Monitoring Crowd Condition in Public Spaces by Tracking Mobile Consumer Devices with WiFi Interface

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Ubicomp/ISWC'16 Adjunct , September 12-16, 2016, Heidelberg, Germany
ACM 978-1-4503-4462-3/16/09.
http://dx.doi.org/10.1145/2968219.2968414

Abstract
We present a systematic study and optimization of crowd monitoring methods based on tracking consumer devices with activated WiFi/Bluetooth interfaces using stationary scanners with directional antennas. To this end we have recorded a large scale, real life data set from a car manufacturers exhibition at the Frankfurt Motor Show IAA that includes data from 31 directional scanners covering a total area of 6000m^2 running for 13 business days and providing nearly 90 million data points from a total of over 300000 unique mobile devices. For seven of the 13 days video ground truth has been recorded and extensively annotated. Questions that we addressed include the mapping from the number of detected devices to the number of people, the ability to generalize the calibration from a small number of ground truth points recorded on one day to other days and the ability to localize individuals in different conditions. Our methods show less than 20% error for the crowd density and less than 8 m localization error for individuals.

Author Keywords
crowd density estimation;sensing unmodified smartphones;WiFi probing;crowd density heat map

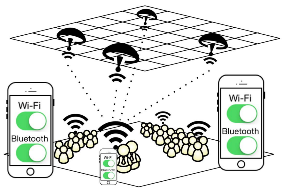

Figure 1: Symbolic sensor setup on the ceiling where the sensors were mounted together with lighting material. The sensors were equipped with directional antennas with free line of sight towards the visitors.

ACM Classification Keywords

C.3 [SPECIAL-PURPOSE AND APPLICATION-BASED SYSTEMS]

Introduction

Analysis of RF signals is a well known technique for human activity monitoring. In general we distinguish three types of approaches (which may be used in isolation or in combination). First are systems where user's mobile devices scan the environment for signals from stationary beacons such as for example WiFi access points or Bluetooth iBeacons. This is a basis for a whole range of indoor positioning systems (see related work). Second are systems where users mobile devices are used to detect the presence of other mobile devices. This approach has been widely used especially for the tracing of social interactions. Third, we have stationary scanners detecting, counting, and tracking mobile beacons carried by the users. Such mobile beacons can either be dedicated devices (e.g. www.gimbal.com) or the WiFi or Bluetooth interfaces of standard mobile devices such as smartphones or smartwatches. In this paper we focus on the later. Specifically we use carefully placed stationary WiFi and Bluetooth scanners with highly directional antennas to monitor crowd conditions during large scale public events (see Figure 1). The advantage of the approach is that the crowd can be monitored without the need for user cooperation in the form of installing and starting an App or carrying a dedicated beacon. As outlined in the related work section below the general feasibility of the approach above has already been demonstrated in individual applications including some crowd density measurement (see related work). The contribution of this paper beyond such work is a systematic study and optimization of crowd monitoring methods using stationary scanners to track consumer devices with activated WiFi/Bluetooth interfaces on a large, real life data set that includes extensive video ground truth.

1. We have recorded a large scale, real life data set from a car manufacturers exhibition at the Frankfurt Motor Show IAA. The data set is based on 31 directional scanners covering 9 'zones of interest' and a total area of $6000m^2$. The scanners were running for 13 business days, providing nearly 90 million data points from a total of over 300000 unique mobile devices. (see Table 1). For seven of the 13 days video ground truth has been recorded and extensively annotated.
2. We have used the data set to systematically analyze the limits and potential problems associated with monitoring crowd density and crowd flow in real world environments. Questions that we addressed include the mapping from the number of detected devices to the number of people (including the ability to generalize from a small number of ground truth points recorded on one day to other days), the ability to localize individuals in different conditions and the ability to reconstruct paths in different conditions.
3. We have developed and evaluated methods for crowd density estimation and visualization that build on the insights from the analysis above. See Figure 2 for an overview.

