The Need and Challenges for Ubiquitous Positioning, Navigation and Timing (PNT) Using Wi-Fi

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Key words: cooperative positioning, indoor positioning, indoor-outdoor smooth transition, challenging environment, mobile mapping vehicles, pedestrian cooperative localization, sensor integration, GNSS, UWB, Wi-Fi, LiDAR, inertial sensors

SUMMARY

This paper presents further results for indoor localization using Wi-Fi RSS (Received Signal Strength) measurements in a typical office environment from a one-week benchmarking measurement campaign carried out at The Ohio State University from the joint FIG/IAG Working Group on Multi-sensor Systems. Based on the paper presented at the FIG Working Week in Hanoi in 2019 significant progress in algorithm development for Wi-Fi localization is reported. Starting from an identification of the key points and challenges of ubiquitous pedestrian user localization in mass market LBS applications the novel probabilistic location fingerprinting approach demonstrates successful pedestrian user indoor localization on the room-level granularity. As for many applications, the determination of the room or a section of the building where the user is currently located is sufficient, this approach is a suitable solution for challenging indoor localization problems. Matching success rates of up to 97% for the localization of a user while walking along trajectories between different cells in an office building are achieved with the new approach.

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1. INTRODUCTION

Positioning, Navigation and Timing (PNT) is very crucial nowadays for many applications. If one considers state-of-the-art Location-based services (LBS), for instance, ubiquitous positioning belongs together with modeling and communication to the inner core of LBS (Huang et al., 2018). These services become increasingly important and pervasive in our daily life, ubiquitous positioning is needed to provide an accurate and timely estimate of a user's or an object's location at all times and in all environments. While Global Navigation Satellite Systems (GNSS), i.e., GPS, GLONASS, Galileo, and BeiDou, as well as regional systems, such as the Indian Navigation Constellation (NavIC) or the Japanese Quasi Zenith Satellite System (QZSS), are available in outdoor environments localization in GNSS-denied or combined indoor/outdoor environments is still very challenging. Especially for indoor environments, while other positioning methods and technologies start to appear, such as using so-called signals-of-opportunity, e.g. Wireless Fidelity Wi-Fi-based positioning, achieving accurate, reliable and robust positioning is still a long way to go. Sensor fusion is a major topic which needs to be addressed in this context. Apart from the absolute positioning technologies and techniques, modern smartphones and other mobile devices have embedded sensors. These are referred to as the inertial sensors, i.e., accelerometers and gyroscopes, which can be employed together with a digital compass (i.e., magnetometer) as well as barometric pressure sensor (altimeter) for determination of the distance travelled, heading of the user and altitude. If these sensory are used for localization of pedestrian users, the technique for obtaining the relative positions from a given start position is referred to as Pedestrian Dead Reckoning (PDR). Then it is possible to position and navigate a user continuously in combination with GNSS or other absolute positioning technologies, such as Wi-Fi.

In this paper basics aspects and key points for robust positioning solutions and an example for indoor localization using Wi-Fi is given. The remainder of the paper is organized as follows: In section 2 the key elements of ubiquitous PNT are summarized followed by the user and application requirements is section 3. Then the positioning technologies adoption is elaborated in section 4. Section 5 focuses then on mass market LBS applications. In section 6 the principle of a Wi-Fi indoor localization approach is presented whereby the basics of the evaluation using a probabilistic fingerprinting approach are discussed in detail in section 7. Results of field tests in an office environment are shown in section 8 and finally a conclusion and outlook are given in section 9.

2. UBIQUITOUS POSITIONING, NAVIGATION AND TIMING (PNT)

Ubiquitous Positioning, Navigation and Timing requires the following two major aspects:
1. to deliver GNSS-like performance anywhere, anytime, under any operating conditions, and
2. to exceed the performance levels of GNSS for safety and liability critical applications.

Figure 1 shows the major key points in this respect and Figure 2 the emerging application areas relying on ubiquitous PNT information. In the following section the major user and application requirements for ubiquitous PNT are discussed.

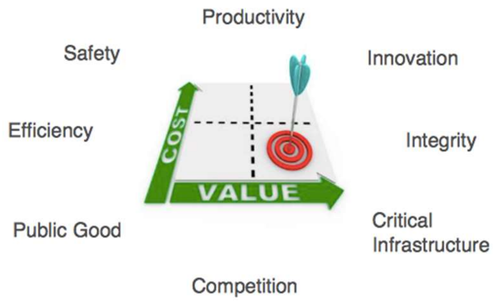

Figure 1. Key points for ubiquitous Positioning, Navigation and Timing (PNT)

