Smartphone-based Indoor Localization within a 13th Century Historic Building

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***Abstract*—Abstracttatatata**

I. Introduction

Setting up a localization solution for a building is a challenging and time-consuming task, especially in environments that are not build with localization in mind or do not provide any wireless infrastructure or even both. Such scenarios are of special interest when old or historical buildings serve a new purpose such as museums, shopping malls or retirement homes. In terms of European architecture, the problems emanating from these buildings worsen with age.

In the scope of this work, we deployed an indoor localization system to a 13th century building. The first 300 years the building was used as a convent, after that it had different functions ranging from a granary to an office for Bavarian officials. Over this period, the building had major construction measures and was extended several times. Since 1936, the $2500\,\mathrm{m}^2$ building acts as a museum of the medieval town Rothenburg ob der Tauber [1].

Such buildings are often full of nooks and crannies, what makes it hard for dynamical models using any kind of pedestrian dead reckoning (PDR). Here, the error accumulates not only over time, but also with the number of turns and steps made [2]. There is also a higher chance of detecting false or misplaced turns, what can cause the position estimation to lose track or get stuck within a demarcated area. Thus, this paper presents a very robust but realistic movement model using a three-dimensional navigation mesh based on triangles.

In localization systems using a sample based representation, like particle filters, the above mentioned problems can further lead to more advanced problems like sample impoverishment [3] or multimodalities [4]. Sample impoverishment refers to a situation, in which the filter is unable to sample enough particles into proper regions of the building, caused by a high concentration of misplaced particles. Within this work we present a simple yet efficient method that enables a particle filter to fully recover from sample impoverishment. We also use a novel approach for finding an exact estimation of the pedestrian's current position by using a rapid computation scheme of the kernel density estimation.

Many historical buildings, especially bigger ones like castles, monasteries or churches, are built of massive stone walls and have annexes from different historical periods out of different construction materials. This leads to problems for methods using received signal strengths (RSS) from Wi-Fi or Bluetooth, due to a high signal attenuation between different rooms. Many unknown quantities like the walls definitive material or thickness make it expensive to determine important parameters, e.g. the signals depletion over distance. Additionally, most wireless approaches adapt a line-of-sight assumption. Thus, the performance will be even more limited due to the irregularly shaped spatial structure of such buildings. Our approach tries to avoid those problems. We distribute a small number of simple and cheap Wi-Fi beacons over the whole building and instead of measuring their position, we use a optimization scheme based on some reference measurements.

A optimization scheme also helps against inaccuracies like wrong positioned access points or fingerprints caused by outdated or inaccurate building plans. It is obvious, that this could be solved by re-measuring the building, however this is a very time-consuming process requiring specialist hardware and a surveying engineer. However, this is contrary to most costumers expectations of a fast to deploy and low-cost solution. In addition, this is not only a question of costs incurred, but also for buildings under monumental protection, what does not allow for larger construction measures.

To sum up, this work presents a smartphone-based localization system using a particle filter to incorporate different probabilistic models. We omit time-consuming approaches like classic fingerprinting or measuring the exact positions of access-points by using a simple optimization scheme. The pedestrian's movement is modeled realistically on a navigation mesh. A barometer based activity recognition enables to go into the third dimension and problems occurring from multimodalities and impoverishment are taken into account.

The goal of this work is to propose a fast to deploy and low-cost localization solution, that provides reasonable results in a high variety of situations. Consequently, we believe that by utilizing our localization approach to such a challenging scenario, it is possible to prove those characteristics. It should finally be mentioned, that the here presented work is an updated and highly re-factored version of the winner of the smartphone-based competition at IPIN 2016 [2].

II. Related Work

We consider indoor localization to be a time-sequential, non-linear and non-Gaussian state estimation problem. Such problems are often solved by using Bayesian filters, which update the state estimation recursively with every new incoming measurement. A powerful method to obtain numerical results for this approach are particle filters.

In context of indoor localisation, particle filter approximate a probability distribution describing the pedestrian's possible whereabouts by using a set of weighted random samples (particles). Here, new particles are drawn according to some importance distribution, often represented by the state transition, which models the dynamics of the system. Those particles are then weighted by the state evaluation given different sensor measurements. A resampling step is deployed to prevent that only a small number of particles have a signifcant weight [5]. Most localisation approaches differ mainly in how the transition and evaluation steps are implemented and the available sensors are incorporated [4], [6], [7]. Additionally, within this paper we present a method, which is designed to run solely on a smartphone.

In its most basic form, the state transition is given by.. einfach distanz und heading.. intersection with walls usw.

TODO nochmal mit frank klren was wir jetzt GENAU machen.

These disadvantages can be avoided by using spatial models like indoor graphs. Besonders geometric spatial models sind beliebt

TODO kurz auf voronoi eingehen mit neueren papern und dann auf grid basierte eingehen. schreiben das wir in previous work auch solche benutzt haben, aber das problem ist halt der gigantische speicheraufwand. deshalb haben wir uns fr triangle based entscheiden, die erstellung ist einfacher, die verfahren sind aus der spieletheorie bekannt und erfolgreich im einatz. natrlich ist das ganze ein wenig rechenaufwendiger, da nun bla und blub gemacht werden muss, jedoch ist das laufen realisischer und nicht auf 45 grad winkel begrenzt. es wird also eine hhere genaugikeit erwartet, bei stark reduzierten speicher und zugrifssbedarf auf das netz.

