video surveillance of specific hotspot. An alternative may be airborne cameras that can cover large areas [16].

Beyond camera-based crowd monitoring, methods based on thermal imaging [17], combination of thermal imaging and cameras, [18], wireless sensor network signal propagation [19], cell tower information [20], and passive RFID monitoring [21] were proposed.

3) Bluetooth Scanning: With the proliferation of mobile Bluetooth enabled devices leveraging the information about discoverable devices has become an active research field in Ubiquitous Computing. Early well known work showed [22], [23] how to recognize social patterns in daily user activity, infer relationships and identify socially significant locations, from using Bluetooth scans. Since then Bluetooth has been widely investigated as an additional source of information for various activity and lifestyle monitoring systems (e.g. [24]).

Towards public spaces and crowd related applications Nicolai et al. [25] looked at the discovery time of Bluetooth devices and the relation between the number of people and the number of discoverable Bluetooth devices. However, unlike in our approach only the absolute number of discovered Bluetooth devices was used. Morrison et al. [26] considered the visualization of crowd density in stadium-based sporting events. In [27] the authors recorded passenger journeys in public transportation by analyzing Bluetooth fingerprints. O'Neill et al. [28] presented initial findings in Bluetooth presence and Bluetooth naming practices. Versichele et al. [29] performed an experiment during a mass event where they covered an area with static Bluetooth scanning devices to extract statistics and visitor profiles. BLIP Systems [30] exploited a stationary Bluetooth based people tracking system. Based on multiple Bluetooth zones scenarios like queue length at airports or travel times by car are indicated.

With respect to large scale applications of mobile Bluetooth sensing Natarajan et al. [31] have had 12 participants scan a city for discoverable Bluetooth devices over a period of three months. A similar study was conducted on larger larger scale (100 devices, nine months) by Henderson et al. [32]. Finally, there were different studies with the scope of university campuses and conference locations (e.g. [33]). Overall the work we present differs from those in this scope (we base our work on an order of a magnitude more of Bluetooth scanning devices and discoveries) and we focus on crowd behavior analysis. In our previous and initial work we have demonstrated the feasibility of an early version of the features described in this work at a small scale experiment with instructed students [2].

II. Data Set

The data set that this work is based on has been recorded during a three day city-wide festival in Zurich (Switzerland) in the summer of 2013 (www.zuerifaescht.ch). The festival takes place every four years and attracts up to 2 million people with a mixture of shows, concerts, sports events, parades and parties distributed all over the city (see Figure 1). The recording had been leveraged by our event management platform developed during the EU Socionical project (www.socionical.eu) and tested (mostly at a smaller scale and without Bluetooth scanning) at a variety of events in London, Zurich, Vienna and Amsterdam. The platform is build around an event information App [34] which the attendees can use to plan their visit and get information on anything: from the location and timing of events through the background of the festival to public transport and route planning. The app also includes a variety of social networking features. In parallel, it integrates a set of safety/security modules which the users could activate on a voluntary basis:

1) A monitoring module that records and transmits data of a set of selected sensors to the server. The sensors are requested once the app was launched for the first time and require explicit user consent for every sensor.
2) A location sensitive messaging module that allows the organizers to send information or instructions to users at specific locations or at users heading in specific directions.
3) A privileged module that is activated via special code when the app is not being used by a visitor but by a member of the civil protection forces.

Considering the event management the collection of anonymized GPS traces, their visualization in form of a heat map (see Figure 1) and the location based messaging capability were the key. For our experimental purposes described in this paper, for the first time of this software platform, users were asked to activate their Bluetooth module if it was not activated previously and if they agree with scanning for Bluetooth devices even when the application is currently not used. Synchronously to collecting the data users were asked to transmit the Bluetooth discovery information, together with signal strength, identifier and timestamp. The Bluetooth data collection procedure has been previously cleared with the Zurich legal authorities.

A. Experiment Advertising Campaign and Distribution

We endeavored to achieve a very high quantity of participators acting as urban crowd probes. There are primarily three goals to achieve. Getting the users to download the application and acquire the permission from the user to collect the sensor data in compliance with the privacy policy (see sub-section II-C for details). The first goal was successfully achieved (55,000 app downloads) by collaborating with the event management, local media featuring the scientific crowd sensing aspects of the event application. Substantive functionality such as the schedule and site information of the festival were of high interest by the users. Once the potential users were aware of the application the users downloaded via the Apple and Google app stores. Most importantly, collecting sensor data (GPS localization and Bluetooth scans) while in the event area in the background must happen with clear communication with the user i.e. why, when and in which area sensor data is collected. To let users easily participate in collecting sensor data no explicit registration was necessary. As a result of the advertising campaign 55,000 people downloaded the application and a total of 30,000 people (approximately 54% of the app downloads) uploaded sensor data to the server. Users not participating either opted-out, deactivated their data uplink, or never initially launched the application after downloading. Application support was built into the application giving hints on how to use the app, the privacy policy, and the possibility how to opt-out regarding the data collection and transmission process.

B. Privacy Policy and Anonymization Approach

Most importantly, data protection officers made clear to precisely communicate that data is used and how it is used. Through press releases the public has been completely aware of this experiment. While the user initially launched the application an indication about scientific and safety rationales behind the data collection and data transfer to the server was shown along with a guide how to opt-out. This had to be confirmed by the user prior to any usage of the application, data collection or data transfer. No information was transmitted to the server which would infer to an identity of a participant.