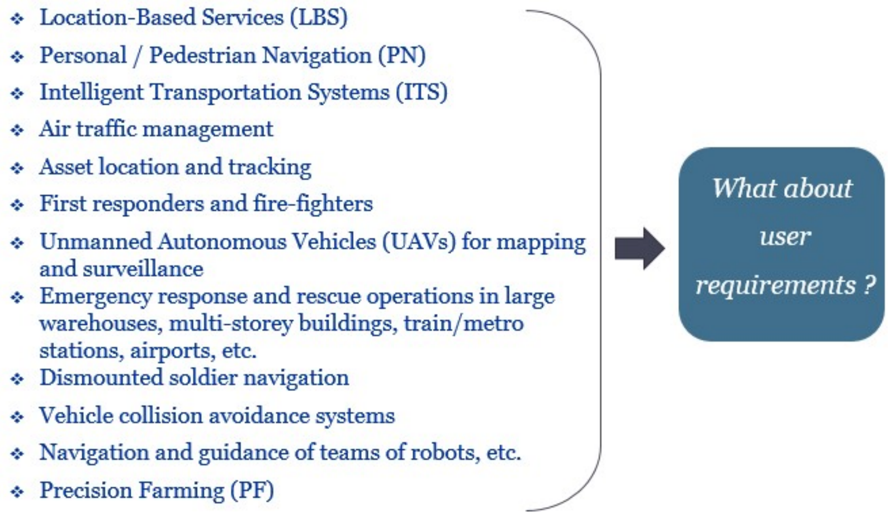

Figure 2. Emerging Application Areas Relying on PNT Information

3. PNT USER AND APPLICATION REQUIREMENTS

An overview about the PNT user requirements is illustrated in Figure 3. These requirements can be categorized in four different classes which are positioning, cost, security and legal as well as interface requirements. Apart from postioning accuracy the most relevant positioning requirements are integrity, availability and coverage, latency and continuity as well as sampling and update rate. The other three requirements, i.e., cost, interface and security and legal requirements, have to be considered. Operational and maintenance costs, for instance, are very important when designing a low-cost positioning system.

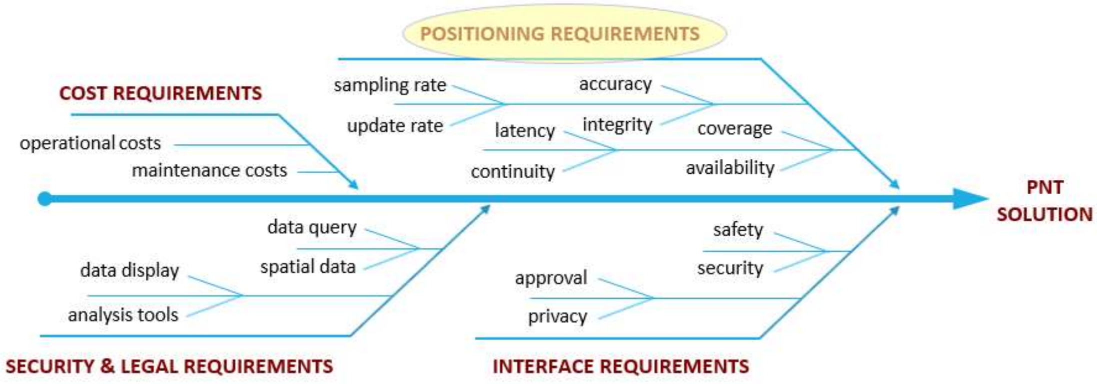

Figure 3. Overview of PNT user requirements (Source: Retscher et. al., 2020)

As identified in the GNSS Market Report of the European Commission in 2017 [1] the key GNSS requirements and performance parameters are described in the following. The key parameters are:

- *Availability*: percentage of time over a specified time interval that a sufficient number of satellites are transmitting a usable ranging signal within view of the user. Values vary greatly according to the specific application and services used, but typically range from 95-99.9%.
- *Accuracy*: the difference between true and computed position (absolute positioning). This is expressed as the value within which a specified proportion of samples would fail if measured. Typical values for accuracy range from tens of meters to centimeters for 95% samples. Accuracy is typically stated as 2D (horizontal), 3D (horizontal and height) or time.
- *Continuity*: ability to provide the required performance during an operation without interruption once the operation has started. Continuity is usually expressed as the risk of discontinuity and depends entirely on the timeframe of the application (e.g. application that requires 10 minutes of uninterrupted service has a different continuity figure than one requiring two hours of uninterrupted service, even if using the same receiver and services). A typical value is 1x10-4 over the course of the procedure where the system is in use.
- *Integrity*: the measure of trust that can be placed in the correctness of the position or time estimate provided by the receiver. This is usually expressed as the probability of a user being exposed to an error larger than alert limits without warning.
- *Time to first Fix* (*TTFF*): a measure of a receiver's performance covering the time between activation and output of position within the required accuracy bounds. Activation means subtly different things depending on the status of the data the receiver has access to.
- *Robustness*: the ability of systems or system elements to withstand a level of interference and/or jamming without significant degradation or loss of performance.
- *Authentication*: the ability of the system to assure that they are utilising signals and/or data from trustworthy source (e.g. GNSS constellation), and thus protecting sensitive applications from spoofing threats.

[1] 2017 GNSS Market Report, https://www.gsa.europa.eu/2017-gnss-market-report

It must be noted that they have to be applied for any other PNT applications not involving only GNSS but also other sensors and technologies which are additionally and independently used. If these key requirements and performance parameters are applied, for instance, for Wi-Fi or UWB (Ultra-wide Band) positioning a similar validity exists. Regarding availability the number of transmitters (UWB stationary transmitters or Wi-Fi Access Points) can be seen as the number of GNSS satellites. Especially integrity is often neglected and not paid full attention. The way that integrity is ensured and assessed, and the means of delivering integrity related information to the user are highly application dependent. TTFF in the case of Wi-Fi positioning is highly correlated to the received signal strength (RSS) scan duration of a certain mobile device. This is especially important in kinematic positioning. As seen by Retscher and Leb (2019) the appearing scan durations can vary significantly for different smartphones which results in a different level of achievable positioning accuracy in dependence of the walking speed in the case of pedestrian navigation. For different users robustness may have a different meaning, such as the ability of the solution to respond following a serious shadowing event. Here, robustness is defined as the ability of the solution to mitigate interference. Other requirements and performance parameters are power consumption, resiliency, connectivity, interoperability and traceability. Especially in the case of mobile devices power consumption is still very critical to provide a long-term solution possibility. Resiliency is the ability to prepare for and adapt to changing conditions, such as it is the case for Wi-Fi RSS signal variations and fluctuations. To encounter for their influence new robust schemes are necessary and need to be developed. Table 1 provides an overview about the key performance parameters and their priorities for mass market solutions and safety and liability critcal applications whereas Table 2 highlights them for lower and higher performance applications. As can be seen the requirements are quite different and therefore different priorities must be considered and applied depending on the type of application. It can be very substantial and critical to decided on the key parameters which have to be achieved in any case for the application in mind.