Related Work

The work most similar to ours is done by Fukuzaki et al. [9] where they collected WiFi probe requests from 20 sensors distributed widely in a shopping mall. They used motion sensors at entrances for retrieving a calibration factor between 2.8 and 3.4 with an average error of 30%. However there is no mention of the expected accuracy

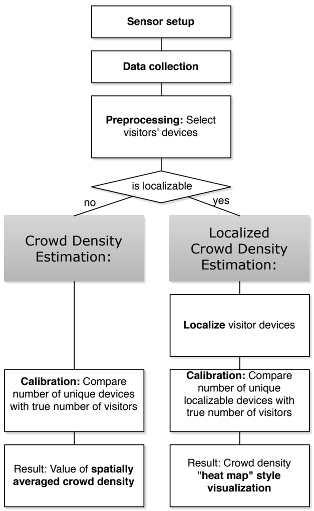

Figure 2: Individual aspects of crowd monitoring starting with data filtering, determine localizable devices, calibrating the the crowd density estimator and crowd density visualization

of the automatic ground truth and how the motion sensor differentiated between inbound and outbound visitors for a correct count. Similar research was done by Schauer et al. [17] by placing Wi-Fi probe sensors at the security check within the Munich airport. They used boarding pass scan numbers as ground truth for the number of people. The accuracy of both crowd density and pedestrian flow estimations was evaluated. A correlation of 0.75 is presented, however the paper does not focus on an evaluation of a factor between ground truth and WiFi measurements. The use of WiFi probes to track pedestrians with multiple sparsely distributed sensors is mentioned by related work [4, 8, 18, 16], however without ground truth evaluation.

In summary while the general feasibility has been demonstrated before, our work significantly goes beyond previous research with respect to a systematic study of various effects and comprehensive analysis of various crowd aspects in a large data set within a complex real world environment. Further away from our work using WiFi probes multiple threads of research aim to analyze social relationships [2], to track people within a city [14, 1] or to estimate waiting times in queues [19]. Aligned to WiFi sensing previous research concentrated in using Bluetooth scans to uncover complex social systems [6, 5], to analyze peoples behavior [12] and crowd sensing [15, 20, 13, 11, 10]. Along other research lines crowd sensing is accomplished with active user participation [3, 21]. The systems widely rely on GPS fixes collected by a smartphone application and sending the data to a server. However the disadvantage lies in the difficulty of recruiting participants to continuously support crowd sensing. A long research history can be assigned to video surveillance based crowd detection [7] . However with continuous video based crowd sensing privacy concerns arise as well as standard issues with computer vision algorithms (occlusion of people, lighting conditions) occur.

Dataset

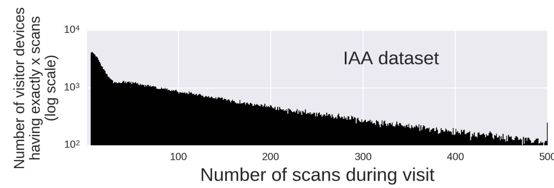

Figure 3: Histogram of the number of WiFi probes during a visit. In total 331369 distinct devices were sending WiFi probes.

We introduce a comprehensive data set (‘IAA data set’) covering 13 days during the ‘Internationale Automobilausstellung 2015’ in Frankfurt, Germany. We cooperated with a car manufacturer to have setup our sensors at a their booth. With 31 sensors which were mounted near the ceiling 1, visitors smartphones were detected through their WiFi interface sending WiFi probe signals. WiFi probes were continuously recorded during the day (9 hours) while visitors could freely move within the area, as well as during the remaining time. In total 209224745 WiFi probes were collected whereof 124276238 were dropped because they were coming from visitors outside or from stationary devices. In fact 84’948’507 WiFi probes are collected from visitors and 331’369 distinct visitors detected (see 1 and see Figure 3 for the distribution of scans). Each of the data set entries consists of timestamp, sensor identifier, visitor device vendor, anonymized MAC address and RSSI value. Concentrating the collected data we collected ground truth during seven days of the experiment. We managed to mount a single video camera with a diagonal view from the outside of the booth. It was mounted on an object with a height of 8 meters.

Event	Duration	Sensors	WiFi Probes	Distinct Devices
IAA exhibition	13 days	31	84'948'507	331'369

Table 1: Statistics about performed WiFi probe based crowd-density experiments.

The camera setup was made every day with the same view in a wide angle mode, thus covering almost the whole exhibition area. The video camera recorded video footage continuously. The video footage was annotate off-line in a labor intensive task by students. 71 images were uniformly selected with about one hour of time difference. Each of these image were annotated in a labor-intensive task by students. All people on the booth have been annotated by a special pixel on a separate layer. Up to 1200 annotations were performed per image. In total: 42444 annotations on all 71 ground truth images. In addition we collected ground truth to evaluate the location accuracy by manually collecting location and signal measurements.