The outcomes of the state evaluation process depend highly on the used sensors. Most smartphone-based systems are using received signal strength indications (RSSI) given by Wi-Fi or Bluetooth as a source for absolute positioning information. At this, one can mainly differ between fingerprinting and signal-strength prediction model based solutions [8]. Indoor localization using Wi-Fi fingerprints was first addressed by [9]. During a one-time offline-phase, a multitude of reference measurements are conducted. During the online-phase the pedestrian's location is then inferred by comparing those prior measurements against live readings. Based on this pioneering work, many further improvements where made within this field of research [10]–[12]. However, despite a very high accuracy up to 1 m, fingerprinting approaches suffer from tremendous setup- and maintenance times. Using robots instead of human workforce might thus be a viable choice, still this seems not to be a valid option for old buildings with limited accessibility due to uneven grounds and small stairs.

Signal strength prediction models are a well-established field of research to determine signal strengths for arbitrary locations by using an estimation model instead of real measurements. While many of them are intended for outdoor and line-of-sight purposes [13], [14], they are often applied to indoor use-cases as well [8], [15]. Besides their solid performance in many different localization solutions, a complex scenario requires a equally complex signal strength prediction model. As described in section 1, historical buildings represent such a scenario and thus the model has to take many different constraints into account. An example is the wall-attenuation-factor model [16]. It introduces an additional parameter to the well-known log distance model [17], that considers obstacles between (line-of-sight) the AP and the location in question by attenuating the signal with a constant value. Depending on the use-case, this value describes the number and type of walls, ceilings, floors etc. between both positions. For obstacles, this requires an intersection-test of each obstacle with the line-of-sight, which is costly for larger buildings. Thus [8] suggests to only consider floors/ceilings, what can be calculated without intersection checks and allows for real-time use-cases running on smartphones.

To further reduce the setup-time, [18] introduces an approach that works without any prior knowledge. They use a genetic optimization algorithm to estimate the parameters for a signal strength prediction, including the access points (AP) position, and the pedestrian's locations during the walk. The estimated parameters can be refined using additional walks. Within this work we present a similar optimization approach for estimating the AP's location. However, instead of taking multiple measuring walks, the locations are optimized based only on some reference measurements, what further decreases the setup-time. Additionally, our approach extends to the third dimension.

Besides well chosen probabilistic models, the system's performance is also highly affected by handling problems which are .. based on the nature of particle filters. One very affecting problem is the before mentioned sample impoverishment. In blabal [] this problems was tackled by and. In [] we deployed a ... . However, deploying a IMMPF is in most cased not a necassary step, thus we present i much simple, but also very heuristic model within this paper.

Finally, as the name recursive state estimation states, it requires to find the most probable state within the state space, to provide the best estimate of the underlying problem. In the discrete manner of a sample representation this is often done by providing a single value, also known as sample statistic, to serve as a best guess. This value is then calculated by means of simple parametric point estimators, e.g. the weighted-average over all samples, the sample with the highest weight or by assuming other parametric statistics like normal distributions However in complex situtations like a multimodal representatio of the posterior, such methods fail to provide an accurate statement about the most probable state. A well known solution is KDE. For example [] used a ... in .... However it is obvious that this method has a massive computation time and is thus not practicle for smartphone-based solutions.

Within this paper we use a rapid bla und blub, what was recently presented in [].

TODO umschreiben mit entsprechenden cites und auf particles

TODO mal die letzten beiden IPIN Jahre durchstbern und deren system raussuchen.
dabei vor allem mit dem fokus, nicht sehr flexibel, braucht fertige ap positionen etc draufschauen
danach ein wenig schaun, ob es andere gibt die einzelne verfahren, wie wir sie haben hnlich machen
nicht verbergen das wir hier viel aus unseren eigenen paper zehren, also ruhig citen.

1/2 bis 3/4 Seite

III. Recursive State Estimation

1/2 Seite, also kurz halten.

- klassiker.. also eigenltich alles beim alten.

IV. Transition

max. 1 Seite

A. Mapping

- Karte wird manuell ber ein Tool erstellt bei dem wnde, tren, fentser etc. eingezeichnet werden
- Karte unterscheidet bereiche, treppen etc.
- dort werden auch metainformationen wie ap etc. eingetragen
- daraus wird ein mesh generiert ber bla blub mit bla blub. cite cite cite :)

B. PDR

- aktuelle bewegungsmodell
- ...

V. Evaluation

3/4 - 1 Seite

A. Wifi

- kleine Wifi Beacons
- optimimierung der ap positionen ber schtzverfahren cite cite cite
- log dist model. knnen wir auch wieder viel citen.
- da vorher nie erwhnt, ggf. bisschen was ber VAPGrouping.

B. Barometer

- activity recognition ber barometer
- rauf/runter/treppe/aufzug etc. pp.

VI. Misc

A. State Estimation

1/2 bis 3/4 Seite

- weighted average
- max particle
- bulli methode (gleich citen :))

B. Sample Impoverishment

- einfache methode um das zu beheben.
- falls ichs schaff, wifi method ber die frank und ich mal gesprochen haben.

VII. Experiments

3 1/2 seiten sollten das schon werden. also eine ausfhrliche evaluation.

- Noch ein paar Dinge ber das gebude und das setup an sich
- auf was wurde geachtet, wie wurden die ap's gesetzt. etc pp.
- wie wurde ground truth gemacht
- wie viele testaufnahmen...
- die einzelnen pfade gegenberstellen. (videos irgendwie bereitstellen?)
- schtzung der ap positionen vs reale ap positionen
- fehler gegenberstellen, genauigkeiten.
- allgemein an den parametern rumspielen: Anzahl Partikel (da wir das eig noch nicht so wirklich oft gemacht haben)
- estimation methoden gegenberstellen (diskussion aus bulli paper)
- aktive probleme aufzeigen (verlaufen, hngenblieben, schlechte ap signale ...

wir experimentieren auf allen vieren.

VIII. Conclusion

Conclusion Conclusion

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