4. POSITIONING TECHNOLOGIES ADOPTION

The PNT technologies drivers pyramid from the GNSS User Technology Report published in 2018 [2] illustrates the most important key points (see Figure 4). There are four main dimensions of PNT systems technology development that enable the future of automated intelligent positioning systems. As presented in the PNT technology drivers pyramid, the location systems must be ubiquitous, secure, accurate and connected to provide basis for modern automation and ambient intelligence. The advent of automated systems has progressed very rapidly recently thanks to the development alongside all four dimensions of the pyramid base.

To summarize, the most important PNT challenges and their possible solutions are:

- Accuracy is obtained thanks to multi constellation, multi-frequency GNSS, augmented by Precise Point Positioning Real-time Kinematic (PPP-RTK) services and hybridized with inertial systems (INS) and other sensors;

[2] GNSS User Technology Report, 2018, https://www.gsa.europa.eu/newsroom/news/gnss-user-technology-report-2018-available-download-now

	Key Performance Parameters								
Application	Availaibilty	Accuracy	Continuity	Integrity	Robustness	Indoor penetration	Time-to-first-Fix (TTF)	Latency	Pover consumption
Mass market	H	H	H	M	H	H	H	L	H
Safety and liability critical applications	H	H	H	H	H	L	H	H	M

Tabel 1. Key performance parameters and their priorities (L: low, M: medium and H: high prority) [1]

Application	**Lower Performance**: navigation, sports, tracking, social networking, enterprise applications, infotainment, games	**Higher performance**: Augmented Reality (AR), mHelath, geo marketing and advertising, fraud management and billing, safety and emergency
Key GNSS requirements	Availability Time-to-first-Fix (TTF)	Accuracy Authentication Availability Time-to-first-Fix (TTF)
Other requirements	Connectivity (including short range Interoperability Power consumption	Connectivity (including short range Interoperability Power consumption

Tabel 2. Requirements for lower and higher performance applications in e.g. mass market applications [1]

- Connectivity relies on the integration with both satellites and terrestrial networks, such as 5G cellular phone networks, Low Earth Orbit Satellites (LEOs) or Low Power Wide Area Networks (LPWANs);
- Ubiquity is provided by complementary positioning technologies and sensors;
- Security is provided by the combination of independent redundant technologies, cybersecurity and authentication.

Thereby maintaining performance in all contexts requires the fusion of multiple positioning technologies and sensors which is briefly discussed in the following.

There are certain contexts where the usage of GNSS services is difficult or even impossible. Urban canyons are an example of the former, due to multipath effects and a reduction of the number of satellites in view. Tunnels, indoors or the underground are an example of the latter. This gap in coverage or performance is not acceptable for many applications, and is addressed by using complementary technologies in the user PNT solution. Their state of adoption and maturity is highlighted in Figure 5. As can be seen the technologies differ quite sihnificantly in respect to their state of maturity. Signals-of-opportunity are highligthed in Figure 5 because their usage are one of the great opportunities for future ubiquitous user localization in any environment.

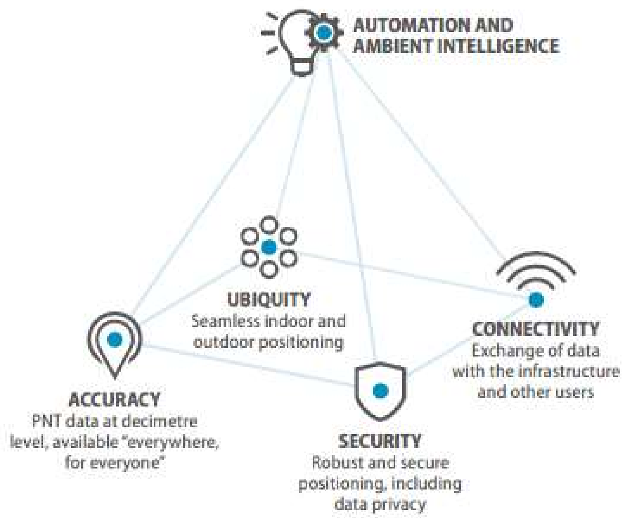

Figure 4. PNT technologies drivers pyramid from the GNSS User Technology Report 2018 [2]

Figure 5. State of adoption and maturityof the PNT ecosystem [2]

5. LBS APPLICATIONS

In the white paper of Huang et al. (2018) the following definition of Location-based Services (LBS) is given:

LBS can be defined as computer applications (especially mobile computing applications) that deliver information tailored to the location and context of the device and the user.

An increasing demand in expanding LBS is seen from outdoors to indoors, and from navigation systems and mobile guides to more diverse applications (e.g. healthcare, transportation and gaming). More and more LBS are entering into the general public's daily lives, which greatly influence how people interact with each other and their behaviours in different environments. With the integration of information and communication technologies (ICT), especially mobile ICT in every aspect of our daily lives, 4A (anytime, anywhere, for anyone and anything) 'services' are being developed to benefit our human society and environment. It also brings many opportunities (e.g. for traffic management and urban planning) and challenges (e.g. privacy, ethical, and legal issues) to our environment and human society (Huang et al., 2018).