Localization

To estimate the localized crowd density visitors need to be localized. The location can be determined on two accuracy levels. Either by assigning the visitor location to the best matching sensor location or by assigning the visitor location to a coordinate. Given N scanners positions and a measurement vector $\vec{x}$ which includes M RSSI scans x_{it} from scanner i at time t, the goal of the localization algorithm is to estimate the coordinate of the mobile device whenever possible. The naive approach of localizing a visitor would be to use every WiFi probe obtained from the visitor at the current time and calculate the location. But signal variations occur. Either because of multi-path propagation and change of signal shielding or by quick movements of the visitors passing sensors quickly. A location is only estimated if the visitor is classified as 'standing' which is derived from a verifiable repeated signal. 'Standing' means there is a significant number of WiFi probes from surrounding sensors which do not change over time (see localization algorithm description for more details). There is no general rule for which visitors are localizable for what percentage of their visit. Short visitors are either not localizable at all or localizable during their short visit. We compare two localization algorithms and evaluate them in context of WiFi probe based signal measurements (with the property of a low number of samples per device).

Location estimation based on RSSI multilateration: The localization method is based on sliding windows with a step-size of ten seconds and a window size of two minutes. For each window, the WiFi probes per mobile device are filtered as follows. The top five highest RSSI values and the corresponding sensors are selected. Multi-path effects and the way how the visitor holds the smartphone affect the received signals and can lead to noisy signals. To be more robust against these noisy signals, the spatial scanner setup is additionally taken into consideration. We exploit the local density information of scanner positions belonging to the scans in the window and compute the kNN-Global anomaly score with k=2. This density based metric identifies single scans which are further away from scans that can be locally clustered. All scans having a score that deviates more than 50 percent from the mean distance will be rejected. For each of three consecutive sliding windows, the filtered scans are used to compute

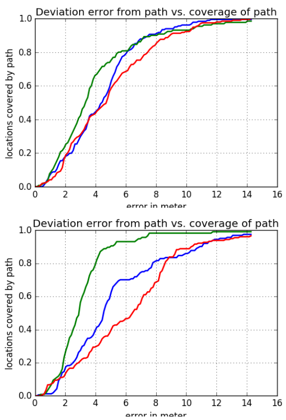

Figure 4: Localization evaluation of a mobile hand-held device (upper image) and mobile device placed in the trousers pocket (lower image). The x-axis describes the offset of the calculated position to the ground truth position (meters) and the y-axis describes the percentage of positions having an offset of at most x meters. Three sessions (blue, green, red) were performed synchronously with hand-held and pocket devices to collect ground truth information. 90% are localized with a maximum of 9m (hand-held) respectively 11m (pocket) away from the true location.

the mean location weighted by the RSSI value. If the maximum pairwise distance between the three estimates is under a threshold, we classify the window as standing and therefore as a valid location not being influenced by a visitor passing by. As a consequence of relying on the scanner positions for computing the weighted mean of scans, our approach has the tendency to estimate the location towards the center of the area: for border locations of the booth, the scans are only collected from scanners on the inside of the booth but not outside the booth. The estimation is therefore strongly biased towards the center of the area. To circumvent this problem, we apply an additional border correction. The correction method is applied if the scan with relatively highest RSSI value within the window belongs to one of the border scanners. We compute (1) the geometric mean of the scanners for all scans and (2) the weighted mean using the RSSI values. For the two estimations the distances towards the scanner with the highest RSSI value are calculated. If the distance to the scanner is closer to the weighted mean than from the geometric mean, we correct the weighted estimate with an additional bias. As correction bias we use the vector from the geometric mean to the weighted mean scaled by 0.5 and add it to the location estimate of the weighted result.

