FLIP – FLexible Indoor Position Estimator

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Extended Abstract

This paper presents FLexible Indoor Position (FLIP), an efficient algorithm for use in fingerprint based indoor localization systems, such as the indoo.rs Navigation System (iNS). Fingerprint based positioning in complex buildings makes comparisons to large reference fingerprint sets. Since mobile devices have limited storage, memory, computation and power usage limitations, making an on-terminal system working well is challenging. Additionally, reported Received Signal Strength Indication (RSSI) values differ between devices, so that naive approaches for fingerprint similarity fail (cf. Caso et al. 2015). This proposal presents the FLexible Indoor Position (FLIP) estimator, which addresses both these issues – efficient device independent positioning for complex buildings. FLIP was evaluated on the raw UJIIndoorLoc data and yielded a median positioning error of 4.8m.

The described approach is applied in the radio based indoor positioning context, but is actually applicable to any kind of transmitter signals in environments where effects like reflections, damping etc. do not allow simpler approaches.

FLIP aims to identify which references are most relevant regarding the observation, and only use these to estimate positions (cf. Swangmuang and Krishnamurthy 2008). The identification first makes an adjustable fast reference selection to reduce further calculations, and then the more elaborate refinement. Since the refinement process effort is arbitrarily configurable, it can be optimized either for accuracy or efficiency. Therefore it can be used in many situations.

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The reported received signal strength of devices is not a physical measurement but only an indication (RSSI) and therefore dependent on the device specifications. As a consequence the reported RSSI of different device types are not directly comparable. In order to make RSSI comparable between diverse devices, the actual distribution of received signal strengths are approximated to a normal distribution (Fig. 1 left) and the standard z-score is transformed to range [0, 1] by the Gauss error function. This transforms the raw device-dependent RSSI to a normalized device-independent representation as shown in Fig. 1 right.

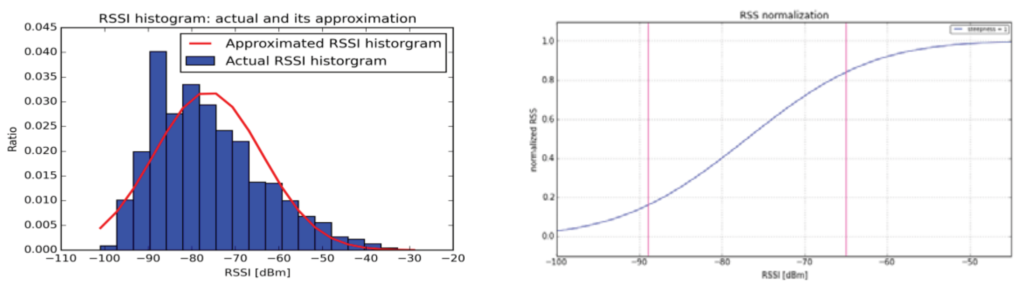

Figure 1. Left: Typical histogram of RSS and its normal-distributed approximation; Right: Received radio signal strength normalization function. Bars represent 1σ deviation.

A fast and simple indicator of similarity between sets of radio observations is the transmitter intersection score – the number of transmitters seen in both sets (cf. Sha et al. 2015). As the points may therefore form multiple disjoint regions, the set is only used to reduce search space in further processing.

Transmitter RSSI maps are typically irregular, as seen in Fig. 2. Instead of operating in ordinary space (as applied in related work, f.i., in Hu et al. 2015) FLIP transforms the transmitter coverage zone to a spherical form, and uses an edge distance score to rate similarity. An even reference density is required for this approach to work well, which is ensured by using interpolation of radio map RSSI data to a uniform grid.
The transformation of the transmitter coverage zone in ordinary space to radio space is realized by determining the number of reference points which receive the transmitter at least the normalized RSSI applying the dimensionality of radio scattering, which depends on the floor radio permeability (Fig. 3).