Transport is one of the main application fields of LBS. Applications include those for driver assistance, passenger information, and vehicle management. Car navigation systems are probably the most popular LBS applications, which provide wayfinding assistance for drivers, and are still being improved with new features, such as real-time traffic information. Crowdsourced traffic and road information to provide, for instance, drivers with real-time navigation supports. LBS and tracking techniques have now been extensively used for vehicle management and logistic tracking. In recent years, applications beyond car navigation and vehicle management emerged. For example, for driver assistance and passenger guidance, applications for finding available on-street parking spaces), safety warning, multimodal routing have appeared. There are also studies using LBS to promote more healthy, greener (lower CO^2 emission), and more active mobility behaviours. Sustainable personal mobility in multi-modal traffic scenarios is a necessity in our modern life. Thus, pedestrian navigation and guidance is a major focus in the course of LBS education.

LBS are also being used as assistive technology to enable visually impaired people, and disabled and elderly people to perform their daily living activities independently and to experience an improved quality of life. These assistive systems provide assisted-living functions, such as personalized navigation and wayfinding, obstacle detection, space perception (Shen et al. 2008), and independent shopping. With the increasingly aging population, one can expect that more and more location based assistive systems will be developed and employed in the future.

Recent years have also seen the application domains of LBS being expanded into disaster and emergency, supporting citizens' involvements in society (e.g. for crime mapping, reporting urban problems), education (learning in the field), entertainment (e.g. music), insurance, billing, and supporting production processes in factories. While most LBS applications are developed primarily for supporting individual users, some researchers have started to develop LBS applications to support groups of users for collaborative task solving, such as wayfinding (Huang et al., 2018).

Especially user localization in indoors environments is required by most LBS applications which leads to many challenges. In the following section, an example of the use of Wi-Fi localization in an indoor office environment is presented.

6. WI-FI INDOOR POSITIONING WITH ROOM-LEVEL GRANULARITY

As a follow-up of last year's FIG Working Week paper from Kealy et al. (2019) further results of indoor environment tests in an office environment of The Ohio State University are presented. The measurement campaign was conducted as part of the joint FIG/IAG Working Group on Multi-sensor Systems to set a benchmark for the use of the most prominent signal-of-opportunity Wi-Fi for localization based on RSS measurements. As in most applications it might be only required to locate persons in a certain room or section of the building only room level granulartity was tested. The achieved room-level or region-level granularity of location is sufficient for the most LBS applications where pedestrians have to be located.

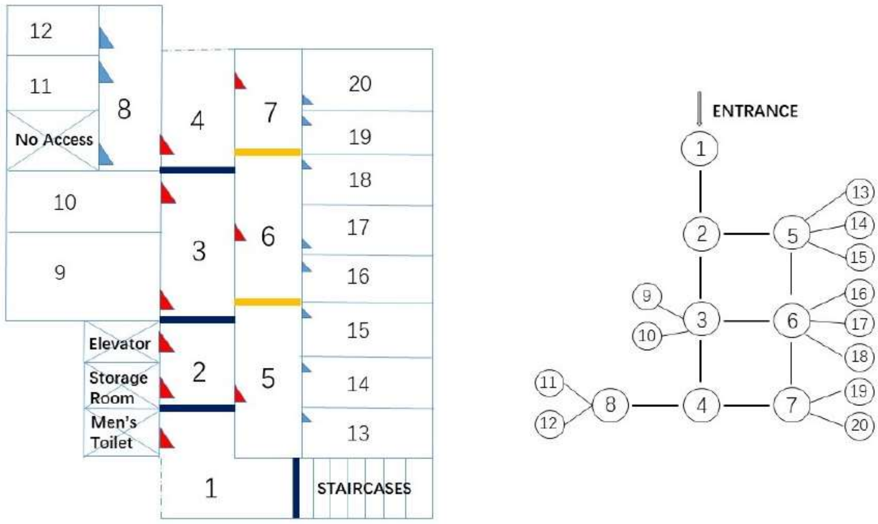

Figure 6. A schematic map of the test site (not to scale) and its topology

In the test area in the building was segemented in cells including rooms and sections of 4 m in lenght in the corridor as well as entrances or exits as depicted in Figure 6. The localization method chosen was location fingerprinting whereby in the training phase 200 RSSI scans of the visible Access Points (APs) at different locations in the different cells were simultaneously collected by all mobile devices to be able to locate a user in the positioning phase who has scanned again for the APs. In this phase, Bayesian inference is applied to calculate the probability that a user is at a certain location given a specified observation. Then the most likely location of the mobile device can be estimated. Thereby the accuracy of the statistical distribution model directly affects the final performance of the probabilistic fingerprint positioning (see e.g. Xia et al., 2017). Li et al. (2018) proposed a statistical approach to localize the mobile user to room level accuracy based on the Multivariate Gaussian Mixture Model (MVGMM). A Hidden Markov Model (HMM) is applied to track the mobile user, where the hidden states comprise the possible room locations and the RSS measurements are taken as observations. Due to the segmentation of the test area in different cells the transition matrix in the HMM is defined in such a way that only adjacent cells have non-zero transition probability while the transition probability between isolated cells is zero.

7. PROBAILITY METHODS FOR WI-FI LOCATION ESTIMATION

Bayesian filtering employing probabilistic techniques are one strategy to estimates the states of a dynamic system with measurement noise (Retscher et al., 2018) It is also applicable to sensor integration consisting of many different types of measurements to achieve higher accuracy. In the following, the Hidden Markov Models (HMM) is applied for such type of application.

