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Real-time Wi-Fi RSS Variation Correction Using a Network Differential Positioning Approach

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***Abstract*—This paper presents an approach for real-time correction of Wi-Fi Received Signal Strength (RSS) variations and fluctuations to improve indoor localization by continuously updating the fingerprint database. For that purpose, a Differential Wi-Fi (DWi-Fi) scheme by analogy to Differential GNSS is developed and applied where reference station (RS) measurements are employed for a network calibration method. Hence, the recorded RSS measurements at the user's end are corrected and the fingerprinting database is continuously updated to account for the possible changes in the dynamics of the environment. The RSS properties stability, variability and visibility of the RSS values are analyzed to estimate the resulting effects of spatial and temporal RSS variations. For this investigation, both static and kinematic tests in an indoor environment using different mobile devices were carried out. They could prove the performance improvement compared to common approaches if continuous RSS measurements are conducted at RSs deployed in the area of interest.**

Keywords—analysis of spatial and temporal variations, area correction parameters, differential Wi-Fi localization (DWi-F), networked approach, real-time calibration, RSS properties.

I. INTRODUCTION

For Wi-Fi-based indoor positioning, fingerprinting is one of the most widely employed method which can offer relatively high positioning accuracy (see [1], [2], [5]) thereby the Received Signal Strength (RSS) is measured to the surrounding Access Points (APs) in a training phase using a site survey [3], [4]. Environmental variations, however, which cause the signals changing from time to time even at the same location, present a challenging task for indoor location estimation in the IEEE 802.11b infrastructure. Due to RSS variations caused by dynamic changes in the environment the training phases need to be periodically repeated. Even though if the updates of the fingerprint database are carried out, it is not possible to account for short-term spatial and temporal signal variations and RSS fluctuations. Thus, a differential approach termed Differential Wi-Fi (DWi-Fi) by analogy to DGNSS is proposed where reference station (RS) measurements are carried out continuously for signal corrections. Using such a calibration method, an improvement in terms of performance and achievable positioning accuracy is achievable due to the real-time correction parameters being derived in networked approach area in the triangle of three RSs. In this paper, both static and kinematic tests using different smartphones are carried out indoors to demonstrate the accuracy of the proposed system.

The paper is organized as follows: In section II the technical features of DWi-Fi are briefly presented followed by a short description of the field test site and the characteristics of the experiments in section III. Then the properties such as variability, stability and visibility of the measurements in the conducted field tests are analyzed in section IV. In section V more details of the real-time correction of RSS variations are presented. Finally, brief conclusions are drawn and an outlook on future work is given in section VI.

II. Operational Principle of DWi-Fi Positioning

In dynamic environments, the fingerprinting database and the associated radio maps obtained in one time period in a single off-line training phase may not be applicable at other time epochs. In this novel method, an estimation by offsetting the spatially and temporally variational environmental factors for certain indoor locations is performed for adaption of the temporal radio maps. For that purpose, Raspberry Pi units are deployed at known location in the surrounding environment to continuously record the RSS in real-time. The DWi-Fi approach was first presented by the first author of this paper at the FIG Working Week in 2016 [7]. In the meantime, significant improvement has been achieved. Following the first approach based on the straightforward DGNSS operational principle, a networked solution is developed. As in Continuous Operating GNSS Reference Station Networks (CORS) area correction parameters – also referred to by the German term Flächen-korrekturparameter (FKP) – are derived in triangles of three RS each [8]. To be able to deduce these FKPs the RSs have to be placed in a triangular network extending to the borders of the area of interest to cover the whole area. Using empirically derived path loss models a conversion of the measured RSS to the corresponding ranges to the APs and RSs have to be employed if a trilateration approach of measurements in the triangular network is performed. Moreover, it has been investigated if range measurements to more than three visible Raspberry Pi units and the RSS measured at a certain location lead to further improvement. Furthermore, in the recent system development, the Raspberry Pi units serve at the same time as APs scanning and emitting Wi-Fi signals. This procedure has the advantage that common hardware can also be deployed in areas, which are not so well covered with Wi-Fi APs, such as underground in buildings or train platforms for public transport. First experiments validated that the DWi-Fi approach is a suitable new solution (see [8], [9]) where highly successful matching rates up to 100% are achievable for observations on reference points (RPs) in stop-and-go mode.

