Dynamic Wi-Fi Reference Point Recognition along Public Transport Routes

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Abstract. The ubiquity of Wireless Fidelity (Wi-Fi) signals in urban environments has the high potential to employ them for numerous applications for localization and guidance in urban environments. The reach of Wi-Fi localization is extended in this study for urban wide applications and therefore user localization is employed for outdoor and combined in-/outdoor environments. The chosen application is the localization and routing of public transport smartphone users. For the conducted investigations, Received Signal Strength Indicator (RSSI) values are collected for users who are travelling from home in a residential neighborhood to work in downtown and return along the same route. Special tram trains are selected which provide two on-board Wi-Fi Access Points (APs). Firstly, the availability, visibility and RSSI stability of the Wi-Fi signal behavior of these APs and the APs in the surrounding environment along the routes is analyzed. Then the trajectories are estimated based on location fingerprinting. A first analyses reveals that significant differences exists between the four employed smartphones as well as times of the day, e.g. in the morning at peak hours or at off-peak hours.

Keywords. Wi-Fi positioning, User localization, Public transport, RSSI measurements, Performance analysis

1. Introduction

Wi-Fi location fingerprinting is a method of finding a mobile device/person's location based on the RSSI of Wi-Fi networks (see e.g. Chen et al., 2012; Honkavirta et al., 2009; Liu et al., 2007; Xia et al., 2017). In an age of growing Wi-Fi coverage this method is becoming increasingly useful in areas where a GNSS signal does not reach, such as underground or within the built-up city area. In the case of this study, the operability and performance of Wi-Fi fingerprinting is investigated at a set number of

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reference points, referred to as Intelligent Check Points (iCPs), along a tram route. Here the major aim is to facilitate localization and optimum routing considering travel times and user preferences in multi-modal transport situations. In the presented tests, a route from a residential neighborhood to an University building in downtown is selected and analyzed. For that purpose, a short system training was performed in the beginning along the selected trajectory at benchmarks and public transport stops where only a few samples of RSSI were collected. Furthermore, long-term repeatedly observations of the Wi-Fi RSSI along the tram route are used for continuous system updating and training. The most significant novelty of this study is the use of the RSSI observations of the mobile Access Points (APs) installed on the trams (Retscher and Bekenova, 2019). In a first step, the RSSIs were analyzed concerning their availability, visibility and RSSI stability of the Wi-Fi signal behavior. Experiments conducted along the selected tram route leading through combined out-/indoor environments are described in the following.