The HMM has the advantages of non-Gaussian assumption and computation efficiency compared to other Bayesian filtering technologies (Seitz et al., 2010). Wi-Fi RSS is used as the observations, while the hidden states can be Wi-Fi fingerprints (Liu et al., 2012) or the reference points (Park et al., 2011). Pedestrian Dead Reckoning (PDR) using the embedded smartphone inertial sensors, for instance, is introduced in Seitz et al. (2010) to generate the state transition matrix. The graph structure which represents the environment, defined by vertices and edges is proposed in He et al. (2015). In particular, the HMM is more feasible to estimate the motion with free moving restrictions (Seitz et al., 2010).

The general definition of a HMM is as follows (Rabiner, 1989): Let the state set *S* consists of a sequence of hidden states $s_1, s_2, \ldots, s_t$. These states then constitutes the user moving trajectory in specific in the case under consideration at time *t*. Given an observed Wi-Fi RSS sequence $O = o_1, o_2, \ldots, o_t$ up to time *t* the model is characterized by parameters $\Lambda = \{A, B, \pi\}$. Thereby *A* is the transition probability matrix characterizing the state transition probability independent of time. *B* is the emission probability matrix characterizing the observation probability of an observation given its state (Li et al., 2018). They are defined by the following equations:

$$A = [P(s_t|s_{t-1})] \tag{1}$$

$$B = [P(o_t|s_t)] \tag{2}$$

π is the initial state probability and normally set to:

$$\pi = P(s_1) = \frac{1}{N}, \, where\ N\ is\ the\ number\ of\ states\ in\ S \tag{3}$$

In the HMM-based tracking system, the Viterbi algorithm (see e.g. Forney, 1973) is applied in this study to calculate the maximum posteriori estimate of the path given the observation sequence.

The fingerprinting method assumes usually a uni-modal distribution of the measured RSSs when averaging the RSS measurements for each AP in stored signatures. This can be seen as a significant drawback. Another drawback is that the algorithm it is not consistent to dynamic environment changes. While using a histogram of the RSS values for a signature at a reference point instead may offer a more accurate description of the environment. The advantage is that these histograms represent various levels of RSS by storing a large number of signatures (Correa et al., 2008).

The histogram method is closely related to discretization of continuous values to discrete ones. In a first step, a room or a section of a corridor in a building, referred to as cell in the following, may be selected where many RSS measurements with different mobile devices are performed. Then in the next step, these RSS measurements for each AP are quantized into *m* values, i.e., *m* bins. This represents a set of non-overlapping intervals that cover the whole range of the RSS measurement where the quantized measurements, i.e., the RSS levels for each AP, are received. Then the probability of each bin given the user is in ther respective cell, i.e., the room or corridor section, is the normalized count of measurements in that bin from inside the cell in the form off:

$$P(RSS \in ith\ Bin) = \frac{Count(ith\ Bin)}{size\ of\ training\ data} \tag{4}$$

In this study, a room-based histogram probabilistic method is proposed to estimate the likelihood function $p(z_k|x_k)$ (Retscher et al, 2018).

In the training phase of the fingerprinting algorithm, a Wi-Fi fingerprint for each cell of a building is generated. Thus, the labour consuming workload can be reduced in this way significantly as the usual training measurements in a regular grid in the area of interest in the building is not required anymore. Multiple RSS scans, however, are still needed at multiple reference points (RPs) in each cell to create the histogram for each AP. RPs within the room, however, are chosen randomly and not in a grid where Wi-Fi signals are collected regardless of the orientation of the smartphone or mobile device. Thus, a measurement in four different orientations is not required as it this course of action is usually performed in location fingerprinting. This leads to a further reduction of workload for system training.

The positioning phase matches real-time received Wi-Fi RSSs to the room fingerprints to determine the mobile device most likely location using maximum likelihood classification for this fingerprinting matching approach. Likelihood of a vector of measurements $Z = \{z_1, z_2, \ldots, z_n, n \in N_{ap}\}$ for a cell within the building $l_k, k \in N_{cell}$ that the user is in is then described according to the Bayes' rule by:

$$p(l_k|Z) = \frac{p(Z|l_k)p(l_k)}{P(Z)} \tag{5}$$

$$\begin{aligned} \max_k(p(l_k|Z)) &= \max_k(p(Z|l_k)) \\ &= \max_{k,i\in m}(\prod_{n=1}^{N_{ap}} hist(Z_n \in ith\ Bin)) \end{aligned} \tag{6}$$

Note, it is assumed that the AP RSSs are independent.

Using the histogram matrix computed at the training phase as a look-up table, then the observation probability for each timestamp, i.e. the emission, is computed. If within one scan, some APs are non-visible, a value of ZERO is assigned to them, and they are not included into the emission probability computation.

Li et al. (2018) proposed a statistical approach to localize the mobile user to room level accuracy based on a Multivariate Gaussian Mixture Model (MVGMM). The developed system is designed to handle practical problems in Wi-Fi fingerprinting, such as heterogeneity of the employed mobile devices, Wi-Fi signal reliability and stability as well as complexity of the environment. Thereby the users do not need the basic knowledge about the location of the APs deployed within the environment in advance. A Hidden Markov Model (HMM) is applied to track the mobile user, where the hidden states comprise the possible room locations or cells and the RSS measurements are taken as observations.

To account for spatial correlation of the RSSs from multiple APs, the MVGMM was fitted to the Wi-Fi training data to provide a probabilistic model for RSS measurements in each cell. It is seen that neither a traditional AP selection rule, such as the use of the strongest RSS value as described in Youssef et al. (2003), nor a stable AP selection algorithm as in Luo and Fu (2017) can guarantee to select an optimal subset of APs that can enhance the localization accuracy in a large scale environment. The proposed crowdsourcing system proposed by Li (2019) mainly focuses on linear regression based calibration, Expectation-Maximization (EM) data imputation, HMM based tracking and MVGMM estimation.

