Demonstrations and people-counting based on Wifi probe requests

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***Abstract*—At demonstrations, counting people based on the Wifi signals that their phones emit, may be a flexible alternative when conventional methods fail. However, at public events like that, such Wifi signals do not only arrive from the targeted crowd but also from bystanders that happen to be in the same area. This raises the question of suitable filtering mechanisms and their impact on the counting setup as well as the accuracy of the method as such. This paper explores distance- and time-based filters and proposes filtering by recognition to estimate the size of a marching crowd. It deploys the resulting setup at two demonstrations each with over a thousand people. The experiments show that the signaling behaviour of different phones varies significantly and that the count of Wifi probe requests after filtering represents a small fraction of the actual attendance.**

***Index Terms*—crowd monitoring, people counting, Wifi probe request, case study**

I. Introduction

Knowing how many people participated in a demonstration is important for the organizers, police, and public as it gives insight to the size and relevance of such an event. However, estimating the attendance is challenging: Manual counting lacks the required overview especially when people mingle. Cameras need an elevated position to ensure that all people are visible. Also, they do not operate well under insufficient lighting conditions like at dusk or during rainy days. Further, the analysis of the recorded material is complex and despite software support still involves laborious manual steps.

Wifi signals that modern phones send to find a Wifi access point (AP) seem promising as they uniquely identify their sender. According to IEEE 802.11 one way of finding an AP is by the mobile device broadcasting Wifi probe requests (hereafter referred to as Wifi probes). These include the sender's MAC address such that an AP can respond and initiate a connection with the sender. Since Wifi probes are not encrypted, dedicated scanners can collect them without connecting to the sender. People-counting based on Wifi probes assumes that the majority of people carry a mobile device whose Wifi interface is enabled such that the count of unique MAC addresses reflects the actual number of people being present.

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Demonstrations typically take place in the city center where they can draw the attention of the public. There, the Wifi probes of the participants mix with those of pedestrians, people in shops, or passengers on public transport. Counting the unique senders of all Wifi probes would include a high number of false positives and distort the result. This raises the question on how to distinguish the Wifi probes of participants from those that only happen to be in the same area?

This paper explores two filtering approaches: First, distance-based filtering assumes that some senders are further away from the scanner than other and that the Wifi probes' received signal strength indicator (RSSI) correlates with the spatial sender-to-scanner distance. This way, Wifi probes too close or too far away will be removed from the data set. Second, time-based filtering assumes that participants march past the scanner and are visible only for a short time much in contrast to static devices that are visible throughout the entire scan time. Further, as participants move, their Wifi probes will be visible at a second scanner along the route. This way the data set is reduced to Wifi probes that have been seen by both scanners removing the Wifi probes of bystanders that occur only at one or the other scanner. The paper studies the signaling behaviour of a set of different phones to evaluate the applicability of these filtering approaches. In particular for the time-based approach, it designs a counting setup and reports on the deployment during two demonstrations taking place in Dresden, Germany in mid-2017 and beginning of 2018. The contribution of this paper is threefold:

- A set of experiments that show how the diversity of the phones' signaling behaviour makes it impossible to derive general RSSI thresholds for distance-based filtering,
- A time-based filtering mechanism that is based on the recognition of devices and its implication on the counting setup, and
- Results from the real-world deployment that show how theory and practise diverge as the count of Wifi probes after filtering represent only a small fraction of the target crowd.

The paper hopes to raise awareness that people-counting based on Wifi probe requests is complex in its own right and that its stand-alone application may only be feasible after a series of deployments at similar events. The paper is structured as follows: Section II gives an overview of work related to crowd monitoring based on Wifi probe requests. Section III describes the scenario of counting people that march in a demonstration and provides details about technical scanner setup. Section IV reports on experiments regarding the suitability of the distance-based and time-based filtering approach. Section V presents the results from the deployment at two demonstrations. Section VI summarizes and concludes this work.

II. Related work

Research on Wifi-based crowd monitoring distinguishes three ways: First, people actively share their Wifi-based position which is useful for indoor navigation and flock detection [1]. Second, people affect certain signal characteristics of the Wifi infrastructure solely by being present and without the need to carry a mobile device [2] [3]. Third, people indicate their presence passively as their mobile phones broadcast Wifi probe requests that allow for estimates on the size and density of a crowd. This paper applies the third way for counting people at demonstrations and focuses its discussion of related work accordingly.