III. Prepare Your Paper Before Styling

Field testing was performed in parts of the Queen Victoria Market (QVM) in Melbourne, Australia. Seven smartphone users were walking along a closed-loop trajectory around the shops comprising of four corridors with 16 RPs distributed in a test grid of 4 m. Seven Raspberry Pi units were deployed to serve both as APs or RSs at the same time and six static UWB (Ultra-wide Band). They were surveyed by a total station. Figure 1 shows the trajectory and the location of the sensors. Both kinematic and stop-and-go measurements were carried out. In the first case, a continuous recording of the RSS scans was performed and in the second case up to ten RSS scans on each of the 16 RPs were carried out. The users started at different RPs while walking along the trajectory. Moreover, the inertial sensor observations from the smartphones were recorded as well. The UWB measurements and the inertial data, however, are not used in the analysis in this paper.

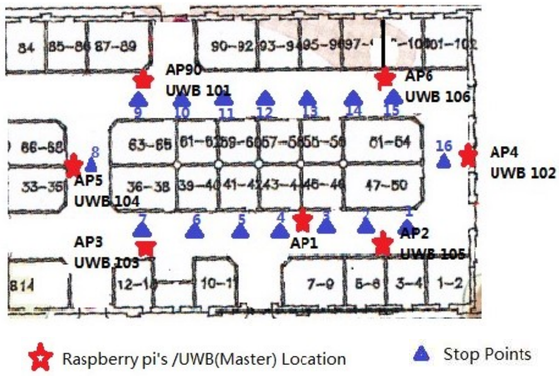


Fig. 1. Layout and sensor deployment in QVM

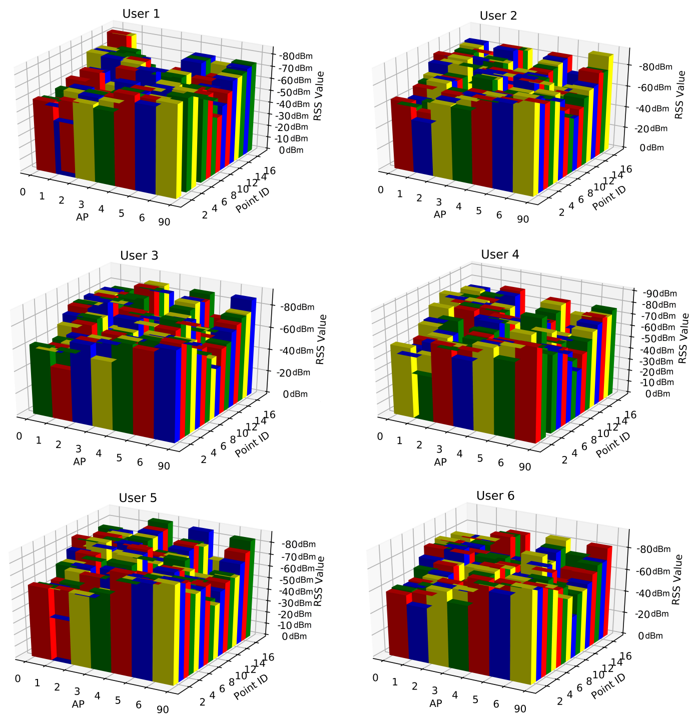
IV. Discussion of Major Test Results

A. Absolute RSS Value Distributions

In the first stage of the analyses, the absolute RSS value distributions of the RSS measurements on the 16 RPs in the test area collected by the seven different smartphone users were analyzed. Figure 2 shows a visualization of the results where the respective horizontal axis in the diagrams is labeled with AP as the seven Raspberry Pi units served also at the same time as APs. The second horizontal axis contains the RPs with their Point ID and the absolute measured RSS values from up to 10 scans at each RP are shown on the vertical axis. As it can be seen clearly from the diagrams the absolute RSS values of the seven APs vary significantly in dependence on the respective location of the user. Such a situation is favorable for positioning if the absolute RSS values are used since the match to the current location can be achieved more easily. Furthermore, a quite similar distribution for the different APs can be seen when comparing the different smartphones. The absolute RSS values, however, can differ in dependence of the smartphone. Figure 3 presents the mean absolute numerical values of the RSS over all smartphones which also includes the averaged RSS values over all performed scans on each of the 16 RPs. This different representation compared to Figure 2 verifies the already aforementioned findings. Further analysis and discussion of the resulting relative RSS value distributions is presented in the following section.