We emphasized not to annotate data transfers to the server with any permanent user name or smartphone identifier (device MAC address, device UUID, etc.). The GPS localization mechanism additionally had to be accepted due to operating system requirements for newly installed applications (on iOS at the first launch of the app, on Android requested device permissions are displayed prior to the download of the app). After the confirmation a temporary *random event device id* was generated which was sent together with the GPS and Bluetooth data packets to the server. The *random event device id* cannot be mapped to a user identity and has the life time of the special purpose event application. Any conclusion of anonymous traces of *event device ids* is not possible since location recording and transmission is limited to the $1.5km^2$ event area and prominent user locations like the beginning and end of a trace (i.e. location of residence, location of work, etc.) were not collected. The IP address of the device (incoming data packet sender) was not stored. Next to the anonymization of the participator we considered the anonymization of Bluetooth discoveries. Each Bluetooth discovery contains a MAC address which is uniquely assigned during the manufacturing of the Bluetooth chipset. We uploaded the MAC address to the server where we used a random salt which was used as an additional input to a one-way hashing function (SHA) to encrypt the MAC addresses irreversibly.

C. Experiment Procedure and Data Collection Process

As we wanted collect data from event visitors, staff members of the event were not instructed to use the application on their smartphone and did not explicitly take part in the experiment. However, the distribution to a wide audience is more complex than to a small set of persons. As we had to distribute the app through the official app stores, certain technical and regulatory requirements had to be met. The team responsible for the app, its release consisted of three persons. According to the app store carrier Apple, the regulations of a background process accessing the GPS location was not allowed without any direct benefit to the user. For this reason a location-based feature called 'friend finder' was integrated into the application for getting Apple's app store approval. After the app download, the initial launch and the privacy policy acknowledgement the application configured itself to start recording experimental data for scientific research in the morning of the first event day. A data packet was sent every two minutes (or buffered in case of 3G network congestion) to the server (4 Amazon AWS server instances) running MongoDB data base instances. When exiting the event zone the GPS localization was switched off. In the night of the last event day the data collection module was deactivated automatically to prevent collecting and uploading of unintended data in case the user kept the application on his device. The experiment logic was integrated into the application. The operating system function called 'geo-fencing' (coarse but power efficient location method based on cell tower locations) automatically activated the data recording process in the background if the user was present in the event area which covered $1.5km^2$. When data recording was activated GPS data was acquired at 1 Hz, and Bluetooth scans were obtaining every minute. The core part of the experiment was the collection of Bluetooth scan information. Bluetooth scanning is defined as the process of recognizing surrounding Bluetooth devices. Each Bluetooth scan can result in $n \geq 0$ Bluetooth discoveries. Each discovery contains information of the device name (ignored), device profile (ignored), supported services (ignored), unique MAC address, timestamp and signal strength. The duration of a Bluetooth scan (as of current Bluetooth chipset and operating system cooperation) is dynamically controlled depending on whether new devices (within the scan period) are detected. This is motivated by energy saving of the Bluetooth module when no devices are discovered. The data was stored on the server for offline analysis.

D. Data Characteristics

Some key statistics of the collected ground truth data and Bluetooth discovery data are shown in Tables I and II. From the about 2 million visitors 55,000 had downloaded our App and 30,000 of those have been actively transmitting GPS data. Of those 971 have also provided Bluetooth scans. This is due to the fact that users had to explicitly activate the Bluetooth module and many were worrying about power consumption issues or simply shunning the effort. Over the course of the event this gave us nearly 200,000 discoveries that belonged to around 20,000 unique devices.

1) Distribution of Bluetooth Discoveries: The vast majority of scans has turned up relatively few devices. Figure 2 shows a comparison of the statistics from Zurich to five other events: two football games (at "Wembley" stadium in London and at the "Allianz Arena" in Munich) , the Munich October Fest, a festival in the city center of Valetta in Malta (very small area compared to Zurich) and a public viewing soccer event in the German city of Kaiserslautern. What all the other events have in common is that a small number (10) of Bluetooth scanners were moving around a constrained, very crowded area. Thus the majority of Bluetooth scanning periods (we defined a consistent period of 15 seconds) turned up a value corresponding to the typical number of discoverable devices in a dense crowd which was somewhere between 5 and 20 depending on the crowd and the location. It is also interesting to note the similarity in the shape of the distribution of the Zurich event, the Malta festival and the Allianz Arena data. The three had a comparatively larger area going beyond a single crowded location (in the Allianz Arena experiment the data was collected around rather than inside the stadium). However, the Zurich distribution is much more distinct, due to the much larger area.

2) Proportion of Relevant Bluetooth Scanning Devices: The vast majority of Bluetooth discoveries comes from a relatively small number of devices. This is illustrated in Figure 3. Exactly 329 devices were accountable for 90% of the total number of discovered Bluetooth devices. Figure 4 visualizes those devices as large blue circles. Again the nature of the event explains the data. Many people would visit the event briefly or stroll through the city streets rather then spending more of their time at crowded locations. Additionally, a num-

TABLE I
EXPERIMENT STATISTICS AND GROUND TRUTH MAGNITUDE

Event duration	Three consecutive days
Scope	1.5 km^2 event area
Estimated number of visitors during the event (according to event organizers)	2 million
Ground truth entities (total number of GPS locations collected and uploaded)	23 million
Number of app downloads	39,300 (iOS) + 15,600 (Android OS)
Devices collecting and uploading GPS traces	23,400 (iOS) + 6400 (Android OS)
Average number of location samples per device	Friday: 586, Saturday: 643, Sunday:703
Average time collecting GPS locations (including pauses)	Friday: 12,840 seconds, Saturday: 14,378 seconds, Sunday: 10,145 seconds

TABLE II
BLUETOOTH SCAN DATA SET STATISTICS

Devices participating in collecting and uploading Bluetooth scan data	971 (Android OS)
Total Bluetooth discoveries	190.600
Distinct Bluetooth discoveries	18.900

ber of participants had the Bluetooth scanning functionality turned on only briefly.