2. Characteristics of the Selected Tram Route

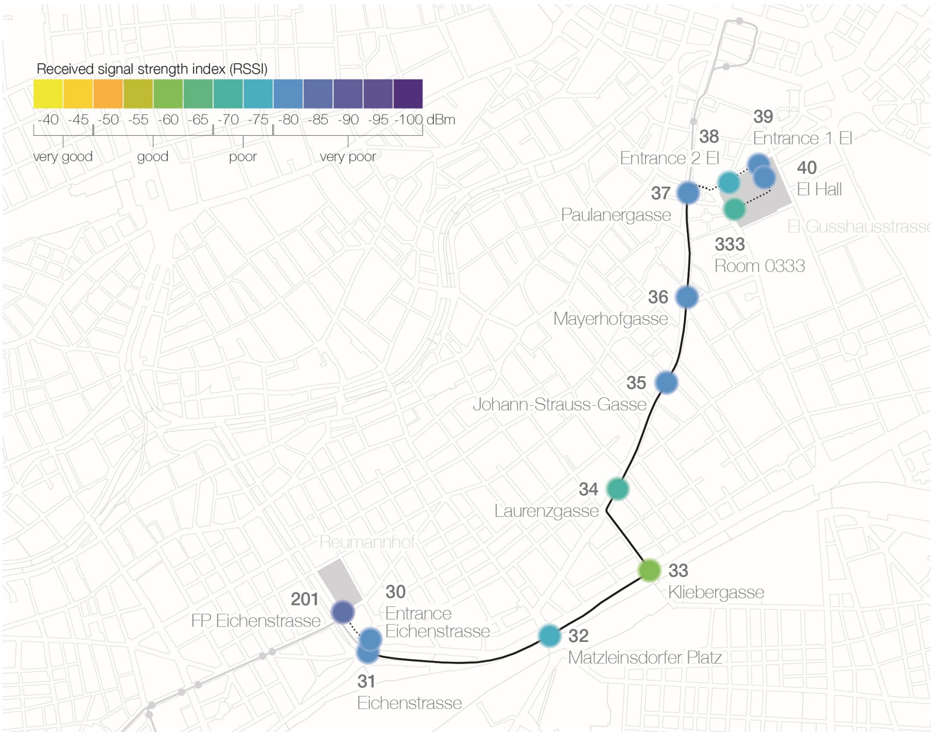

Figure 1. Tram route showing the average RSSI values recorded at each iCP

The particular feature of the tram route is that it runs on different levels partially underground and then above ground in the middle of a road (see *Figure 1*). Checkpoints are employed which are either benchmarks at the start or from a University campus wide network as well as station buildings and stops. The route starts at checkpoint 201 (which is a benchmark) and ends at the office 0333 on the third floor in the multi-story office building leading over the checkpoints 30 to 40. Checkpoint 30 is at the entrance of the first underground public transport stop and checkpoint 31 at the platform. Checkpoint 34 is located at the last station in the tunnel and then the tram travels above ground from the stops 35 to 37 in the middle of a road. At checkpoint 37 the user exits the tram and walks then to the University building along checkpoints 38 to 39 whereby the second checkpoint is front of the main entrance of the building. Checkpoint 40 is located inside the building on the ground floor and checkpoint 0333 in front the respective office in the corridor on the third floor. The total one way travelling time is around 15 to 20 minutes depending on the waiting time for the tram. In the presented tests, the trains with on-board Wi-Fi networks are selected.

3. Availability, Visibility and RSSI Stability of the Wi-Fi APs

Figures *2* and *3* show two different ways of presenting the changing RSSI values, *Figure 2* for the Samsung 1 (S1) smartphone in 2D and *Figure 3* in 3D for all four phones employed in this study.

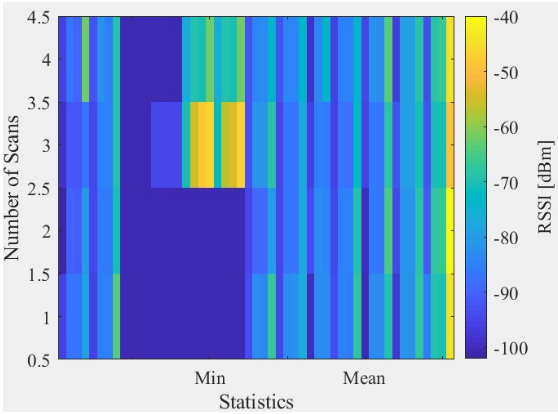

Figure 2. 2D plot for the Samsung 1 smartphone showing the RSSI values along the route

Figure 3 shows more similarities than differences between the graphs as all four smartphones follow a similar trend. The tunnel is very pronounced with a clear channel of -100 RSSI values. Before and after the tunnel values fluctuate around -80 dBm before sharply increasing to exceptional signal (around -45 dBm) inside the office building. These graphs indicate that the environment had the dominating influence on the RSSI values rather than the phones specifications, for example being underground leads to worsened RSSI values.