Location estimation based on crowd-sourced RSSI fingerprinting:
The idea of creating crowd-sourced RSSI fingerprint maps is to enhance locations of devices with a low WiFi probe frequency by learning statistical RSSI distributions from mobile devices which are reachable by many surrounding sensors. Instead of using the absolute RSSI values (works comparing RSSI values for one device between multiple sensors) for computing a weighted mean, we normalize the RSSI values and use the fingerprint maps of those scanners contained within the sliding window. From the maps we take the regions which represent the exact or higher normalized RSSI value and compute the overlap or regions among all relevant maps. We do a sampling without replacement from regions with the highest values and compute the mean location from the samples. Generating fingerprinting maps for later lookup: For each scanner, the according RSSI values follow a normal distribution. We assume that the best 10% originate from locations under the scanner. Ten percent of the highest RSSI-values and not belonging to stationary devices are selected. With this selection process we extracted 7.6 Million scans for all 31 scanners. Due to the large number of scans, we assume to achieve some robustness towards noisy signals. For each selected device scan at timestamp *t*, we construct a window centered at *t* with length of 30 seconds and select all scans seen from other scanners for that device in the window. We normalize the RSSI values by the maximum RSSI value for the device to be independent of absolute RSSI values. All normalized scans seen by other scanners are averaged. For creating the map we set the normalized values for the corresponding scanner position and interpolate for positions between scanners.

Evaluation of localization methods based on collected ground truth paths:
We consider shielded mobile devices and unshielded mobile devices. Shielded mobile device have a shorter signal range and more noisy RSSI measurements. We consider the typical places where people are placing smartphones. Usually carrying it in their trousers front or back pocket or a in a bag (shielded) or holding it in their hands to i.e. take a picture (unshielded). We developed a mobile ground truth application to easily record the location of the test subject. We equipped our subject with two

	Absolute	Percentage
Visitors with WiFi probes	331369	-
Localizable visitors	301038	90.8%
Localizable visitors with path	284940	86.0%
Localizable visitors without path	16098	4.9%

Table 2: Number of visitors which (a) remain from the filtering step or (b) having locations or (c) having locations and a path. A path is a sequence of locations with a diameter larger than 1 meter.

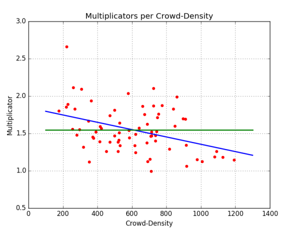

Figure 5: The connection between the number of people retrieved from ground truth and the number of distinct WiFi devices. In average the number of discovered devices has to be multiplied by 1.5. The factor varies between 1.0 and 2.6 with an average value of 1.5.

phones. One in the trousers front pocket and one holding naturally like while reading a message. To evaluate our localization approaches with ground truth data the subject stayed with two smartphones at 63 randomly selected different locations covering five minutes at each location. From the 63 locations, 38 are positioned directly under the scanners, the remaining 25 locations are between the scanner positions. We collected multiple sessions of series of locations that as ground truth for evaluating the methods. The RSSI multilateration localization method has a mean error of 4.5m and the crowd-sourced RSSI fingerprinting location method has a mean error of 5.6m. This means the more simple first method outperforms the crowd-sourced RSSI fingerprinting method. Since a WiFi device is shielded differently based on the position within the body area, we evaluated the localization with a mobile hand-held device (Figure 4 upper image) and mobile device placed in the trousers pocket (Figure 4 lower image). The x-axis describes the offset of the calculated position to the ground truth position (meters) and the y-axis describes the percentage of positions having an offset of at most x meters. Three sessions (blue, green, red) were performed synchronously with hand-held and pocket devices to collect ground truth information. 90% are localized with a maximum of 9m (hand-held) respectively 11m (pocket) away from the true location.

Filtering
During the total exhibition duration we scanned 987681 unique devices. We applied the following filtering criteria to select the relevant devices representing the crowd. Other devices are ignored. WiFi probes can be received from mobile visitor devices and stationary devices (i.e. laptops,tablet computers used as product displays, WiFi enabled machines). The WiFi probe does not tell anything about the device properties. Properties need to be extracted by analyzing the presence over time. A device is categorized as **stationary devices** when it is continuously detectable before, and during the exhibition hours. A devices is categorized as **out of bounds** when it is not detected by a sensor within the center of the area at any time. Obviously the sensors also detect mobile devices from other regions within the hall, as it is not possible to setup an electro-magnetic (WiFi absorbing) shield around the area of interest. The area of interest which we covered with WiFi-scanners accounted for half of the exhibition floor, having one side open to the other half. We grouped scanners into six rows in parallel. Visitors standing not within the area of interest should have many scans from the boundary scanner rows compared to inner scanners. For each visitor we compute the distribution of scans among the six scanner rows and cluster visitors based on a similar scanning pattern. With hierarchical clustering we selected two clusters: devices within the boundary and devices outside boundary.