3) Uniform Event Area: Of the nearly 1000 scanning devices only 13 have seen each other over the course of the festival. Given the large temporal and spatial extent of the festival and the fact that the scanners were a random selection of the participants this is not surprising. People were at different places at different times. What is surprising is the fact that over 700 scanners shared at least one device that they have both discovered over the course of the festival. In fact more than half of the scanners shared at least 20 devices. This implies that the festival did not strongly separate into distinct events with little shared spectators.

The above points illustrate that participatory Bluetooth sensing is not only suitable for assessing crowd density (as is the focus of this paper) and flow directions but that it contains information about more complex aspects of an event and may be used to recognize different types of events taking place in a city.

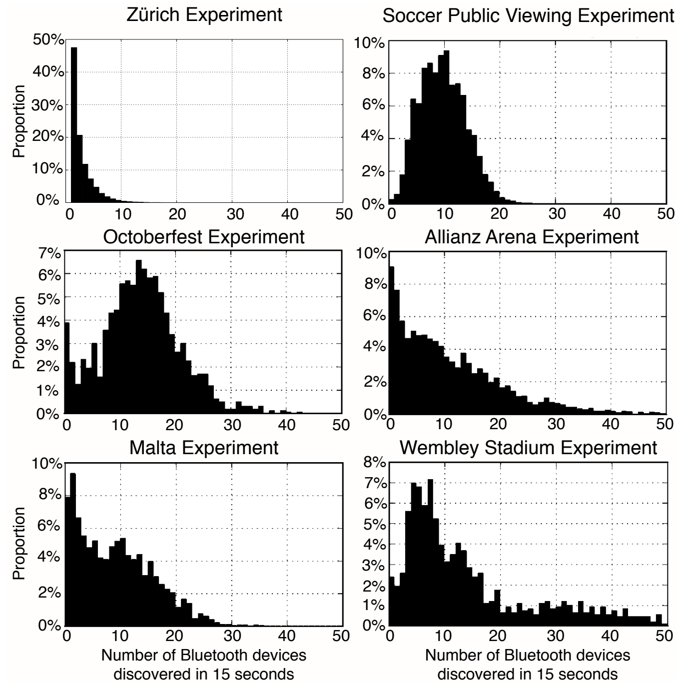

Fig. 2. Visualization of Bluetooth discoveries in relation to a consistent 15 second time windows. The x-axis of each sub-plot represents the number of Bluetooth discoveries and the y-axis represents the proportion (percentage) of time windows with a certain number of Bluetooth discoveries. The time windows are based on the whole experiment duration and on all experiment participants. Each sub-plot represents one experiment. Shown on the top left: the largest scale and lasting several day festival in Zurich (Switzerland) (nearly 1000 participants, 72 hours, 1.5 km^2 area), which is presented in this paper. For comparison we added visualizations of multiple previous small scale and short time experiments in no specific order: An experiments at a soccer public viewing event in Kaiserslautern (Germany) (10 participants, 4 hours, 1600 m^2 area), an experiment at the Octoberfest in Munich (Germany) (2 participants, 3 hours, 7500 m^2 area), an experiment around the soccer stadium "Allianz Arena" in Munich (Germany) before and after a soccer match (8 participants, 2 hours, 14,000 m^2 area), an experiment at a street festival in Valetta (Malta) (10 participants, 2 hours, 57,000 m^2 area), and an experiment in and around the soccer stadium "Wembley" in London (Great Britain) before and after a soccer match (10 participants, 2 hours, 18,000 m^2 area).

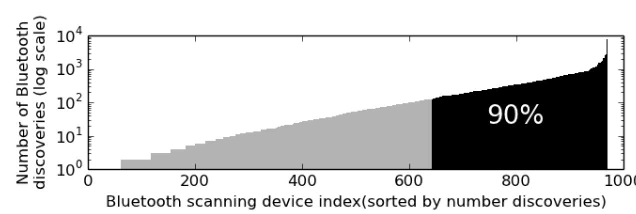

Fig. 3. Distribution showing the proportion of Bluetooth scanning devices to be accounted for Bluetooth discoveries. The bar chart shows the index of the Bluetooth scanning devices in sorted order (x-axis) with respect to the number of individual Bluetooth discoveries (y-axis). The y-axis is shown in log scale to visualize the wide range of discoveries from one to 7964 Bluetooth discoveries per Bluetooth scanner. Apparently broad bars are not to be confused with a single bar but multiple bars close to each other.