A study on indoor crowd monitoring on a university campus deployed scanners in four adjacent rooms to understand the signaling behaviour of phones and to estimate the rooms' occupancy [4]. Cases, in which multiple scanners detected a phone at the same time, were filtered for the dominant scanner, i.e. the scanner that received the strongest signal of the phone.

Exploring the flow of passengers at a major German airport, two time-synchronized laptops scanned for WiFi probe requests at the entrance and exit of a targeted area [5]. Boarding pass scans served as ground truth i.e., the reference for the actual flow. The study found that naïvely counting MAC addresses that have been captured by both scanners within a certain time interval over-estimated the ground truth. This was due to insufficient space between the scanners and detected devices that did not actually pass through the targeted area. A combination of time-based and RSSI-based filter improved the estimations such that strong linear dependency to the ground truth could be established. Devices passed this filter if, it was detected by both scanners with a positive delay and with at least one RSSI above a scenario-dependent threshold.

Similarly, a study at a music festival in Belgium tracked the paths of visitors by correlating data from different scanners over time [6]. Filters defined that Wifi probes of visitors are those that appeared in two different locations at different times. This excluded Wifi probes from static devices or people passing by in cars but also from visitors stayed in one scan area. This paper picks up on the idea of following the path of Wifi probes. Participants in a demonstration, however, move somewhat more homogeneously and over a greater distance. This raises the question of whether the time-based filtering yields better results in such a scenario.

Experiments during the International Motor Show in 2015 in Frankfurt (Germany) mounted 31 scanners on the ceiling of the exhibition area to have free line of sight to the visitors and avoid signal attenuation [7]. The data set was focused on visitors that roamed the event area crossing the center at least once. The filters removed stationary devices i.e., device that were detected over the entire course of the event. Additionally, they removed out-of-bound devices i.e., devices that had high detection rates at the grid boundaries or no detection in the grid center. The comparison with manual counts from video footage revealed that two thirds of the visitors got detected this way. A grid-based scanner setup, however, is limited to indoor events. For demonstrations, the scanners need to be mobile so they can relocate quickly in case of last-minute route changes which are rather common for safety reasons.

While fixed scanner installations work for indoor scenarios, experiments outdoors may require mobile scanners. One study [8] explored whether mounting a WiFi scanner on an unmanned aerial vehicle (UAV) would be a suitable option. The experiments showed that the increased distance to the signal source and the alternating movement of the UAV located WiFi probes as much as 14 meters off their original position. While such a setup may be feasible for search and rescue operations, it may not be applicable for demonstrations because of safety concerns.

A study at a citywide festival in the Netherlands showed that analysing WiFi probes may not be as straightforward as it seems [9]. The study uncovered a high number of detections that did not follow any logic. Sources for that erratic behaviour include faulty or unsynchronised scanners, devices with seemingly random transmission rates, and incoherent RSSI values across different scanners due non-standardised RSSI measurements. Cleaning the data set should consider eliminating detections with RSSI values below a threshold (similar to [5]), identifying the dominant server for time intervals (similar to [4]) and removing corresponding detections at non-dominant scanners. The authors note that thresholds and time intervals depend on the particular data set and cannot be determined in general. This paper provides evidence that RSSI-based thresholds cannot be determined at all if the set of phones is diverse as it implies high RSSI variations.

III. System setup

One way of counting the participants is when they gather for the opening rally. The crowd's size and density, however, requires scanners not only on the periphery but also in the center of the crowd. This may be an issue for those who carry the scanners but otherwise do not want to be associated with the demonstration and its theme. Instead, this paper focuses on the marching part of the demonstration where scanners and their carriers are placed alongside the route watching the particpants of the demonstration pass by. The safety clearance ensured by the police, however, means that capturing the moving crowd can only take place from some distance. Figure 1 depicts the resulting setup and highlights the challenge of distinguishing participants from bystanders. Participants are assumed to be about 10 to 25 meters away, while pedestrians may be either very close or very far from the scanner.