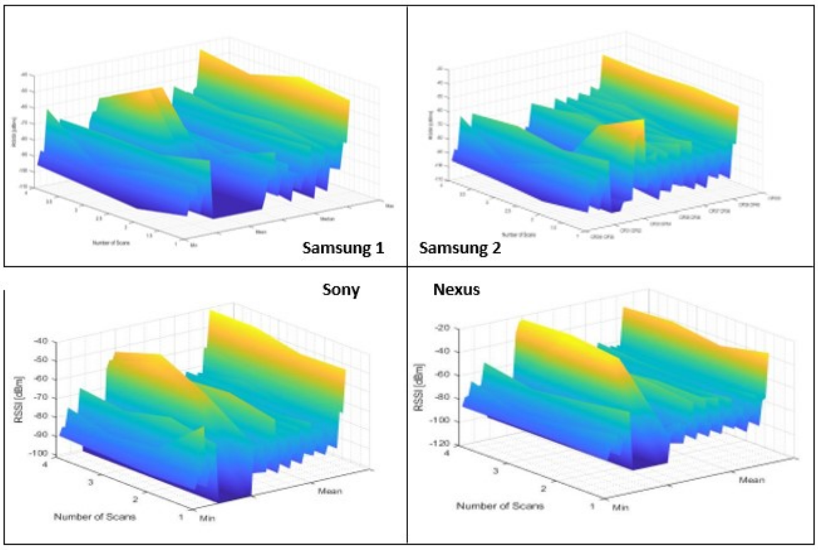

Figure 3. 3D line plots for each smartphone

The 3D bar graph presented in *Figure 4* clearly shows how the number of APs changes along the tram route. The visualization shows a clear drop in the number of APs received by the phones between reference points 31 to 34 where the tram passes underground through a tunnel. This can be explained as a case of the underground segment of the public transport network simply having less Wi-Fi coverage than the areas above ground. The walls of the tunnel are blocking any APs situated on the surface and therefore only Wi-Fi APs within the tunnel (e.g. hotspots from people's phones and the two on-board Wi-Fi APs) will be registered by the mobile devices. The graph also allows for the comparison of each mobile device. It can be clearly seen that the Nexus smartphone picks up the largest number of APs out of all of the smartphones. Despite Samsung 1 and 2 being the same smartphone model, Samsung 2 received notably more APs than Samsung 1. This may result from a number of reasons such as battery life, type of case on the phone and/or where the individual taking the measurements was standing. As for the LG Nexus, due to the high number of APs received, compared to the other phone models it must be assumed that this device has a much better receiver for picking up Wi-Fi networks. This phone can be considered the best device for Wi-Fi fingerprinting as it will give the highest number of APs and in turn RSS values therefore providing the most accurate tool for measuring Wi-Fi coverage, operation and performance.