As the room-level localization, i.e., referred to as cell-based localization in this work, is obtained by segmenting the building floor plan into cells, training data collection is carried out by fusing the RSS measurements taken within each cell by all contributed mobile devices. A multivariate linear regression model is then applied to calibrate the RSS measurements collected from the different devices involved in the crowdsourced training phase. If RSS values to certain APs are missing in the scans the conventional approach is to set low RSS values, such as -101 dBm (Retscher and Hofer, 2017) or even lower as to -110 dBm (Shahidi, 2016), or assign a penalty in the matching process (Berkvens et al., 2016) to replace the missing data in the fingerprinting database. These conventional methods of dealing with missing data, however, may distort the RSS distribution and cause biased estimation. Thus, the EM imputation method is used by Li (2019) instead for the estimation of the missing RSS values in the incomplete RSS measurements. Different features of the RSS spatial correlation for both fixed single location and across-cell measurements have been studied. Further details about these approaches would go beyond the scope of this paper and therefore the interested reader has to be referred to the PhD thesis of Li (2019). In the following only the basics and selected results are presented.

The developed MVGMM uses a high-dimensional probabilistic fingerprint for each cell to take into account the spatial correlation of the RSS of multiple APs. The benefits of using information provided by not visible APs, i.e., APs where no RSS value is obtained at a certain scan epoch, in differentiating between cells is investigated, by incorporating a geometric distribution to provide a probability of exisstence of an AP that was not visible in the training phase. The employed joint histogram model to generate the signal probability distribution for each cell has the disadvanatge, however, that in a complex and noisy wireless environment, for example a university office building, a large number of APs can be scanned during both the training and positioning phase. Matching a quantised histogram from 100 APs exactly almost never happens, thus an AP selection rule is required to achieve reduced-dimensional quantized states for each cell (Kushki et al., 2007). Proper AP selection methods are required to select a subset of APs in order to reduce the computational load and improve the localization accuracy (Zou et al., 2015). As aforementioned, conventional AP selection rules either choose the APs with strongest RSS or the most stable APs. The reason for this is that it can be expected that the APs with the highest RSS are those that appear in most of the samples (Youssef et al., 2002).

Crowdsourcing for system training is a promising solution that reduces the required site survey and maintenance expense for updating the fingerprinting database compared to a conventional approach. It is possible to construct a radio map by spreading the data collection task across multiple users, and fusing appropriately the fingerprints thereby collected. Different devices, unfortunately, give varying RSS readings and have differing AP sensitivities because of a range of factors, including antenna geometry, transmission power and hardware performance (Lee et al., 2010). This leads to the RSS variance and dimension mismatch problem in a cross-device fingerprint database that the fingerprints contributed by different devices are not compatible with each other. To support different participated devices, a linear regression calibration model is implemented to mitigate the RSS variance problem caused by device heterogeneity and map the fingerprints for multiple devices to a single radio map.

Apart from the fact that APs may not be visible in every scan, leading to missing data, the different sensitivity of each device to the APs leads additionally to further dimension mismatch. While the incompleteness in the sensing data can lead to bias in the estimation of parameters, the most successful approach, reported here, invokes the EM imputation strategy. This method, widely used in statistics, provides a method to impute the missing data and simultaneously learn the parameters from the incomplete data (Ghahramani and Jordan, 1994). The key idea of EM imputation is to iteratively fill in the missing data under the current estimation of the unknown parameters and re-estimate the parameters from the observed and filled-in data (Schafer and Graham, 2002).

More challenges in location fingerprinting arise due to the involvement of heterogeneous mobile devices, especially if a new device is used in the positioning phase when it has not been used in system training. Usually then the system fails to maintain the reported accuracy based on the fingerprint database previously built by other different devices. Results reported in Laoudias et al. (2013) and Yen and Wang (2017), for instance, have demonstrated that, when the test device was not considered for training the crowdsourcing fingerprint, the system reported an inferior localization performance compared to the accuracy when the test device contributed in the RSS radio map construction. Thus, a calibration and learning of the fingerprint database for the different devices must be applied. Further investigation is currently under way regarding the issue of using different heterogeneous mobile devices.

Besides, different rooms have both different visible and invisible AP sets, which is also a signature that can be used to differentiate between cells. By taking advantages of invisible APs, i.e., to use so-called 'unseen properties', a conditional probabilistic observation model is utilised to describe the likelihood of receiving a particular invisible AP set at a certain cell. The hypothesis is that if an AP is invisible during the whole training phase at a specific cell, then a device with observation containing RSS from that AP has low probability belonging to the same cell. The information of invisibility of APs enabling the introduction of rigorously motivated trustworthiness for updating the conditional likelihood observation function (Li, 2019).

8. WI-FI POSITIONING RESULTS IN AN OFFICE ENVIRONMENT

In total, 11 kinematic walking trajectories were carried out with different smartphones. Figure 7 shows an example of an obtained trajectory where one smartphone user walked in the study area between different defined cells. As proven by Li et al. (2018) the trajectories along the reference points could be obtained with matching success rates of up to 97%. The MVGMM is efficient at approximating the RSSI distribution for each room that takes the signal correlations into computation. Figure 8 presents the matching accuracies with different training sizes. It can be seen that the proposed method is nearly insensitive to the size of the training samples, even presenting more robust localization accuracy to lower sample sizes. This result is similar to the work from Zhou (2006) where the authors found that, given denses training samples for the area may introduce more noise to distinguish from other areas. It can be finally summarized that the proposed system and algorithm demonstrated a reliable room location awareness system in a real public environment.