B. Relative RSS Value Distributions

In the next step of the analysis, the relative RSS distributions were examined. From Figure 3 the order of magnitude for the RSS values for each AP can be seen. For instance, on RP 1 the ascending order is: AP 2 > AP 1 = AP 4 > AP 3 > AP 6 > AP 5 > AP 90 ranging between -44 to -82 dBm. Overall, on all RPs the RSS values lie between -44 to -86 dBm whereby the highest most significant value of -44 dBm occurred on RP 1 for AP 2. Further analysis showed that for smartphone user 1, several APs are not visible on some of the RPs (see Figure 4). Such a situation was not the case for most of the other smartphones.



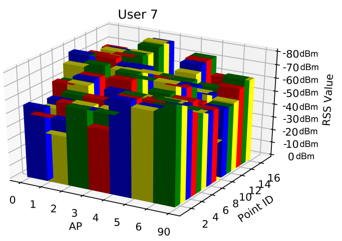


Fig. 2. Comparison of absolute RSS values on the 16 RPs collected by seven different smartphone users

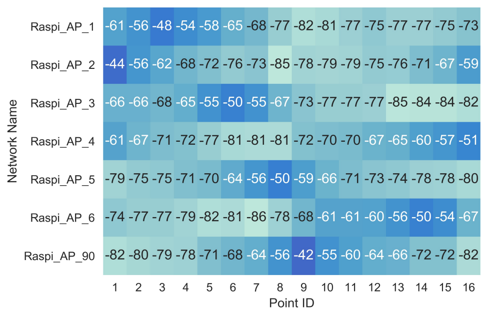


Fig. 3. Mean absolute numerical values of the RSS including measurements from all smartphones

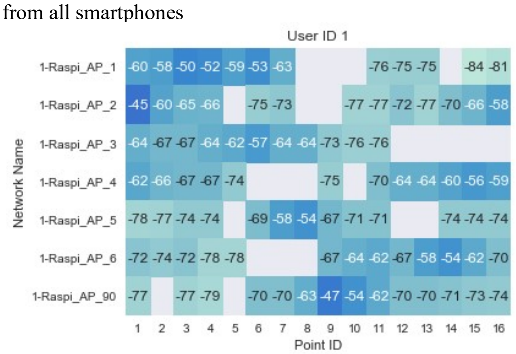


Fig. 4. Mean absolute numerical values of the RSS for one smartphone (user 1)

A more in-depth analysis of the ascending order of the RSS values on all RPs is shown in Table I. The sorting was done from the strongest signals of an AP to the weakest. The order is consecutively starting from 1 up to 7 (if not the same RSS value is obtained for two or more APs). Overall, the resulting averaged relative RSS value distribution are AP 5 > AP 4 > AP 1 = AP 90 > AP 2 and AP 3 > AP 6. If one compares this order with the individual results of each user in the Table it can be seen that each user shows a different order. This should be the case as the RSS values for each APs depend on the RP location and the distance to the respective AP. If they differ as in the obtained results, a match of the correct location is achieved more easily. Furthermore, it can be seen from the Table that a change in order is seen as the user moves along the trajectory away and towards the APs. It can also be said that the number of used APs is sufficient to be able to distinguish the certain RP location. In the following, the RSS properties are analyzed in regards to stability, variability and visibility of the RSS values of the different AP Wi-Fi signals in order to estimate the resulting effects of spatial and temporal RSS variations.