III. CROWD DENSITY ESTIMATION

A. General Principle

An obvious way to estimate the crowd density is to perform a scan for discoverable devices and assume that the number is an indication of the number of people in the vicinity defined by the Bluetooth range (typically around 10 meters). Unfortunately, this simple approach contains a number of problems. Firstly, there is the issue of sufficient statistics. With the scan limited to a radius of about 10 meters (approximately a circle with an area of 300 m^2) anything between a few and a few hundred people can be within range. While in a dense crowd with a few hundred people we may get a representative sample, in less crowded areas we are likely to see very strong variations between samples. Assuming the probability of any single user having a discoverable Bluetooth device to be averagely 10% and 20 people are within range the average number of discovered Bluetooth devices will be only two. While meeting in a space with exactly two technophile friends

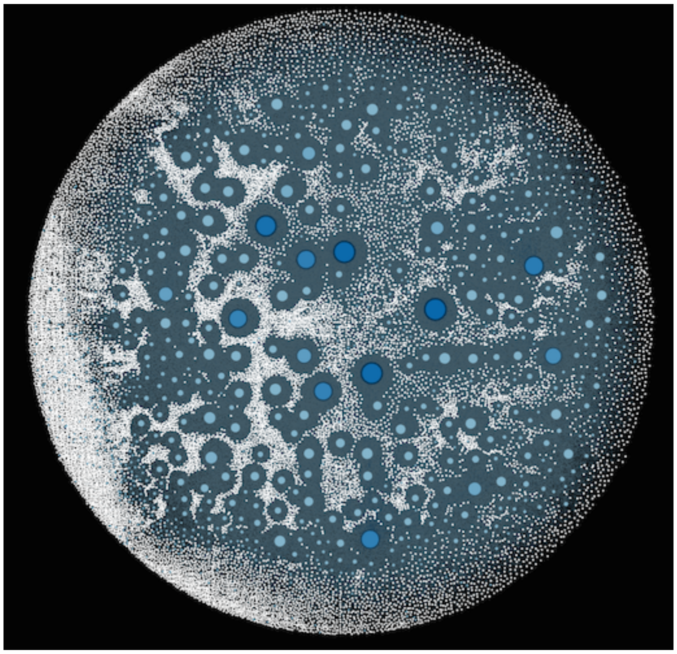

Fig. 4. The aggregated Bluetooth topology of the whole event duration visualized as a graph. The circular layout is caused by the spring-embedder based ForceAtlas2 (gravity and repulsion based) graph visualization algorithm. Due to the large number of edges (an edge equals a distinct Bluetooth discovery) these appear as bluish blur in the background. Blue dots represent Bluetooth scanners. The larger a blue circle (and proportionally more blue) is the more discoveries were made by a certain device. Small white circles represent discoveries.

having Bluetooth switched on will also result in two Bluetooth discoveries. Thus we may sometimes be in a group of people who do not even have activated mobile phones while at other times we may be surrounded by a group where everyone has an active Bluetooth device. Secondly, there is the question of signal attenuation. At 2.4 GHz (which is the transmission frequency of Bluetooth) the human body has a high absorption coefficient. This means that in a dense crowd (where we would expect to have good statistics) the effective scan range is reduced and therefore "falsifying" the results. Finally, we have to consider cultural factors. This means that the average number of people carrying a discoverable Bluetooth device may significantly vary depending on who the persons in the crowd are. For the same crowd density at a student party of a technical university a different number of devices may be present than at a fifth division soccer game in a poor rural area.

In our previous work [2] we investigated a collaborative Bluetooth based crowd density measurement approach. However, the methodology of the previous experiment was different and served as an initial study on the feasibility of Bluetooth based crowd density. In the previous work we performed an experiment in a controlled environment during a public viewing event during the european soccer championship (see Figure 2, a soccer public viewing event in Kaiserslautern (Germany)). The experiment persisted of 4 hours (1 hour during arrival, 2 hours during and 1 hour during departure). The experiment took place in a 1600 m^2 rectangularly fenced area with just a single entry and exit point while most of the event visitors stood on the spot without moving after the arrival. During the experiment we instructed students in five groups of each two people to move consistently along a pre-defined imaginary path within the fenced area during the three periods of the experiment. A walk along the path was finished in less than three minutes and then repeated in reverse. In the previous approach we developed features and built the method on Bluetooth discovery of constantly two nearby scanning devices (one device per person, two per group) where we analyzed variations of Bluetooth discoveries between both participants with a fixed spatial connection.

In the work described in this paper we have not set any requirements to the participants behavior. Nearly 1000 participants moved freely at any desired speed and direction without any influences from us. Neither we applied methods from previous work or analyzed continuous groups of participants since time periods of two constant close-by Bluetooth scanning participants was insignificant. The covered experiment area is heterogenous consisting of many streets, footways, pedestrian zones, parks, stages and food courts which are divided by buildings, bridges, a river and a lake. Visitors either stood statically at one point (i.e. at a music stage, at the water-front spectator zone, etc.) or move in the same (before beginnings of mass events) or move in different directions while strolling around or spreading out (from train stations, etc.).

B. *Advanced Method*

The proposed advanced method builds on features which go beyond of just counting Bluetooth discoveries. Our main contribution lies within the new features presented in paragraph III-B1. Bluetooth scan information is the main component of the feature set but also GPS sensor information is taken into account. Our approach was to aggregate sensor data from multiple participants to obtain a statistical validity which had the aim to achieve a higher robustness regarding noise and estimation accuracy compared to the trivial approach by just counting the Bluetooth discoveries. This aggregation was applied to twelve different event zones defined by us according to the event schedule and event map. Secondly, we aggregated the sensor data by time, either with a time window of ten or 30 minutes. As a result of the spatio-temporal aggregation we obtained one 12-dimensional feature vector per time window and event area. All in all we obtained 5184 (for a 10 minute time window) respectively 1728 (for a 30 minute time window) feature vectors. For our regression analysis we built on top of established methods. We applied a feature selection using M5's method (step through the features removing the one with the smallest standardized coefficient until no improvement is observed in the estimate of the error given by Akaihe information criterion) and eliminated collinear features. After we obtained the set of feature vectors we built a regression model based on the feature vectors and computed the ground truth value for each feature vector (see section III-B2). This crowd density estimation method was then applied on the feature set for evaluation in section III-C.