The scanner used in the experiments is a Raspberry Pi 3 (Modell B) with a Wifi stick (TP-Link TL-WN722N) that

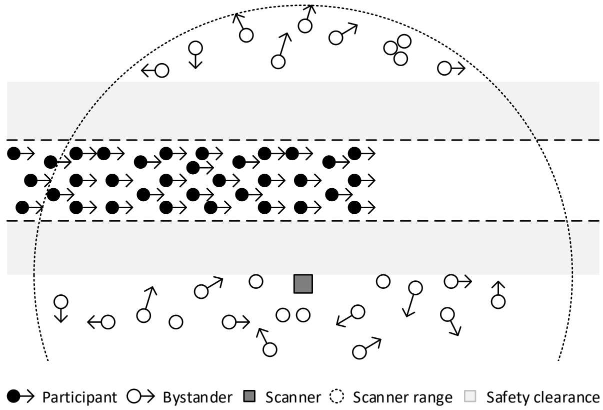

Fig. 1. Scenario

turns the Pi into monitoring mode and enables it to receive Wifi probes. The *aircrack-ng suite*[1] was used to activate the monitoring mode and to configure and test the monitoring interface. A python script handled the data collection and used *scapy*[2] to analyze the network traffic. The script listened to packets of sub-typ 4, which are Wifi probe requests, and extracted the timestamp, the sender's MAC address and RSSI.

IV. Filtering approaches

Distinguishing the Wifi probes received from participants from those received from bystanders requires some form of filtering. Distance and time are two approaches for that.

A. Distance-based filtering

Distance-based filtering assumes a correlation of the RSSI and the distance between the sending phone and the scanner. A strong RSSI would indicate that the phone is close to the scanner wheres a weak signal would mean it is further away. Clear RSSI thresholds would allow for filtering for Wifi probes that were sent from a particular area. In case of demonstrations, the filter would exclude any probe that is closer than 10 meters and further than 25 meters away.

Figure 2 shows the Wifi probes' RSSI received from a LG G4 phone outdoors. Even at 50 meters probes still arrive at the scanner. Notice, the bursts of probes that were received at the same time but with different RSSIs. This is because the phone sends the probes on different Wifi channels to find an Wifi access point quickly. Further, notice how the signal looses its strength with increasing distance. The distinction past ten meters is, however, blurred. If it was not for the color in the diagram, one could not tell by the RSSI alone whether the phone is 15 or 50 meters away. The figure, however, suggests that there are three distance categories, namely that of devices being as far as five, ten, and over ten meters away with RSSIs corresponding to -50, -60, and lower than -60 decibel. This would at least allow for removing those probes that are too close.

[1] https://www.aircrack-ng.org/
[2] https://scapy.net/

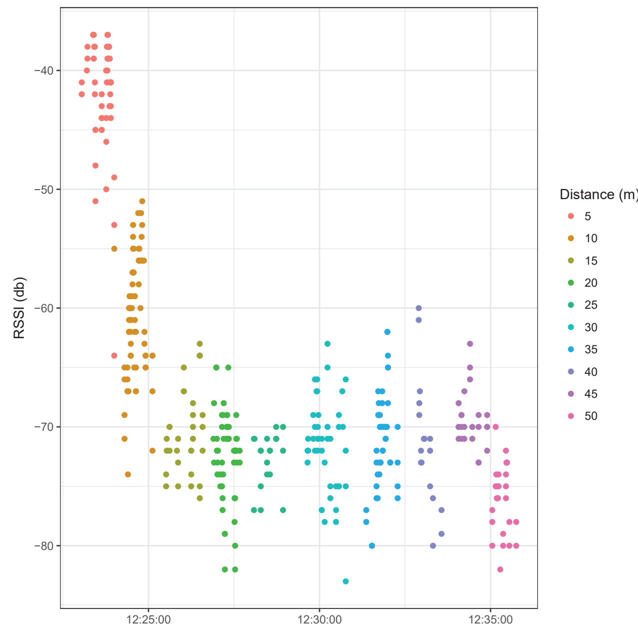

Fig. 2. RSSI changes with distance from receiver for LG G4 phone.

The next experiment used the same setup with a set of phones to verify whether these thresholds hold in general. The analysis showed that the behaviour is similar in that each phone sent bursts of probes that could be grouped into distances of five, ten, and more than ten meters. Condensing the bursts to the strongest signal strength for each distance, however, shows that the phones' RSSI is highly dependent on the phone model and a general threshold is not apparent (cp. Figure 3). Although it may be possible to derive the manufacturer from the first part of the MAC address, a per-phone analysis is not viable since RSSIs vary even for different models of the same manufacturer. Generally, these results suggest that RSSI filtering is unsuitable since there are no general thresholds that distinguish between devices sending from different distances.