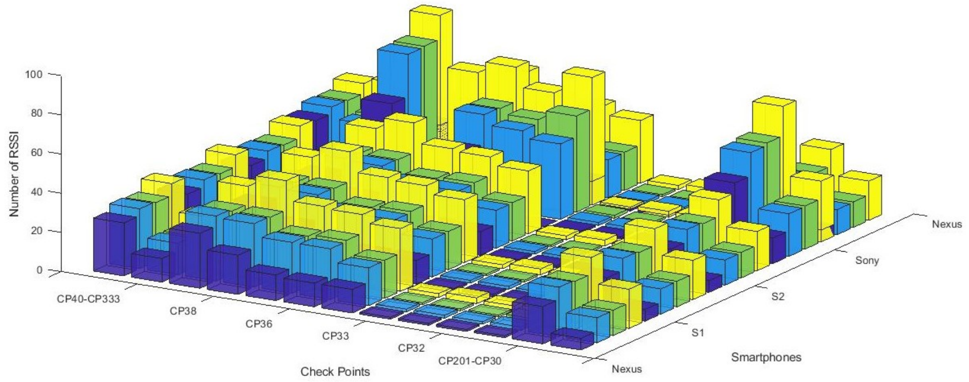

Figure 4. 3D bar graph of RSSI for all mobile devices at each iCP

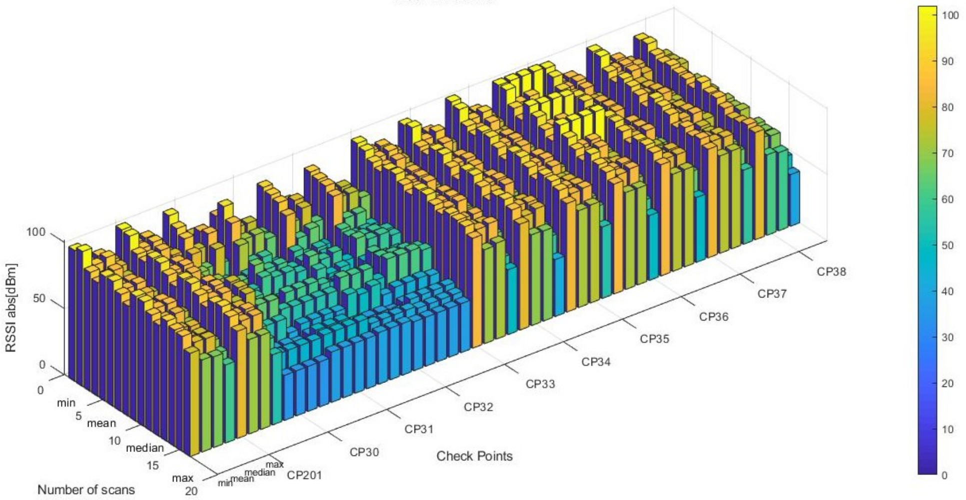

Figure 5. 3D visualization of RSSI variations for all mobile devices at each iCP

The 3D bar graph shown *Figure 5* visualizes the RSSI variations of all the mobile devices at each iCP. At each reference point (Z-axis) the minimum, mean, median and maximum RSSI values are represented against the number of scans at each location (20 for each mobile device) shown along the X-axis. The colour scale signifies the RSSI with blue characterizing a poor signal and yellow a strong signal. At reference point 37 the signal is strongest with values well into the 90s range. This could be due to the number of people with hotspots in the vicinity or a particularly large number of APs in the neighbouring buildings which are subsequently received by the mobile devices. As expected and seen previously the worst signal is in the tunnel where the least number of access points exist and signals from the surface cannot penetrate.

4. RSSI and AP Count Comparison

Figure 1 is a map output showing the average RSSI recorded across all phones at each iCP. These calculations presented a different picture to all other analysis undertaken in this study. Most notably the underground stations (Eichenstrasse, Matzleinsdorfer Platz, Kliebergasse and Laurenzgasse) have the highest RSSI values and inside a technical university has some of the lowest recorded. To try and understand the reasons for this trend the analysis shifted focus to the count of APs for each phone at every stop. *Figure 6* presents the AP count for each phone at each iCP. Here it is clear that there are considerably less APs collected inside the tram tunnel. This indicates that RSSI values are not positively correlated with the AP count (the higher the RSSI doesn't necessarily mean more AP signals being received). *Figure 6* also shows the Samsung phones have received considerably less AP signals than the LG Nexus and Sony Xperia. Despite *Figure 4* this shows that LG Nexus has similar RSSI values despite receiving more AP signals at the majority of the iCPs. This further supports the inference that the higher RSSI doesn't always result in more AP signals being received. The chart in *Figure 7* compares the average number of APs, received across all four phones at each tram stop, with the respective average RSSI. Both, the number of APs and the RSSI follow a similar pattern in that they both change visibly when the iCPs are at street level and in the tunnel. However, the results came partly as a surprise when analyzing the data captured by the phones. Whilst the number of APs received in the tunnel are low, presumably because of the few APs available (such as nearby fellow passengers), the RSSI was at its highest in the tunnel, at iCP 33 (Kliebergasse) even as high as -62 dBm which is considered as a good RSSI value. The possible reasons for this unexpected result are further investigated by looking into the whole dataset. It was seen that the LG Nexus at iCP 31 (Eichenstrasse) did not receive many APs at this location but the ones it did were received very well with an RSSI of up to -34 dBm which is considered as very good. The AP that shows up most often in this and similar environments, such as iCPs 32 to 34, come from the network called “ArberFazliu” which was owned by team member Arbër carrying out the survey. As we worked in a team taking measurements close together and always facing in the same direction at the same time, it is believed that this spatial constellation led to the very good RSSI results.