Crowd Density Estimation
Related work lacks on information about the performance of crowd density estimation based on WiFi probes. We performed our experiment to fill this gap and (1) present the ground truth used for the performance evaluation and (2) present the connection between the number of people retrieved from ground truth and the number of distinct WiFi devices (3) evaluate the performance depending on all or only localizable devices and (4) evaluate the performance depending on the number of calibration points. We can distinguish between two device groups. Devices fuzzily known to be on the booth and devices we can localize more exactly. We evaluate the performance of using either one or the other group. After the labor-intensive task of ground truth extraction we compare it with the number of mobile devices extracted with our

Samples	*All*	*Localizable*
1	22.1%	18.9%
2	20.9%	17.2%
3	20.4%	16.3%
4	20.0%	15.6%
5	19.6%	15.0%
6	19.2%	14.4%
7	18.8%	14.0%

Table 3: Evaluating the performance of our crowd density estimation with WiFi probes with a few calibration points and showing the impact of the number of calibration points needed. Regression results based on training of all combinations of calibration points from one up to 7 calibration points per day and computed the mean error. The absolute error of the estimation and the percentage to the ground truth is shown.

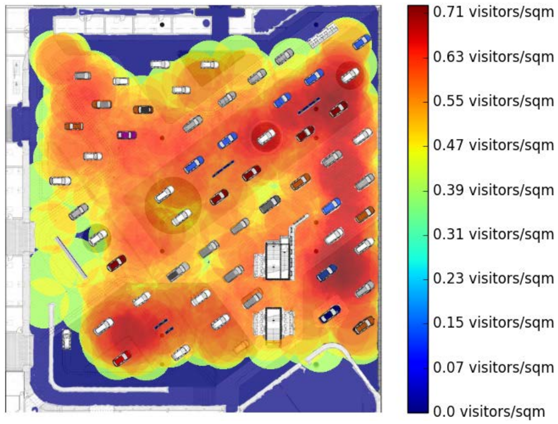

Figure 6: Crowd density estimation heat map.

method to present the connection between the number of people retrieved from ground truth and the number of people measurable with WiFi probes. The ratio between both values gives At 71 points in time we compare the manual counted visitor number with the extracted value of discovered devices. In average the number of discovered devices has to be multiplied by 1.5 (1.7 for localizable devices)to obtain the true crowd density. The factor varies between 1.0 and 2.6. To see this in comparison: The CeBIT dataset has an average ratio of 1.15 and varies between 1.0 and 1.5.

We evaluate the estimation depending on the number of calibration points. Our approach is steady over time and not many calibration points are needed. Using a single calibration value for training we get 22.1% deviance (15.8% with localizable devices). By using up to 7 calibration points only decreases the error by 3.3% (3.9%) (see Table 3). We demonstrate that the further inclusion of calibration points covering multiple days does not improve the performance. We used all combinations of days starting from one up to all seven days and computed the mean error to the ground truth. We demonstrate that our approach is steady over time and that sets of calibration points from multiple days do not improve the estimation error significantly. The average error for using all calibration points from all seven days is 15.8% (11.7%) which is only a small decrease of 3.3% (2.1%) compared of relying just on a single day.

Localized crowd density ('heat map'):

We define the localized crowd density estimation as the estimated number of people per m^2 at timestamp *t*. Having the calibration factor and the location of the visitors and the average displacement error at timestamp *t*. Now both a time-referenced and topological transformation is made into a 2-dimensional heat map. A visual interpretation is easy while numbering regions with values is not easy to quickly grasp by the viewer. A high crowd density is marked in red and a low crowd density is marked as blue. Figure 6 show the resulsting visualization of the crowd density heat-map.

Conclusion

We performed an experiment with 31 WiFi scanners mounted on the ceiling with directional antennas sensing 7.6 million WiFi probes from consumer devices. The evaluation of our real life data set demonstrated the feasibility of sensing unmodified WiFi enabled consumer devices for monitoring crowd conditions. With our setup we evaluated that 90% of the calculated locations are within 5 to 11m event with a shielded device in the pocket. Regarding our video based ground truth comparisons, in average two thirds of the visitors can be mapped to one detected mobile devices, 90.8% can be localized, 86.0% can be tracked at more than a single location. We presented a initial method of visualizing the crowd condition based on a heat map. Further work needs to be done to evaluate detailed crowd conditions like crowd density, crowd movement and common patterns.

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