B. Time-based filtering

Time-based filtering assumes that participants of a demonstration march into the scanner range, are visible for a short period of time, and march out of the scanner range. Further, they are visible to two sufficiently spaced scanners at different times which does not apply to bystanders. Such a reasoning, however, requires knowledge of the circumstances under which phones issue Wifi probes. In the case study, people participating in a march mostly leave their phones unattended and carry them in bags or pockets. This raises the question whether probes are then sent at all and if so, how long it takes for consecutive probes to arrive at the scanner. For this, the experiment placed the scanner and a set of phones with their displays turned off and their Wifi disconnected in a backpack and explored different motion scenarios. Figure 4 shows how differently the phones responded. In the still

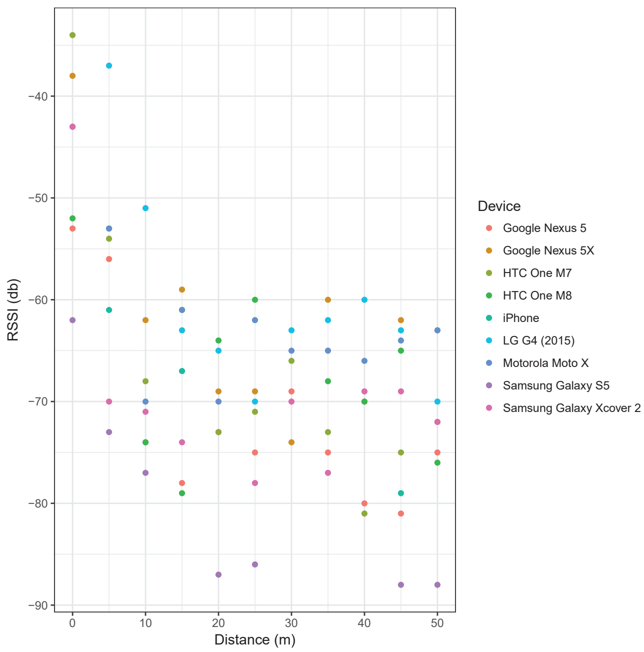

Fig. 3. There are not any general RSSI thresholds that correlate with the phones' distance to the scanner.

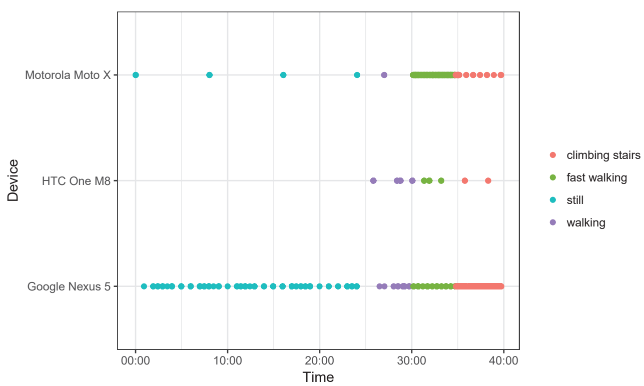

Fig. 4. Probe intervals vary depending on the phone model and activity. HTC One M8 was not part of still experiment.

scenario, the Motorola Moto X sent probes every eight minutes while the Google Nexus 5 did so every 30 seconds. The Samsung Galaxy Xcover2 did not send any probes at all. Some devices increased the probe intervals with increased activity, while others remained indifferent. The longest interval measured during the experiments was 2.5 minutes. This is slightly longer than previous research suggests [6].

This means that even though people carry a mobile device, they may not get detected by a scanner because: First, the phone does not send any probes when left unattended. Second, while in the range of the scanner, the phone does not send any probes because of its long probe intervals. Third, as noticed in earlier experiments, probes may get lost due the shielding affect of the human body. While the first issue cannot be addressed, multiple scanners carefully positioned along the route and filtering by recognition may mitigate the latter two issues.

Filtering by recognition requires at least two measuring stations that are far enough apart such that their scanner ranges do not overlap. This way phones captured by both stations actually moved from one station to the other instead of occurring in the overlap only once. As previous experiment show the scanners receive signals as far away as 50 meters such that the two stations need to be apart 100+ meters. Each of the stations needs to ensure that all phones sending Wifi probes can be captured. Under the assumption that a demo is up to 15 meters wide and has a safety clearance of up to 10 meters, a single scanner would reach far enough to cover the width of the demo. Further, with the longest probe interval t of 2.5 minutes (= 150 seconds) and an assumed marching velocity v of 10 meters per 15 seconds, the covered distance d=v*t is 100 meters. A single scanner with a range of 50 meters would suffice to capture even those phones that have a long probe interval. Multiple scanners at a measuring station decrease the probability of signal attenuation since people move uniformly and create space for the signal to propagate. Multiple scanners at one station, however, require further space between the stations as the overall scanning range of one station increases.

