Multi-pedestrian tracking by moving Bluetooth-LE beacons and stationary receivers

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***Abstract*—In this paper we propose an approach for tracking multiple pedestrians with head mounted Bluetooth low energy (LE) beacons in experiments for pedestrian dynamics. To simplify the setup and decrease the costs we invert the common setup for localization with stationary installed Bluetooth beacons for tracking smartphones. Our approach leads to multiple stationary installed receivers and moving Bluetooth beacons attached to peoples' head. Thus we develop a common architecture setup for both scenarios where the independent positioning solver remains untouched even if the scenarios differ. We use fingerprinting based on stochastic regression for locating individuals in sub areas of rooms instead of determining their exact position.**

***Index Terms*—Bluetooth, fingerprinting, pedestrian tracking**

I. Introduction and Related Work

In the field of evacuation and pedestrian dynamics research experiments are made to get a deeper insight into the dynamics between people in crowds, to calibrate arising computer models and to evaluate computer simulations and route choice models [1], [2]. In those experiments with up to 1000 participants tracking of multiple pedestrians in an indoor environment is essential. In the majority of cases, special camera equipment is used to gain precise trajectories with centimeter accuracy of all pedestrians also in dense crowds [3]. Additionally, installing multiple cameras inside a building is coupled with high deployment effort. In this paper we propose a low cost and easy to install approach for tracking multiple pedestrians in experimental indoor environments.

For the use of RSSI-based technologies in indoor navigation there is a well known concept for setting up scenarios and designing or improving algorithms: Multiple emitters (beacons, access points) are installed stationary in different parts of the building and a single receiver is moving around, while determining and tracking its position [4].

However, smartphones are unsuitable as receiver in a multi-pedestrian tracking scenario because of signal absorption by human bodies. Especially for tracking multiple pedestrians in the same room, multi-path propagation and signal absorption can lead to erroneous localization results for RSSI-based methods. Therefore, we invert the standard scenario using moving emitters plus stationary receivers by attaching a beacon to every participant.

Broadcasting Bluetooth signals with beacons has become fairly cheap (<\$20). In addition, they have already been adopted for indoor positioning [5]. Furthermore, they are portable, small and battery driven. Hence, they are easily mountable at positions of peoples' body with low absorption.

RSSI-based localization techniques are distinguishable in fingerprinting and lateration. Fingerprinting methods lead to more precise localization results [6]. For that reason we chose a fingerprinting approach.

The remainder of this work is organized as follows: Sec. II describes the inverted scenario and technical setup for tracking moving beacons, Sec. III pictures the experimental setup which is evaluated in Sec. IV. Sec. V concludes the paper.

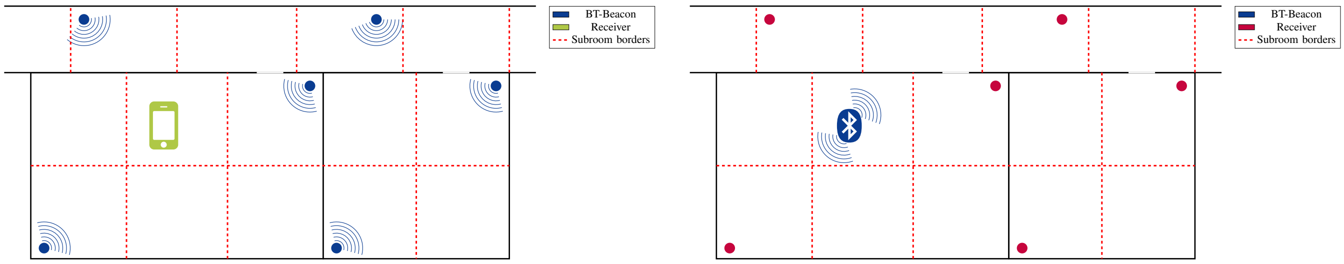
II. Localization architecture setup

In the standard scenario for smartphone-based positioning using fingerprinting as shown in Fig. 1a, many stationary, emitters are sending signals to a moving receiver, who is implicitly synchronizing them by their time of arrival. To determine the position of the receiver, incoming signals have to be matched against a fingerprint database. The best match is assumed as correct location of the receiver.

We propose the inverse scenario displayed in Fig. 1b where Bluetooth beacons are used as moving emitters with receivers installed stationary inside the building.