1) Feature Definition: We introduce 12 features which were computed based on the Bluetooth discoveries and the GPS location information of the nearly 1000 Bluetooth scanning participants. The data was stored in the MongoDB database and features were developed later after the end of the event. Information from other participants which served as a source of ground-truth was intended not to be involved in computing the features. Following, the proposed features are described. (1) The *average speed* of the scanning devices (sensors) indicates different crowd states: If the speed is low either the scanner is stationary and crowd is stationary (due to high crowd density or on-going event) or the scanner is stationary (spending time at food or drink stand) and crowd is passing by. We calculated the *average speed* by averaging the speed values of all sensors during discovering Bluetooth devices. We did not take the speed of other non-Bluetooth scanning devices into account. (2) The *average Bluetooth signal strength* (RSSI value) reflects a rough statement about the average distance and signal attenuation between the scanning device and discovered devices. We calculated the average signal strength of all Bluetooth identifiers including multiple discoveries of the same Bluetooth identifier by oner or multiple scanners and then averaged the value. (3) The *variance of the Bluetooth signal strengths* indicate the deviation (due to different distances and signal attenuation) of signal strengths. We calculated the variance of the signal strength of all Bluetooth discoveries including multiple discoveries of the same Bluetooth identifier. (4) The *variance of subsequently measured Bluetooth signal strengths* for a specific Bluetooth identifier is influenced by the crowd behavior. Are two devices in same distance to each other and does the crowd not move in between the signal link, the variance is lower than in a moving crowd. We calculated the variance of the signal strength of Bluetooth discoveries with the same Bluetooth identifier detected by the same sensor. We then averaged the values of all discoveries and sensors. (5) The feature is defined as the *average value of re-discoveries of each Bluetooth identifier address* by all sensors represents the overall crowd motion in an event area. We calculated this by counting the re-discoveries of the same Bluetooth identifier by any sensor. All sensor act as an aggregated sensor, as if the discoveries were coming from one sensor. If a re-discovery was made by the same sensor or another sensor is irrelevant. We then average the number of re-discoveries over all current Bluetooth identifiers. (6) By analyzing the *average number of scanners discovering a certain Bluetooth identifier* per time window we can make an assumption of the coverage and scanner distribution in the event area. We calculated this feature by the sum of sensors which discovered a unique Bluetooth identifier and then averaged this over all current Bluetooth identifiers. (7) The *diversity of individual sensors* is defined by the overall average of the relation of uniquely discovered devices to the sum of non-unique devices discovered. This feature was calculated by the sum of Bluetooth identifiers which were only discovered by one sensor, divided by the sum of Bluetooth identifiers discovered by two or more sensors. (8) We define the *duration of device visibility periods* in a given time window as the maximum timespan a Bluetooth identifier was recognized by all sensors. Averaged over all scanners the length of the stay depicts the potential to be discovered by any sensor in the area. This feature was calculated by retrieving the first and last occurrence of a Bluetooth identifier which was discovered by any sensor in the time window. We then averaged the duration of all Bluetooth identifiers. (9) The *average time of Bluetooth sensors in the area* measures the "scan-ability" of an area and takes time spans into account where no or few Bluetooth devices were found. We averaged the duration of active sensors in the given time window and of course the given area. We include three basic features in our feature set. (10) The *total number bluetooth discoveries* reflects the sum of all Bluetooth discoveries including re-discoveries of the same Bluetooth identifier by any sensor. (11) The *unique Bluetooth device discoveries* reflects the sum of all Bluetooth discoveries excluding re-discoveries of the same Bluetooth identifier by any sensor. (12) The *number of active scanners* is another measure of the "scan-ability" of a certain time window and event area. This is calculated by the sum of all active sensors in the given time window and of course the given area.

2) Ground Truth Definition: To evaluate our proposed Bluetooth based crowd density estimation method we had to consider a comparison with the actual number of people in a certain area. Manual methods for obtaining ground truth information with a granularity of 10 minutes for each of the 12 event areas were not feasible. First, we did not have the resources to deploy multiple persons all day long for multiple days at the wide spread event areas manually noting the number of people around. Even having the man-power it would be impossible to continuously count the number of constantly moving people in a complex area with multiple entry and exit points. For this reason we designed our experiment to collect additional ground truth information. While nearly 1000 participants were obtaining Bluetooth discoveries, nearly 30,000 participants (23,400 iOS and 6400 Android OS) obtained ground truth information with an average daily duration of 3.5 hours on Friday, 4.0 hours on Saturday, 2.8 hours on Sunday with potential pauses in between (we defined an event day from from 4 a.m. to 4 a.m.). The average number of samples per GPS trace was 586 samples on Friday, 643 on Saturday, and 703 on Sunday (see Table I). We extracted the ground truth values from the collected data set by counting the unique *event device identifiers* in a certain time window and event area. While we are aware that our ground truth value is a value smaller than the real number of people (not all people present participate in the experiment with the provided apps) we assumed a constant factor to be multiplied with our ground truth values to achieve the real number of people. Since we are interested to evaluate our approach as a method to obtain the crowd density based on a small sample (971 participants vs 2 million event visitors) compared to a larger sample we consider calculating the calibration factor in future work.