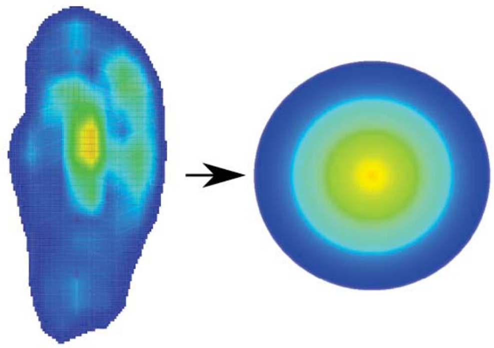

Figure 2. Left: Transmitter coverage zone on a floor plan (in physical space). Right: Same zone transformed into radio space. Lighter colors mean higher received signal strength of the transmitter.

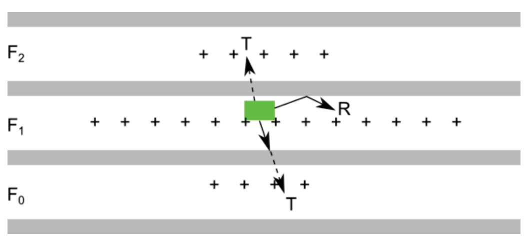

Figure 3. Due to reflections and damped transmissions through floors the spread dimensionality is higher than quadratic but lower than cubic. The green box represents a transmitter and the + signs are representing reference points.

A reference point is considered to be geometrically close to the observation if the normalized RSSI to a set of commonly visible transmitters is close to equal where the number of commonly visible transmitters related to the union of the visible transmitters by both - reference and observation is high and at least 3. Intuitively, a difference in the normalized RSSI of the stronger transmitter has a higher impact than the same difference of a weaker transmitter. This is reflected by the distance difference to the transformed coverage zone center in radio space. This center distance difference is an indicator for dissimilarity. Since the similarity is going to be calculated, the distances to the edge of the transformed coverage zone are used (Fig. 4).

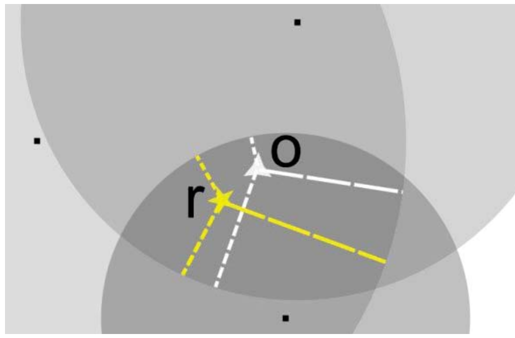

Figure 4. Transformed transmitter coverage zone edge distance of a close reference point (r) and the observation (o).

The similarity between a reference to an observation is obtained by calculating the sum of the common part of the commonly visible transmitter edge distances normalized by the sum of both observation and reference edge distances of all their visible known transmitters. Unknown transmitters are observed transmitters which were not visible by any reference of the FLIP map and are therefore not considered.

The most similar and therefore relevant references wrt. the observation are ordered by their similarity score and are used for the building, floor and position estimation; using the score as a weight.

References are grouped by their assigned building and floor and
The summed similarity scores of the (building and) floor grouped references as a weight is used for calculating the estimated probability being the correct building and floor of the observation.

A 2d Gaussian fit (Fig. 5) is applied on the reference positions weighted by their similarity score. The estimated position of the observer is the centroid of this fit.

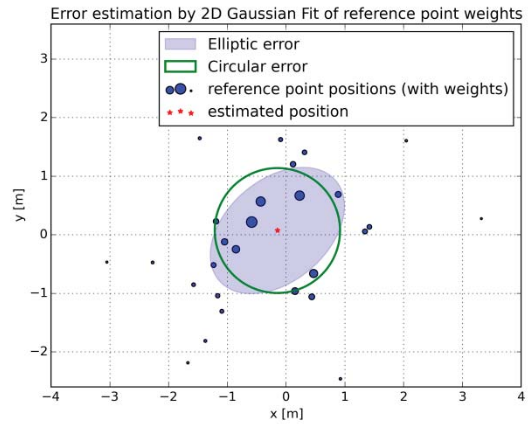

Figure 5. The position and error is estimated by the most relevant reference points, by their position and weight. The position is estimated by the mean of the weights. The light blue area is the 1σ of the weights. The green circle represents the circular error.