Every beacon emits signals at a nearly fixed rate which leads to raw tuples $[(t_1, RSSI_1), \ldots, (t_n, RSSI_n)]$. However, those raw data cannot be used effectively for localization algorithms because of signal noise. Therefore, they are consolidated over a short period of time, resulting in signal captures for time frames $(t_{f_1}, RSSI_{f_1 t_1}, RSSI_{f_1 t_2}, \ldots, RSSI_{f_1 t_n})$.

Combining these signal captures with location information for the offline-phase leads to the tuples $(x, y, t_{f_i}, \overline{RSSI_{f_i}})$ for every emitting beacon$_i$ where x and y are location coordinates, t is a discrete time frame and $\overline{RSSI_{f_i}}$ is the mean of all emitted RSSI-values by beacon$_i$ in the time frame. Afterwards the synchronized tuples are passed to a location solver. Since we only need area information in our approach, the tuples reduce to $(a, t_{f_i}, \overline{RSSI_{f_i}})$ for area a. Synchronizing and transforming raw signals into time framed signal captures are done implicitly by the receiver in common setups.



(a) Standard scenario setup with a single smartphone as receiver and multiple Bluetooth beacons as emitter distributed over several rooms.

(b) Inverse scenario setup with multiple stationary receivers and a moving Bluetooth beacons which will be tracked.

Fig. 1: Classic scenario setup vs. proposed inverse scenario setup

To prepare this setup for inversion a feature transformer, that converts raw signal tuples into fingerprints with different features of the signal captures, is introduced as shown in Fig. 2.

Raw values are sent through the same feature transformer in the online phase who is then passing them to a location solver as illustrated in Fig. 3.

A. *Inverse system setup with multiple receivers*

Due to our architecture-setup for the standard scenario the red framed parts in Fig. 2 and Fig. 3 can be hosted off-site. Hence, the localization server is not effected by any change of the scenario setup. We use Raspberry Pis as receivers since they are of low hardware cost and easy to deploy.

The only reliable data received on the Raspberry Pis are Beacon-Mac-Address ($address$) and RSSI. Thus, we need to add the time of arrival as timestamp on the Raspberry Pis to the signal captures for signal synchronization. If the measurement startup is synchronized, all tuples of the form $(address, RSSI_i, t_i)$, where t_i is the *i-th* timestamp, are synchronized as well.

To achieve a synchronized measurement start with no offset, we need to introduce a message broker, that sends a start signal to every receiver at the same time. After the offline-phase is started, signals are gathered by each Raspberry Pi. After 30 s the raw signal captures are cut in time frames of 0.7 s by every receiver. These signals can then be stored to the framed signal database as in the standard scenario. The message broker is needed again to synchronize all signals send by the Raspberry Pis to the server as illustrated in Fig. 4.

Note that only the left part differs in Fig. 4 compared to Fig. 2. The server part remains unchanged. Hence, the localization server just needs an interface to the message broker for dealing with the inverted scenario of multiple receivers.

Introducing a message broker to synchronize framed signal captures also causes the server side to remain unchanged for the online-phase as shown in Fig. 5. The conceptual difference to the offline-phase is that signals are not gathered for a period of time, but send to the message broker directly after the time frame has passed.

B. *Location solver*

Position identification of pedestrians in indoor environments is made difficult by various reasons of signal noise which include measurement errors, obstacles (like humans in the same room), walls and angle between receiver and emitter. Solely the presence of human bodies inside a room is sufficient for causing a significant noise [7] even if they are not directly positioned in the line of sight. Therefore, a robust signal classification is needed to match fingerprints with subrooms. Most commonly KNN and Bayes-classification are used where KNN-approaches may vary by their choice of metric.

However, we choose the *stochastic kernel logistic regression* (SKLR), as proposed in [8] with $\eta = 0.6$, non-conservative updating and PUK-kernel [9], since we only need area accuracy for sparse routing experiments. Hence, we also use an one-vs-all classifier to distinguish between multiple areas. This approach enables real-time localization.