C. Evaluation and Results

We applied a feature selection using M5's method and eliminated collinear features. We identified features (feature identifiers (2), (4), and (9) defined in previous section) which did not contribute to information content of the feature vectors. We then evaluated our crowd density estimation method in

TABLE III
RESULTS BY EVALUATING THE MODEL WITH DATA SUBSETS REGARDING DIFFERENT EVENT AREAS. FOR GENERATING THE MODEL ALL FEATURE VECTORS OF ALL EVENT AREAS WERE SELECTED, WHILE EACH SET OF FEATURE VECTORS OF EVENT AREAS WAS USED AS A TEST SET. A 10 MINUTES TIME WINDOW WAS USED FOR DATA AGGREGATION. A PREVIOUS METHODOLOGY ($basic_2$) FOR CROWD DENSITY ESTIMATION WAS COMPARED AGAINST OUR NEWLY PROPOSED METHODOLOGY ($advanced$).

Event Area	1	2	3	4	5	6
Relative absolute error						
...$basic_2$	75.6%	80.0%	77.2%	92.3%	61.4%	95.0%
...$advanced$	67.4%	47.1%	78.9%	88.3%	47.7%	71.8%
Event Area	7	8	9	10	11	12
Relative absolute error						
...$basic_2$	79.8%	80.4%	87.8%	62.8%	99.2%	80.1%
...$advanced$	69.7%	70.6%	80.0%	69.3%	52.5%	97.4%

TABLE IV
LINEAR REGRESSION RESULTS WITH DATA SUBSETS. SHOWING THE IMPACT OF THE NUMBER OF SCANNERS (x) INVOLVED TO THE CROWD DENSITY ESTIMATION BOTH ON THE CORRELATION COEFFICIENT AND RELATIVE ABSOLUTE ERROR.

	10 min window		30 min window	
	Corr.Coeff.	Error	Corr.Coeff.	Error
$x \geq 2$	0.76	65.44%	0.87	49.73%
$x \geq 3$	0.75	66.44%	0.86	50.88%
$x \geq 4$	0.75	59.77%	0.85	49.41%
$x \geq 5$	0.75	52.46%	0.84	45.71%
$x \geq 6$	0.74	44.89%	0.86	38.54%
$x \geq 7$	0.76	39.79%	0.80	33.03%
$x \geq 8$	0.64	34.47%	0.83	29.44%
$x \geq 9$	0.67	35.71%	0.83	27.47%
$x \geq 10$	0.54	28.89%	0.80	26.11%

multiple ways. First, by comparing our new crowd density method ($advanced$) to two kinds of basic methods previously used in literature. One basic method is defined by simply counting discoverable Bluetooth devices ($basic_1$), which counts multiple discoveries with the same Bluetooth identifier multiple times. Another basic method is defined by simply counting unique Bluetooth device discoveries ($basic_2$), which counts multiple discoveries of the same Bluetooth identifier only once. For each method we generated an individual regression model which is based *on all event areas* and a temporal aggregation of ten minutes. As described before we have 5184 feature vectors, while they either have a dimensionality of one (basic methods) or twelve (our method).

As the evaluation metric we selected the the relative absolute error, expressed as the percentage of our calculated value deviates from the absolute ground truth value. As a result, method $basic_1$ results in a high relative absolute error of 75%, while $basic_2$ results to a slightly better relative absolute error of of 57%. Our $advanced$ method leads to a relative absolute error of 47%. This was a decrease of 28% regarding the relative absolute error compared to $basic_1$, which denotes a significant improvement of our method. We visualized the individual error values of 5184 feature vectors with the $basic_2$ method in Figure 5 and the error values of the $advanced$ method in Figure 6 which show the deviations between actual value (x-axis, ground truth) and predicted value (y-axis, estimation) with a temporal aggregation of ten minutes. As visualized in the scatter plots the approach $basic_2$ tends to exaggerate lower crowd density values to higher crowd density values, while our $advanced$ method tends to concentrate values near to the diagonal line (0% relative absolute error).

Secondly, we evaluated the method of simply counting unique Bluetooth devices ($basic_2$) and our new crowd density method ($advanced$) on *individual event areas*. With this evaluation we wanted to see whether the regression model generated on $n-1$ event areas fits to the n^{th} event area. We generated a regression model for all $n-1$ combinations while the set of feature vectors of the n^{th} event areas was used as a test set. A 10 minutes time window was used for data aggregation. The results are shown in Table III. While our method outperforms the $basic_2$ method in nine of twelve event areas, our method has a higher relative absolute error at two event areas and approximately the same relative absolute error at one event area.

Last, we analyzed the impact of the number of Bluetooth scanners involved in the crowd density estimation with the $advanced$ method. For each method we generated an individual regression model which is based *on all event areas* and a temporal aggregation of ten and 30 minutes. The raw data was not reduced by selecting a range of Bluetooth scanners on the data set but by selecting subsets of the feature vectors (each feature vector corresponds to a time-window and an event area) which complied to the given criteria. We filtered the feature vectors by the number (x) of Bluetooth scanners actively scanning (not to be confused with the number of Bluetooth discoveries). Multiple subsets of the feature vectors with the attribute of $x \geq 2$ up to $x \geq 10$ Bluetooth scanners were selected. For evaluation we used 10-fold cross-validation. The resulting relative absolute errors are shown in Table IV, which are ranging from 65% ($x \geq 2$) to 28% ($x \geq 10$), and respectively regarding a time window of 30 minutes ranging from 49% ($x \geq 2$) to 26% ($x \geq 10$). If the minimization of the relative absolute error is considered, each additional Bluetooth scanner decreases the error in average by 5% (ten or 30 minutes time window). If the time window duration is considered, the relative absolute error decreases by 9% in average while choosing a window size of 10 minutes respectively 30 minutes with the same number of Bluetooth scanners available. The error decrease is more significant when $x \geq 2$ (16%) as if $x \geq 10$ (3%) is considered.