V. Real-world Deployment

The setup that would allow for filtering by recognition was tested at two demonstrations that took place in Dresden, Germany in mid-2017 and beginning of 2018. The plan was to deploy three measuring stations each with one scanner that was carried by a person and pointed towards the marching people. Both times, however, the anticipated route changed after the demonstration had started such that the scanner positions became obsolete and scanners had to be relocated quickly. This meant that the required space between the measuring stations could not be maintained and scan areas partly overlapped. The ground truth for Demo A was established by analyzing recorded video material. For Demo B manual counting by the scanner carries soon proved impossible as the demonstration changed speed several times and people started to mingle. This is why Table I shows an estimate of the actual attendance that is based on camera-based counts of previous demonstrations.

A. Results

Table I shows that none of the applied filters reflects the actual number of participants. The filter *seen by at least one scanner* is the union of unique probe senders across all scanners and does not make any distinction between participants and bystanders. The filter *seen by all three scanners* is the intersection of unique probe senders across all scanners. Its distinction is too rigorous, especially since the scan areas partly overlap, and excludes those senders that have a long probe interval. Considering the actual scanner setup, the filter *seen by at least two scanners* is a good basis for further analysis. The next filter adds the constraint that sightings need to be received by *some delay*. This works only for non-overlapping scan areas as senders seen by two scanners see at the same time are discarded. Comparing Demo A and Demo B in this respect shows that the scanner overlap was less severe in Demo B as the filter did not change the prior count. The delay could be further specified in that there is maximum delay. This, however, depends on the scenario. For example, Demo B slowed down and at times came to a halt such that delays of up to five minutes are reasonable. If the order of scanners is known, the data set can be further filtered for senders that were *moving into the marching direction*. The results show that Demo A was scanned with many bystanders around while Demo B was scanned at a rather quiet part of the route. Calculating the ratio between the counting result after the last filter and the actual attendance show that counting Wifi probes accounts only for a fraction.

Each filter reduces the count of unique Wifi probe senders and ensures that those remaining are likely to be participants of the demonstration. The ratio for the two data sets varies, partly because of the last-minute changes in the scanner setup. It does, however, show that a series of data sets from similar events are necessary to uncover the hidden relationship between the count based on Wifi probes and the actual number of people participating in the demonstration. A camera-based technique has the advantage that it delivers a reliable count without the need for a history. Further, in terms of human resources, it takes just one person to operate a camera while a technique targeted at filtering by recognition requires at least two people covering a measurement station each.

B. Lessons learned

Based on the experience of previous deployments that have failed prior to the presented data sets, there are some details to remember when setting up a experiment like this: First, all scanners need to be synchronized such that the calculated delay is correct and reflects reality. Second, notes about the event help later in the data analysis. This relates to recording the order in which the crowd passed the scanners as well as the times the crowd was actually approaching and leaving a scanner. Third, a demonstration may quickly pass a scanner such that stationary devices cannot be distinguished. One way to address this, is to extend the scan time to after the crowd has passed and scan for probe senders that linger on. This requires some care as participants may return on the same route after the demonstration has finished.

TABLE I
FILTERS APPLIED TO THE DATA SET RECORDED AT DEMO A IN MID-2017 AND DEMO B AT THE BEGINNING OF 2018.

	Demo A	Demo B
Actual attendance	1.494	∼1.500
Seen by at least one scanner	703	1.354
Seen by all three scanners	139	198
Seen by at least two scanners	323	601
Seen by at least two scanners with some delay	208	601
Moving into marching direction	103	468
Count-to-attendance ratio (%)	6.9	31.2

VI. CONCLUSION

This paper addresses the problem of counting participants of a demonstration based on the Wifi probes their phones broadcast. It is particularly challenging to distinguish participants from bystanders in a public place. The paper investigated the basic signaling behaviour of a set of phones and showed that distance filters based on RSSI are impractical since no common thresholds apply. Time-based filters, especially the proposed filtering by recognition, have extra requirements regarding the scanner setup and increase the likelihood that counted devices actually belong to participants. Overall, the count derived from analyzing Wifi probes represents only a small fraction of the actual attendance. Many data sets of similar events are required to identify the true ratio between probe counts and reality and to deploy probe counting stand-alone. Meanwhile it may be suitable for combinations with other crowd monitoring techniques.

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