9. CONCLUSIONS AND OUTLOOK

In this paper, the key points and challenges of ubiquitous pedestrian user localization are elaborated and a solution on the example of Wi-Fi positioning for indoor user localization is demonstrated. Thereby the Wi-Fi data was collected in a one-week benchmarking measurement campaign of the joint FIG/IAG Working Group on Multi-sensor Systems where the main focus was led on CP of different platforms, i.e., vehicles, bicyclists and pedestrians, in GNSS-denied/challenged in-/outdoor and transitional environments. For localization a Wi-Fi probabilistic fingerprinting approach is introduced which enables user localization within room-level granularity. It is demonstrated that matching success rates of up to 97% for the localization of a user while walking along trajectories between the different cells in an office

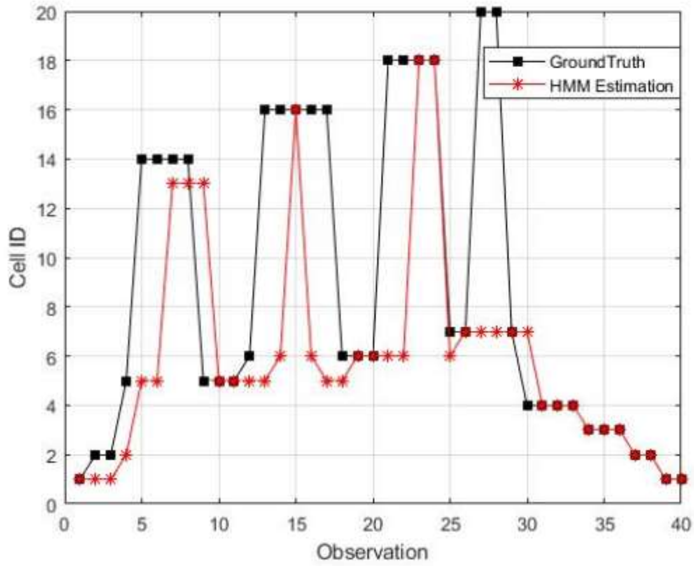

Figure 7. Example of a kinematic walking trajectory

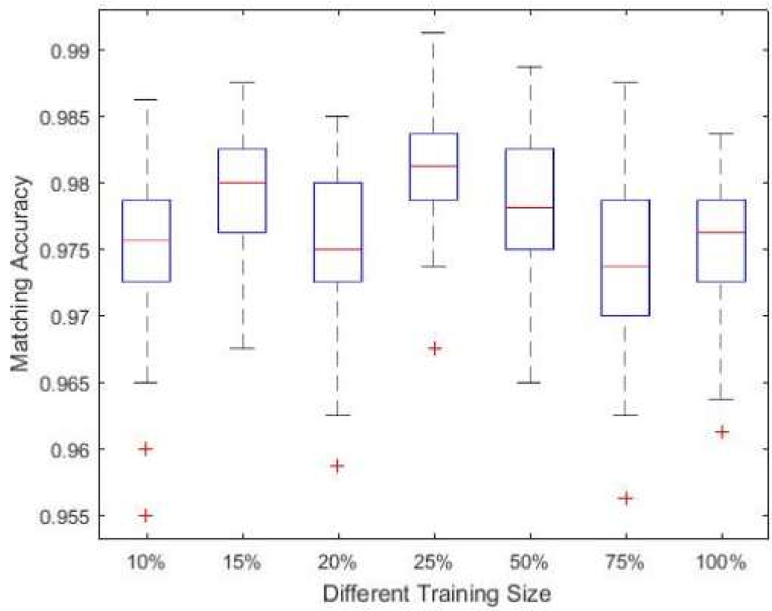

Figure 8. Matching accuracies with different training sizes

building are achievable with the new approach. These predefined cells are either rooms or sections of the hallway.

Further data processing and analyses is currently in progress whereby an emphasis is especially led on the achievable localization accuracies and performance in the transitional and indoor environments. Apart from absolute localization of the users, dead reckoning with the inertial sensors is a further point for future investigations. Especiaally the use of the smartphone inertial sensors in combination with Wi-Fi and cameras is considered. Moreover, using an embedded barometric pressure sensor also the correct floor in which the user is currently located in a multi-storey building can be determined which enables then redundancy in 3D localization.

REFERENCES

Berkvens, R., Peremans, H., Weyn, M. (2016): Conditional entropy and Location Error in Indoor Localization Using Probabilistic Wi-Fi Fingerprinting. Sensors, 16:10, 1636.

Correa, J., Katz, E., Collins, P., Griss, M. (2008): Room-level Wi-Fi Location Tracking. Report, Carnegie Mellon Silicon Valley.

Forney, G. D. (1973): The Viterbi Algorithm. Proceedings of the IEEE, March, 61:3, 268-278

Ghahramani, Z., Jordan, M. I. (1994): Supervised Learning from Incomplete Data via an EM Approach. Advances in Neural Information Processing Systems, 120-127.

Huang, H., Gartner, G., Krisp, J. M., Raubal, M., Van de Weghe, N. (2018): Location Based Services: Ongoing Evolution and Research Agenda. Journal of Location Based Services, 12:2, 63-93, DOI: 10.1080/17489725.2018.1508763.

Kealy, A., Retscher, G., Gabela, J., Li, Y., Goel, S., Toth, C. K., Masiero, A., Błaszczak-Bąk, W., Gikas, V., Perakis, H., Koppanyi, Z., Grejner-Brzezinska, D. A. (2019): A Benchmarking Measurement Campaign in GNSS-denied/challenged Indoor/Outdoor and Transitional Environments. FIG Working Week, April 22-26, 2019, Hanoi, Vietnam, and FIG Article of the Month July/August 2019, 19 pgs. (paper 9837).