IV. CROWD MOTION CHARACTERISTICS

We evaluate the general feasibility to detect crowd flows in relying on mobile Bluetooth scanning devices and present qualitatively results by matching the extracted information to event schedule ground truth. The motivation of Bluetooth based crowd flow sensing is based on the assumption that just a few actively participating Bluetooth scanners are needed. Other surrounding people contribute indirectly just with their enabled Bluetooth radio module without the need of an explicitly installed application. For example if a single Bluetooth scanner senses five surrounding devices the statistical validity id higher than if a single sensor is measuring only its own movement.

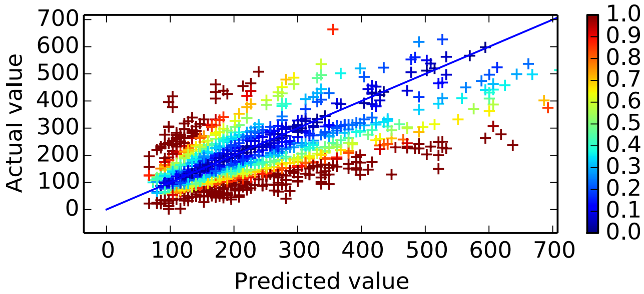

Fig. 5. The scatter plot shows the result of the linear regression evaluation with *basic* crowd density features. Each "+" symbol denotes a 10-minute snapshots from one of the 12 event areas. The x-axis shows the resulting linearly combined value of the feature vector, and the y-axis is defined by the ground truth value. The blue diagonal line denotes the 0% relative error value. The coloring visualizes the relative error of the predicted value (x-axis) regarding the actual value (y-axis). The range of the color scale is limited from 0.0 (0%) to 1.0 (100%) and values with a relative error larger than 1.0 are also colored red.

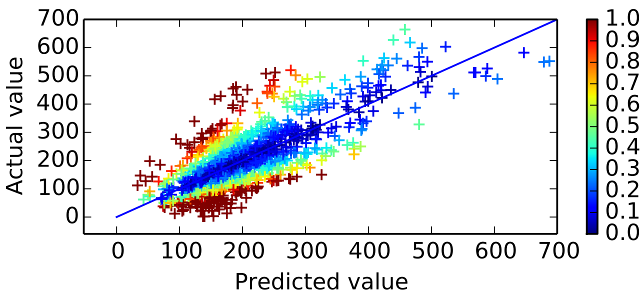

Fig. 6. The scatter plot shows the result of the linear regression evaluation with *advanced* crowd density features. Each "+" symbol denotes a 10-minute snapshots from one of the 12 event areas. The x-axis shows the resulting linearly combined value of the feature vector, and the y-axis is defined by the ground truth value. The blue diagonal line denotes the 0% relative error value. The coloring visualizes the relative error of the predicted value (x-axis) regarding the actual value (y-axis). The range of the color scale is limited from 0.0 (0%) to 1.0 (100%) and values with a relative error larger than 1.0 are also colored red.

Bluetooth scanners might be static or moving. Those can be selected dynamically by their current association (which might change) to a certain area. The crowd flow can be measured between two areas. An area acts as a *virtual checkpoint* where Bluetooth devices are discovered. If a Bluetooth device identifier is discovered at another checkpoint a transition from area A to area B can be determined. Each transition detection is attributed with the duration of the transition. Virtual checkpoints can cover corridors (i.e. bridges, underpasses, streets) or any other places (larger and more distant areas) with numerous paths between two locations. While the latter might be interesting for analyzing patterns in visitor flows for marketing reasons, the former is most interesting for real-time analysis of emergencies in crowded areas. The tragic example of the Love Parade 2010 in Duisburg (Germany) demonstrated that such bottle necks can lead to fatal accidents.

We demonstrate the general feasibility to detect crowd flows in relying on mobile Bluetooth scanning devices by Figure 7 which visualizes all Bluetooth device identifiers compared to the number of Bluetooth scanners discovered a Bluetooth identifier. In total 12933 discovery identifiers are involved. Around 3700 Bluetooth identifiers were discovered by just one scanner. In contrast some Bluetooth identifiers were discovered by up to 67 scanners. Figure 8 visualizes all Bluetooth device identifiers compared to the number of locations they were rediscovered. Locations are defined individually for a Bluetooth identifiers. A new location is represented by a discovery which is at least 10 meters away from any other discovery of the same Bluetooth identifier. Nearly 6000 Bluetooth discovery identifiers were not re-discovered at another location. In contrast around 7000 were re-discovered at another location at least once, with a maximum number of 75 locations.

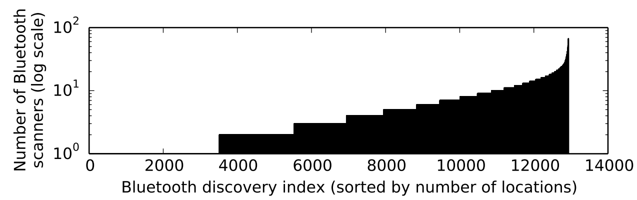

Fig. 7. Bar chart visualizing the Bluetooth discovery identifiers (x-axis, sum: 12933 discovery identifiers) which were discovered by different Bluetooth scanners (y-axis, log scale). The values are sorted by the ascending number of Bluetooth scanners. Wide bars are not to be confused with a single bar, but many contiguous equally high bars. 3700 Bluetooth discovery identifiers were discovered by just one scanner, while the remainder was discovered by at least two different Bluetooth scanners (maximum 67 Bluetooth scanners discovered the same Bluetooth discovery identifier).