A visual overview of the algorithm is shown in Fig. 6.
The algorithm is separated in two phases:

- Processing the radio map to get the FLIP map and derived data for the second phase. Required once per radiomap.
- Processing the observation for location estimation of the observer.

FLIP uses a memory efficient pre-calculated compact summary representation of radio fingerprint reference maps (FLIP map) that can be loaded and used offline even on weak mobile devices. The FLIP map contains the required data in a way to minimize both, the data space requirements and the calculation effort for the refinement process.
Based on the FLIP map a reference point based view is required to get a comparable similarity score.

To estimate the position of the terminal device, its radio measurements (observation) are used, which have to be transformed to a representation to be processed by FLIP.
At that point the actual position estimation is ready to be performed. In the first step the most relevant reference points regarding the observation are going to be identified.
The next step calculates the similarity of the references, which are identified as

most relevant to the observation. This leads to a differentiated evaluation of reference point relevance.
Based on the most relevant reference points enriched with similarity information the location of the radio observing device is estimated. This includes the estimation of the building and the floor.

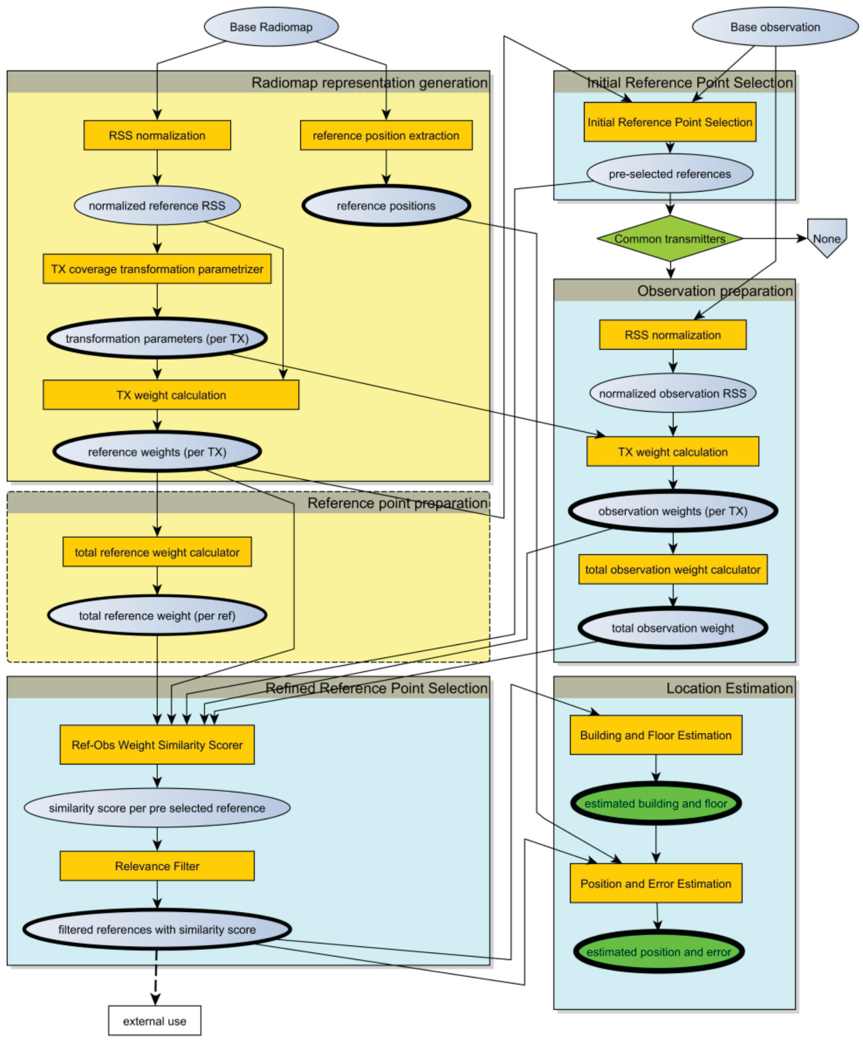

Figure 6. Overview of the FLIP algorithm. Elliptic boxes represent data, rectangle boxes functions, and diamonds conditions. Yellow groups belong to phase 1, bluish to phase 2.