Kushki, H., Platanoitis, K. N., Venetsanopoulos, A. N. (2007): Kernel-based Positioning in Wireless Local Area Networks. IEEE Transactions on Mobile Computing, 6:6, 689-705.

Laoudias, D, Zeinalipour-Yatzi, C., Panayiotou, C. G. (2013): Crowdsourced Indoor Localization for Diverse Devices Through Radiomap Fusion. 2013 International Conference on Indoor Positioning and Indoor Navigation, IPIN 2013. DOI: 10.1109/IPIN. 2013.6817906, 7 pgs.

Lee, M., Yang, H., Han, D., Yu, C. (2010): Crowdsourced Radiomap for Room-level Place Recognition in Urban Environment. 8th International Conference on Pervasive Computing and Communications Workshop, 648-653.

Li, Y. (2019): A Probabilistic Approach for Wi-Fi Based Indoor Positioning. PhD Dissertation, The University of Melbourne, Australia.

Li, Y., Williams, S., Moran, B., Kealy, A., Retscher, G. (2018): High-dimensional Probabilistic Fingerprinting in Wireless Sensor Networks based on a Multivariate Gaussian Mixture Model. Sensors, 18(8), 2602, DOI 10.3390/S18082602, 24 pgs.

Liu, J., Chen, R., Pei, L., Guinness, R., Kuusniemi, H. (2012): A Hybrid Smartphone Indoor Positioning Solution for Mobile LBS. Sensors, 12:12, 17208-17233.

Luo, J., Fu, L. (2017): A Smartphone Indoor Localization Algorithm Based on WLAN Location Fingerprinting with Feature Extraction and Clustering. Sensors, 17:6, 1339.

Park, I., Bong, W., Kim, Y. C. (2011): Hidden Markov Model Based Tracking of a Proxy RP in Wi-Fi Localization. 2011 IEEE 73rd Vehicular Technology Conference (VTC Spring), 1-5.

Rabiner, L. R. (1989): A Tutorial on Hidden Markov Models and Selected Applications in Speech Recognition. Proceedings of the IEEE, 77(2), 257-286.
Retscher, G., Hofer, H. (2017): Wi-Fi Location Fingerprinting Using an Intelligent Checkpoint Sequence. Journal of Applied Geodesy, 11:3, 197-205, DOI 10.1515/jag-2016-0030.
Retscher, G., Kealy, A., Gikas, V., Gabela, J., Goel, S., Li, Y., Masiero, A., Toth, C. K., Perakis, H., Błaszczak-Bąk, W., Koppanyi, Z., Grejner-Brzezinska, D. A. (2020): A Benchmarking Measurement Campaign to Support Ubiquitous Cooperative Platform Localization in GNSS Denied and Indoor Environments. IAG Symposia Series, 27th IUGG General Assembly 2019 'Beyond 100: The Next Century in Earth and Space Science', July 8-18, 2019, Montreal, Canada.
Retscher, G., Leb, A. (2019): Influence of the RSSI Scan Duration of Smartphones in Kinematic Wi-Fi Fingerprinting, Proceedings of the FIG Working Week, April 22-26, Hanoi, Vietnam, 15 pgs.
Retscher, G., Li, Y., Williams, S., Kealy, A., Moran, B., Goel, S., Gabela, J. (2018): Wi-Fi Positioning Using a Network Differential Approach for Real-time Calibration. in: Papers presented at the IGNSS 2018 Conference, February 7-9, 2018, Sydney, Australia, 15 pgs
Schafer, J. L., Graham, J. W. (2002): Missing Data: Our View of the Stae of the Art. Psychological Methods, 7:2, 147.
Seitz, J., Vaupel, T., Meyer, S., Boronat, J. G., Thielecke, J. A. (2010): A Hidden Markov Model for Pedestrian Navigation. 2010 IEEE 7th Workshop on Positioning Navigation and Communication (WPNC), 120-127.
Shahidi, S. (2016): Unsupervised Indoor Localization for Smartphones. PhD Dissertation, University of Toronto, Canada.
Shen, H., Chan, K.-Y., Coughlan, J., Brabyn, J. (2008): A Mobile Phone System to Find Crosswalks for Visually Impaired Pedestrians. Technology and Disability 20 (3): 217-224.
Xia, S., Liu, Y., Yuan, G., Zhu, M., Wang, Z. (2017): Indoor Fingerprint Positioning Based on Wi-Fi: An Overview. ISPRS International Journal of Geo-Information, 135(6), DOI: 10.3390/ijgi6050135, 25 pgs.
Yen, H. C., Wang, C. C. (2017): Cross-device Wi-Fi Map Fusion with Gaussian Process. IEEE Transactions on Mobile Computing, 16:1, 44-57.
Youssef M. A., Agrawala, A., Shankar, A. U., Noh, S. H. (2002): A Probabilistic Clustering-based Indoor Location Determination System. Technical Report.
Youssef M. A., Agrawala, A., Shankar, A. U. (2003): WLAN Location Determination via Clustering and Probability Distributions. 1st International Conference on Pervasive Computing and Communications, 143-150.
Zhou, R. (2006): Wireless Indoor Tracking system (WITS). Aktuelle Trends in der Software Forschung, doIT Software-Forschungstag, dpunkt Verlag, Heidelberg, Germany, 163-177.
Zou, H., Luo, Y., Lu, X., Jian, H., Xie, L. (2015): A Mutual Information Based Online Access Point Selection Strategy for Wi-Fi Indoor Localization. 2015 International Conference on Automation Science and Engineering, 180-185.

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