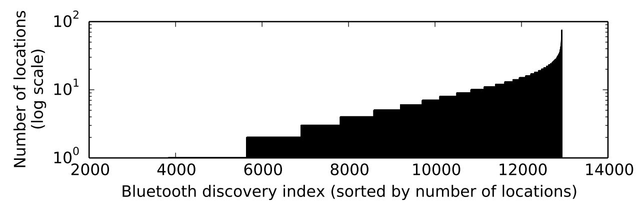

Fig. 8. Bar chart visualizing the Bluetooth discovery identifiers (x-axis, sum: 12933 discovery identifiers) which reappeared (by proof of discovery) at least once and the respective number of different locations (y-axis, log scale) defined by a minimum distance of 10 meters to any previous discovery of the same identifier. The values are sorted by the ascending number of locations. Wide bars are not to be confused with a single bar, but many contiguous equally high bars. Nearly 6000 Bluetooth discovery identifiers were not rediscovered at another location, while around 7000 were re-discovered at least once (maximum location of re-discoveries: 75 locations).

We studied the crowd flow on the Quaibridge which acted as a corridor between the western and eastern part of the city and as a spectator area at the same time. Figure 9 shows a satellite view with marked zones we used for transition monitoring. We aggregated all available scanners in each zone and time window. The extracted transition information on the Quaibridge during two days is shown in Figure 10 where separate time series show the crowd flow from the west to the east and the other way around. The time series simply represent the count of consecutive Bluetooth identifier observations within a 30 minute time window. Figure 10 qualitatively reveals a matching between the time series and the event schedule ground truth. A strong connection between events times where spectators were stationary or walking around could be determined with the event calendar ground truth information. During three major events on lake Zurich the crowd flow on the monitored region quickly declined. At time (A) fireworks with music were presented (ground truth event calendar entry: Friday 10:30 p.m. to 11 p.m.), at time (B) a skydiver show was performed (ground truth event calendar entry: Saturday 4 p.m. to 4:30 p.m.), and at time (C) an acrobatic show was performed (ground truth event calendar entry: Saturday 10 p.m. to 10:15 p.m.).

This underlines our hypothesis that besides Bluetooth based crowd sensing we can also achieve Bluetooth based crowd flow monitoring with mobile Bluetooth scanners. This observation is new compared to previous literature where stationary Bluetooth scanners were used.

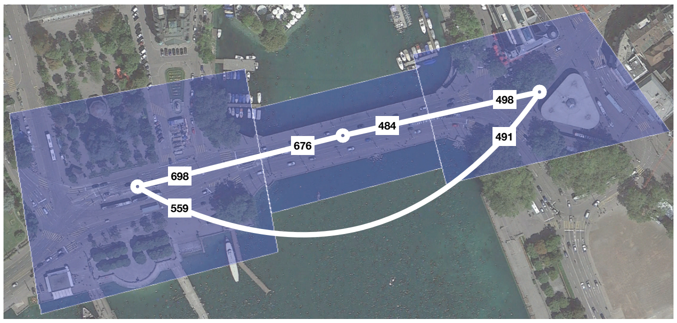

Fig. 9. Diagram showing Bluetooth re-discoveries on the Quaibridge. The numbers towards the end of a line section represent the number of Bluetooth devices re-appearing afterwards at the target zone. The blue colored regions represent the detection area.

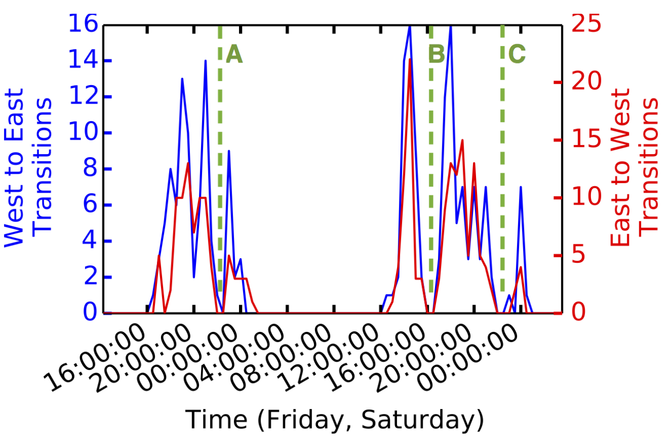

Fig. 10. Time series of the crowd flow from the west (left blue area in figure 9) to the east (right blue area in figure 9). (A) fireworks (ground truth event calendar entry: Friday 22:30 to 23:00), (B) skydiver show (Saturday 16:00 to 16:30), and (C) acrobatic show. The maximum time lag between consecutive observations of the same device at different locations are 30 minutes. A strong peak can be detected on Friday during the arrival time between 6 p.m. and 9 p.m. and at around 11 p.m. during the departure time.

V. Conclusion

The work presented in this paper clearly shows the potential of using Bluetooth scanning as means of monitoring crowds in urban environment. The accuracy of our density estimation is well within needs of typical crowd management applications. The analysis of the data set (section II) has demonstrated that the analysis strongly depends on a relatively small number of highly mobile nodes. This means that, for more spatially constrained events just equipping the security personnel with scanners may be enough. Similarly the technique could support urban crowd monitoring outside specific events. To this end one would need to recruiting volunteers who regularly move around the city a lot. How many people need to be recruited and what mobility patterns would be needed is something that would have to be studied empirically in a real life experiment.

Building on insights from section II in future work we will investigate which types of users contribute to the result better, whether different different patterns can be extracted at different time periods, and to what degree aspects such as the distribution of the number of found devices per scan and the temporal and spatial distribution of the reoccurrence of devices in the scans can be used to reason about the character of events on a more complex level.

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