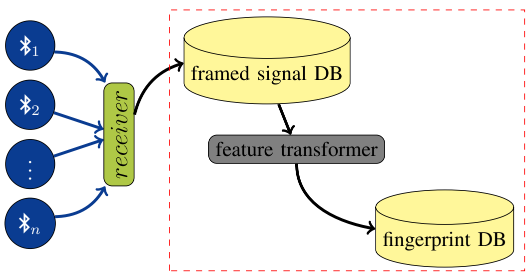


Fig. 2: Enhanced offline-phase of fingerprint-based positioning (training data gathering)

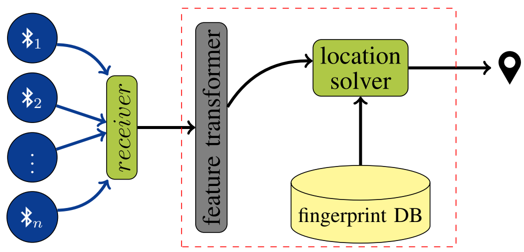


Fig. 3: Enhanced online-phase of fingerprint-based positioning (possible in real time)

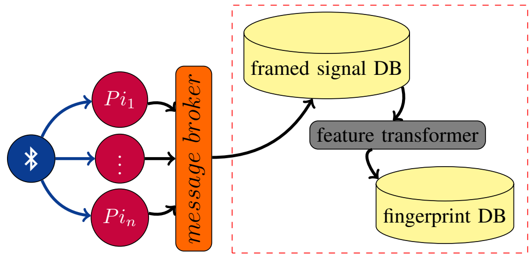


Fig. 4: Inversed scenario process after synchronized offline-phase start through the message broker

C. Majority voted fingerprinting

Instead of using a single classifier for localization ensemble-techniques we take multiple classifiers into consideration. In this paper we utilize a majority vote [10]. Thereby, we implemented different feature transformers – mean, median, percentiles – to gain multiple classifiers. An area is considered as correct if the majority of all used classifiers voted for it. Nevertheless, they are all based on SKLR. As a consequence of our architecture we simply have to exchange or add feature transformer to gain a new classifier. Hence, all used classifiers have their own database of training fingerprints and are brought together by majority voting.

III. Inversed Scenario Demonstration Setup

We decided to place the beacon on the head for all experiments to minimize possible signal absorption caused by human bodies. In our evaluation we initially tried to track the area of a single pedestrian inside only one room as illustrated in Fig. 6. The Raspberry Pis are located at the corners. Red dashed lines are showing borders of subrooms where each subroom has a size of $3\,\mathrm{m} \times 3\,\mathrm{m}$.

Gathering raw data for fingerprints was done with a single pedestrian walking around in each subroom for $30\,\mathrm{s}$ resulting in 43 time frames of $0.7\,\mathrm{s}$ for each Raspberry Pi.

To examine the accuracy of the position of the proposed system, we gathered another set of signal-captures where we knew the correct area. At each reference position in Fig. 6 signals were captured under the same circumstances.

Tables inside of subrooms may cause difficulties during the offline- and online-phase, since no fingerprint data can be gathered there. However, this setup is close to reality. Additionally, we extended the experimental area for a walk

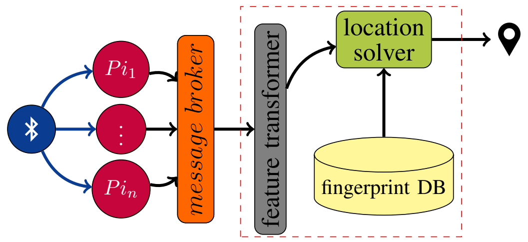


Fig. 5: Inversed scenario process after synchronized online-phase start through the message broker

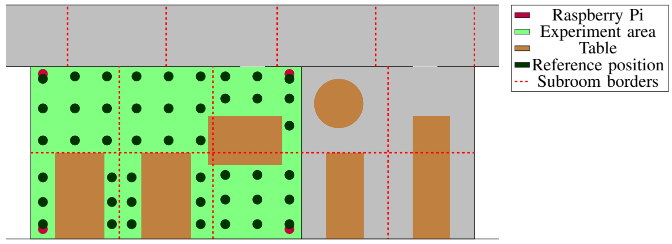


Fig. 6: Illustrated setup inside the experiment room (green area) with positions of installed Raspberry Pis, tables and with positioning reference points. The room is divided into smaller areas of $3\,\mathrm{m} \times 3\,\mathrm{m}$ by red dashed lines.

through to the hallway in front of the green area and observed on our visualization if positions were determined correctly.

IV. Evaluation

We focus on three subrooms in this evaluation: top-mid, bottom-mid and bottom-right. Results from the bottom-right area are directly applicable to other corner areas.

Initially we used the arithmetic mean as feature to test our setup for tracking moving beacons. As shown in TABLE I the location rate for the bottom right corner with 75% is quite good. However, areas located at the middle of the room have a much worse location rate (27% and 39%). In addition, most signal captures from the bottom-mid area were located in the top-mid area.