TABLE I. ORDER OF THE RSS VALUES ON THE 16 RPS

AP	Point ID															
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
1	2	1	1	2	2	1	4	4	7	7	5	6	5	6	5	4
2	1	1	2	6	5	5	5	7	6	6	6	5	5	3	3	2
3	3	2	3	1	1	1	1	3	5	5	5	6	6	7	7	6
4	2	3	4	4	6	6	6	6	4	4	3	3	2	2	2	5
5	5	4	5	3	3	2	2	1	2	3	4	4	4	5	6	1
6	4	5	6	7	7	6	7	5	3	2	2	1	1	1	1	3
90	6	6	7	5	4	4	3	2	1	1	1	2	3	4	4	6

C. Stability, Variability and Visibility of the RSS Values

The three properties: stability, variability and visibility characterize the quality of the Wi-Fi signals from the different APs on the respective RPs. In this case, stability is defined as the property that an AP can always be scanned at each time instance for the duration of RSS training measurements collection. The results showed that across almost all users AP 4 is consistently the strongest as it is the only AP in which data is able to be scanned at each time instance during the whole collection; barring the results from user 1, due to the incomplete scans from all APs (compare Figure 4). The visibility of AP signals can be described as the presence of RSS signals from the respective AP during the entire measurement collection. All APs, during the collection, for all users have RSS signals and are therefore are classified as visible. If one looks further at the variability, it can be seen that the obtained results as a whole indicate that APs across each location have a visible consistency. As expected, APs tend to provide strong signals at the closest RP locations while the locations farthest from an AP have weaker signals. Although this does not hold entirely true as at RP 9, AP 1 has a weaker signal compared to AP 2 despite AP 2 being physically farther away. Additionally RP 16 which is located near AP 2 and

AP 6, receives signals from both APs with 8 dBm difference in respect to absolute RSS value.

V. Correction Approach for Spatial and Temporal RSS Variations

The conducted field tests indicate a high variability behavior of the RSS values and therefore proves that corrections for spatial and temporal signal variations are necessary to improve the achievable positioning accuracies together with a satisfactory performance. A possible solution strategy is developed. In the approach, a modeling of the RSS variations using continuous measurements at RSs is performed. Raspberry Pi units are deployed in the environment for that purpose. Similar as in DGNSS, corrections are derived in the RS network. The difference to DGNSS, however, is that RSS corrections are derived and not range or coordinate corrections. From the known range between all APs and RSs the nominal RSS is derived and compared with the currently measured RSS at a certain time epoch. Then it is possible to apply this model at the user's side using the measurements conducted in real-time over all available RSs. Fingerprinting radio maps of RSS distribution are then derived to be able to deduce the FKPs. Temporal variations of the RSS are considered from continuous long-time measurements. Then it is possible to analyze different time epochs with different conditions, e.g. a different number of people in the building when measured during the day and at night. A flowchart of the approach to derive radio maps in real-time from previous RSS measurements is shown in Figure 5. In the first step, an average vector $\hat{\hat{r}}$ containing the RSS values derived from long-time measurements over a certain time period (e.g. one day as indicated in the Figure) to the *n* visible APs is calculated to get a numerical value which describes the fluctuation of the Wi-Fi signals. This vector is representative for the average behavior of the APs RSS. In the following step, the mean RSS vector $\vec{r}_{\overline{lt}}(t)$ for the current time epoch t is calculated. Then an RSS correction vector $\vec{r}_{corr}(t)$ is derivable. Finally, the improved RSS fingerprint vector $\vec{r}_{imp}(t)$ for the particular users' location can be estimated [6].

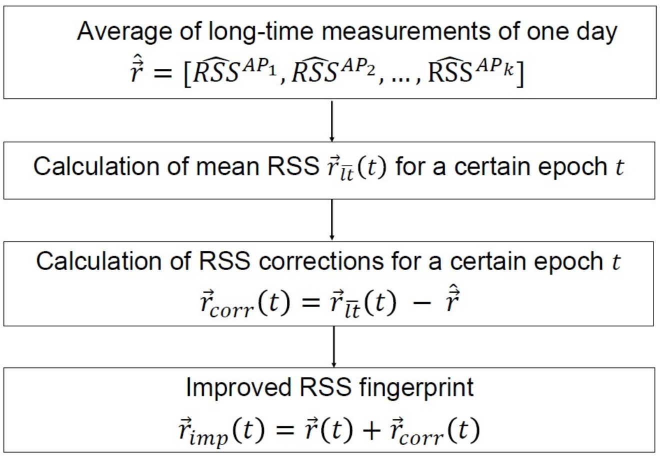


Fig. 5. Flowchart for the derivation of RSS corrections for the current users' location from long-time RSS measurements [6]