FLIP was compared to other methods [Berkvens et al. 2015, Choi et al. 2015, Knauth et al. 2015] using the UJIIndoorLoc [Torres-Sospedra et al. 2014] database, as shown in Table 1. The error quantile distribution and the floor accuracy in Fig. 7.

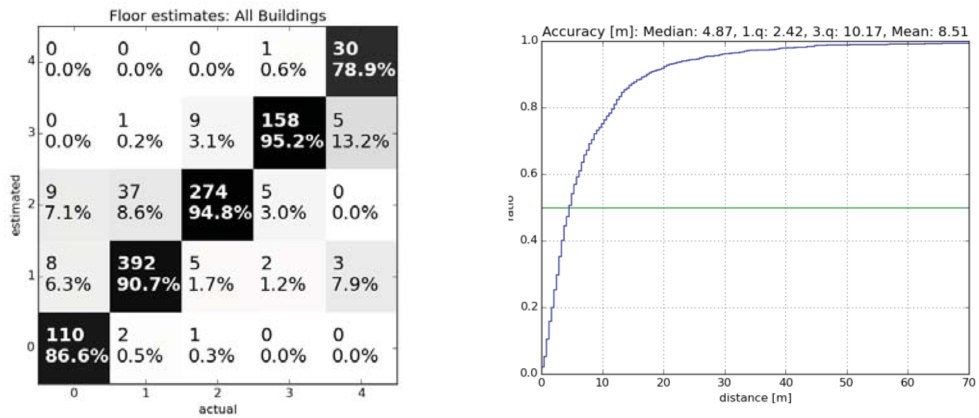

Figure 7. Left: Floor confusion matrix over all buildings. Right: Quantile distribution of position error distance. The blue curve indicates the results over all buildings, the median is indicated by the horizontal line.

It could be shown that the results are similar to competing approaches but more flexible to be also able to be deployed in mobile devices for longer use without much battery loss and still acceptable accuracy.

The median error obtained was 4.87 m (4m when separating data by building). The mean positioning error of 8.5 m is significantly larger than the median, due to outliers 70 m when building was misidentified. Building and floor misidentification rate was at 0.3% and 8.3% respectively. Results are comparable to other more elaborate methods [Choi et al. 2015 (2), Knauth et al. 2015 (3)], and far superior to other [Berkvens et al. 2015 (1)].

Only FLIP deals with device differences, and only flip and FCWC is fast performing.
The results refer to an initial selection of reference points of $N_{ref} = 300$, which is 1.5 of the total number of reference points.

Approach	Building	Floor	Pos error [m]		Comp.	Fast
	err [%]	*err [%]*	*mean*	*median*		
SPFP [3]	0	4	7.7	N/A	No	No
FCWC [3]	0	6	9.7	7	No	Yes
MLE [1]	4.86	14.76	19.13	8.29	No	No
kNN [1]	4.86	14.58	18.96	8.29	No	No
kNN [2]	0.2	11.5	9.69	N/A	No	No
PCA-LDA [2]	0	7.7	8.16	N/A	No	No
PCA-LDA (AP) [2]	0	3.6	7.59	N/A	No	No
ELM-AE [2]	0	7.3	7.65	N/A	No	No
ELM-AE (AP) [2]	0	6.7	7.64	N/A	No	No
FLIP	0.3	8.3	8.51	4.87	Yes	Yes

Table 1. Positioning results on UJIIndoorLoc data.

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