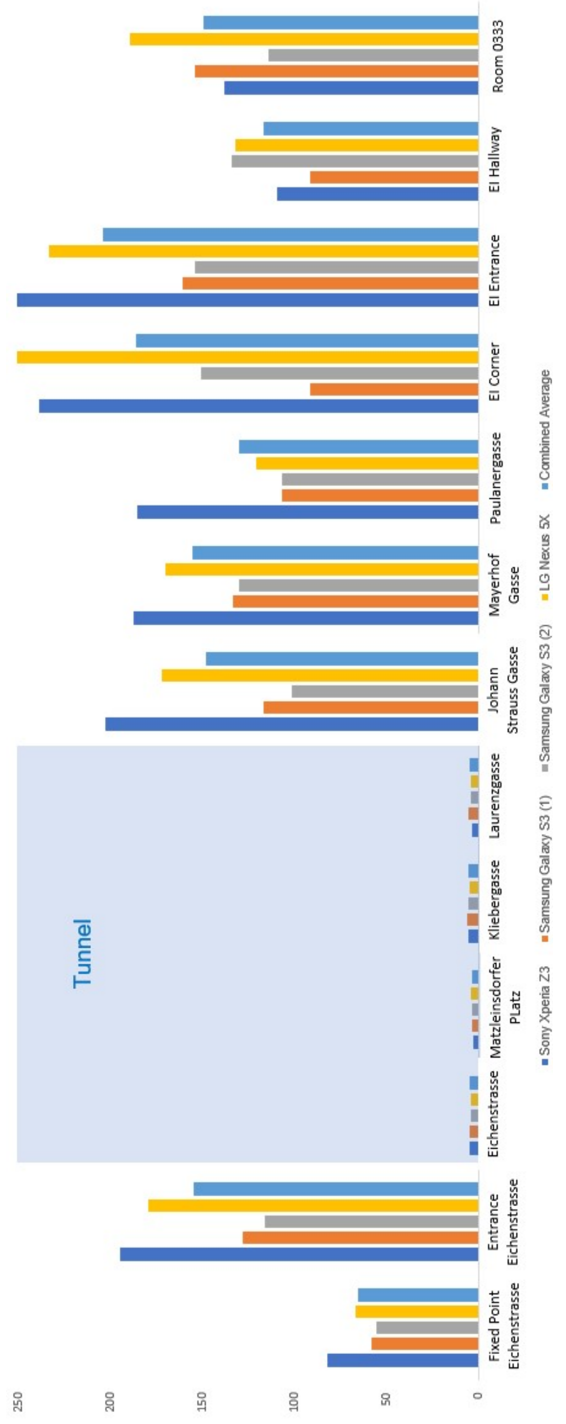

Figure 6. Comparison of the number of AP received per phone and iCP

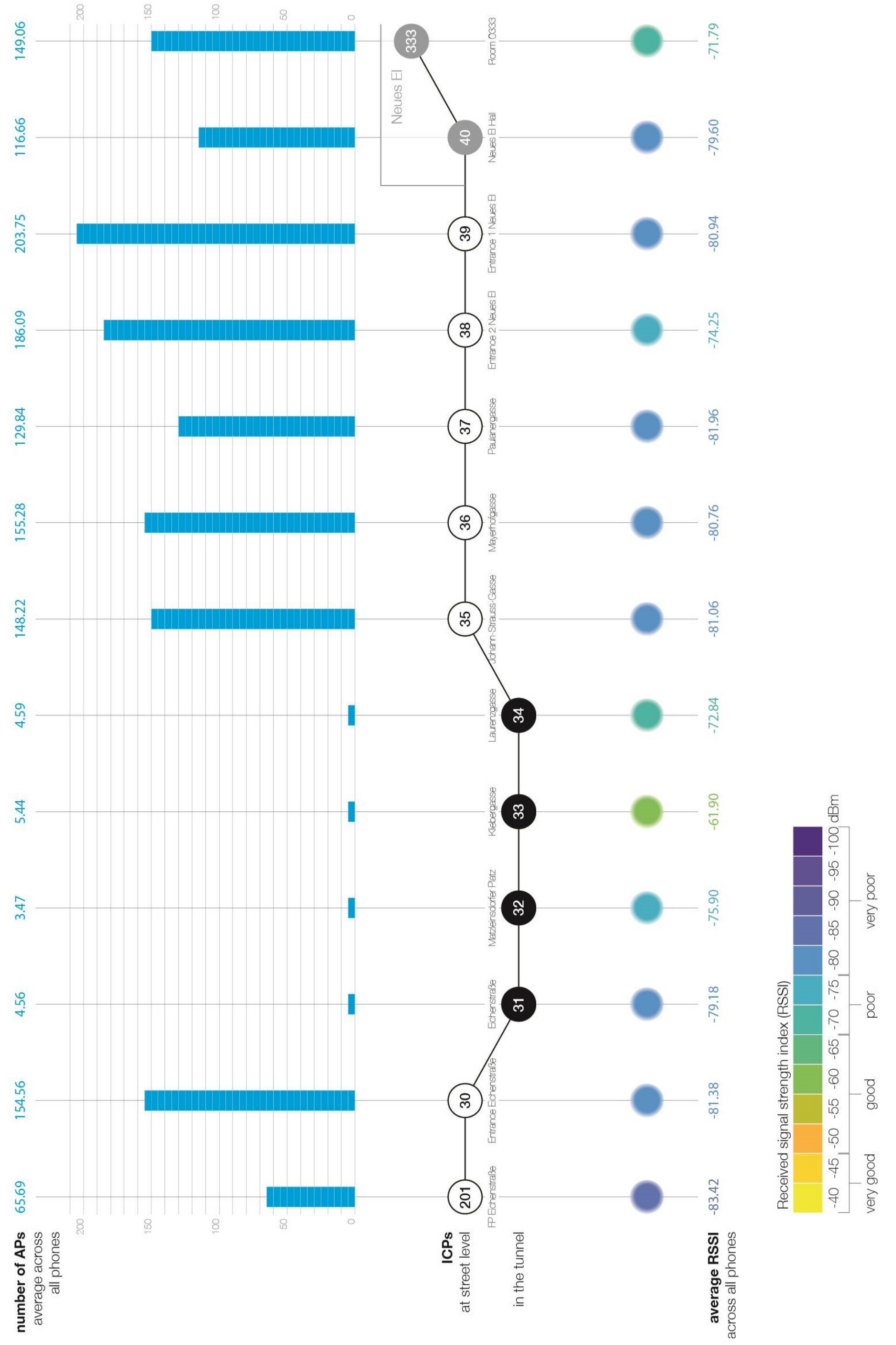

Figure 7. Direct comparison of average number of APs and average RSSI at each iCP

5. Conclusion

In conclusion, there is high variability in the RSSI values found along the tram route and this study has shown that there are many factors that influence this. The RSSI is heavily influenced by the position of buildings or other infrastructure, the most notable example in this study being the underground section of the route. Orientation of the device also played a role, particularly in the underground iCPs due to the presence of physical barriers that can block or impede the signals. If there is an AP originating from an underground environment this typically leads to very high RSSI values being received due to the close proximity of the hotspot APs to the devices. Different phones yielded different results for both RSSI values and number of APs received. This is suspected to be down to the phone specifications with the LG Nexus having the most sensitive receiver and therefore picking up the highest number of APs at each iCP. However this cannot account for the differences between the two Samsung devices which were the same model and therefore had the same specifications. Their difference can be justified by comparing the phone's battery life, type of phone case and the position that the user holding the phone was standing in. These can be considered possible future avenues for research which would require further measurements with phones of the same model.

Overall, the Wi-Fi fingerprints at each iCP were distinguishable from one another and would therefore allow for the accurate positioning of a user at these points. To improve these databases the number of measurements taken at each point could be increased to improve the accuracy and therefore the reliability of the iCP recognition. Measurements at different time periods and at different times of year could also help improve the checkpoint recognition as this study was focused on only two days of the year in May. These improvements are required to improve the overall accuracy because the RSSI values change throughout the year and, in general, are affected by the number of people present at that particular time (mobile hotspots, blocking of the signal, etc.). Finally the use of a greater range of smartphone devices would further increase the accuracy of the database as the majority of people are not limited to owning a Samsung Galaxy S3, LG Nexus 5X and Sony Xperia Z3.

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