VI. Conclusions

In this study, the behavior of measured RSS values for indoor Wi-Fi positioning is analyzed. For that purpose, field tests in an indoor market scenario were carried out where the Wi-Fi signals were scanned on several reference points (RPs). The RSS properties variability, stability and visibility of the RSS values to the seven APs realized by low-cost Raspberry Pi units are investigated. The Raspberry Pi units can serve at the same time as reference stations (RSs) broadcasting and scanning the receivable Wi-Fi signals. Especially in environments that are not suitably covered with Wi-Fi APs the use of Raspberry Pi units is very economically. Further investigation concerning the costs are currently under way. In practical case studies, such as in underground environments in buildings or public transport metro train stations, the use of APs and RSs is analyzed in order to guarantee a low-cost solution. In the property analysis, it could be seen that the absolute RSS values can vary significantly in dependence on the location of the user and differs for the different smartphones. The relative RSS distributions reveal a different ascending order in dependence of the RP location. The case that APs are invisible on a certain location occurred only once for one of the smartphones. The results indicate that corrections for spatial and temporal RSS variations are usually required. An approach to achieve an improvement of the performance of Wi-Fi positioning by real-time modeling of the RSS variations is presented at the end of this paper.

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References

[1] R. Chen, L. Pei, J. Liu, H. Leppäkoski, "WLAN and Bluetooth Positioning in Smart Phones," In R. Chen (Ed.): Ubiquitous Positioning and Mobile Location-based Services in Smart Phones. Hershey PA, USA: IGI Global, 2012, 44-68.

[2] D. Han, S. Jung, M. Lee, G. Yoon, "Building a Practical Wi-Fi-based Indoor Navigation System," IEEE Pervasive Computing, 13(2), 72-79.

[3] K. Kaemarungsi, P. Krishnamurthy, "Properties of Indoor Received Signal Strength for WLAN Location Fingerprinting," IEEE International Conference on Mobile and Ubiquitous Systems: Networking and Services (MOBIQUITOUS), 2004. 14-23.

[4] Y. Li, S. Williams, B. Moran, A. Kealy, "Quantized RSS Based Wi-Fi Indoor Localization with Room Level Accuracy", IGNSS 2018 Conference, February 7-9, 2018, Sydney, Australia, 14 pgs.

[5] D. Milioris, G. Tzagkarakis, A. Papakonstantinou, M. Papadopouli, P. Tsakalides, "Low-dimensional Signal-strength Fingerprint-based Positioning in Wireless LANs," Ad hoc networks, 12, 2014, 100-114.

[6] G.Retscher, "Fusion of Location Fingerprinting and Trilateration Based on the Example of Wi-Fi Positioning," ISPRS Annals of the Photogrammetry, Remote Sensing and Spatial Information Sciences, Volume IV-2/W4, 2017, ISPRS Geospatial Week 2017, 18-22 September 2017, Wuhan, PR China, 377-384.

[7] G. Retscher, H. Hofer, "Wi-Fi location Fingerprinting Using an Intelligent Checkpoint Sequence," FIG Working Week, May 2-6, 2016, Christchurch, New Zealand, 16 pgs.

[8] G. Retscher, H. Hofer, A. Kealy, V. Gikas, F. Obex, "Cooperative Localization in Indoor Environments Using Constrained Differential Wi-Fi and UWB Measurements. ION GNSS++ Conference 2017, Institute of Navigation: Portland, Oregon, USA.

[9] G. Retscher, T. Tatschl, "Indoor Positioning with Differential Wi-Fi Lateration," Journal of Applied Geodesy, 11:4, 249-269.