TABLE I: Location rate confusion matrix with arithmetic mean

captured from	**top-mid**	**bottom-mid**	**bottom-right**
located in			
top-left	16%	2%	0%
top-mid	**39%**	**36%**	12%
top-right	29%	2%	5%
bottom-left	0%	7%	0%
bottom-mid	8%	**27%**	8%
bottom-right	8%	26%	**75%**

The affection of desks to reference positions as shown in Fig. 6 is a possible reason for differences in the location rate between the top- and bottom-mid area.

Using the combination of 25th, 50th and 75th percentile as features for the SKLR instead of using a single feature leads to TABLE II where the bottom-right outcome did not change notably. Notable is, that positions of the pedestrian can be clearly determined for corner areas.

The location rate in both middle areas is still a lot worse. However it was slightly improved for the bottom mid. For the top-mid area the location rate dropped a little from 39% to 34%. This reveals that combining multiple features can lead to overall improved results. This shows that different features provide an enhanced location rate for certain areas.

For that reason we decided to introduce a majority vote between multiple SKLR with different features and a sliding window over multiple time frames. Additionally, the use of different numbers of time frames for every classifier allows

TABLE II: Location rate with the combination of 25th, 50th and 75th percentile

captured from	top-mid	bottom-mid	bottom-right
located in			
top-left	21%	2%	0%
top-mid	**34%**	27%	10%
top-right	25%	4%	5%
bottom-left	1%	10%	1%
bottom-mid	8%	**29%**	9%
bottom-right	11%	27%	**75%**

the adoption to fast and slow movements which leads to TABLE III.

TABLE III: Location rate with minimal correlated majority vote of arithmetic mean over one frame, combination of arithmetic mean and 50th percentile over to frames and combination of 25th, 50th and 75th percentile over three frames

captured from	top-mid	bottom-mid	bottom-right
located in			
top-left	21%	1%	0%
top-mid	**35%**	26%	6%
top-right	25%	0%	0%
bottom-left	0%	6%	0%
bottom-mid	12%	**40%**	9%
bottom-right	7%	27%	**85%**

The results are showing that the majority vote improved the overall location rate. The location rate of the bottom-right area increased by 10% to 85% in total. Additionally the location rate in the bottom mid area has been improved by 11% up to 40%. However, the location rate in the top-mid area is still 4% lower than by using only the mean as feature. Nonetheless, majority voted positioning overall is most precise of the evaluated methods.

A. General observations for walkthroughs

While testing our setup we made observations on factors influencing the positioning accuracy and robustness.

1) Observations inside a room: Up to seven pedestrians were walking through the experimental area of Fig. 6 while tracking them with our real time visualization. The location rate decreases drastically if a larger pedestrian was standing between a pedestrian and a Raspberry Pi. However, smaller or same sized humans did not hace a bad influence on the results. Furthermore walking speed is crucial for positioning accuracy. The faster a pedestrian walks, the less precise is the positioning.

In the experiment, when some individuals were walking around as moving obstacles without being tracked by mounted beacons, some of them carried along their smartphone with activated Bluetooth. As a consequence they were also being tracked and visualized by accident. In fact most of the time they were located correctly although the SKLR had not been trained with signal captures from a smartphone. Hence, the multi-pedestrian tracking works even with smartphones.

2) Observations while changing rooms: During changing between the experimental area and the nearby hallway the room detection rate has reached up to 99%. In all experiments a miss-positioning outside the actual room occurred only twice nearby the corresponding door. With minor improvements such as map matching up to 100% could be reached.

V. Conclusions and Future Work

Providing a low cost solution with still sufficient precision for tracking multiple pedestrians in routing-experiments is a challenging task. We propose a system using beacons where area or room precision is acceptable. Our approach is not only applicable for tracking beacons but also for the tracking of smartphones due to their ability to emit iBeacon signals as well. Tracking an additional pedestrian or object with a mounted beacon is done by simply turning on the beacon.

Additionally, we propose to use multiple fingerprint features and ensemble techniques in fingerprinting since it improves the location results significantly. In the presented approach we solely used SKLR based fingerprinting. Better results could probably be obtained if other fingerprinting methods were considered as well. Since we merely experimented with a simple majority vote, it could also be weighted, based on known precision in special areas.

Furthermore, smartphones acting like beacons leads to the possibility of combining the standard scenario with the inverted scenario: Smartphones could emit Bluetooth signals and receive WiFi signals at the same time so information of both can be combined. This enables new setup possibilities for indoor tracking systems.

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