Indoor Positioning
Evaluating INS/BLE integration

What if the GNSS is not suitable and the positional accuracy is a key issue?

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Internet Of Things and RTLS/IPS

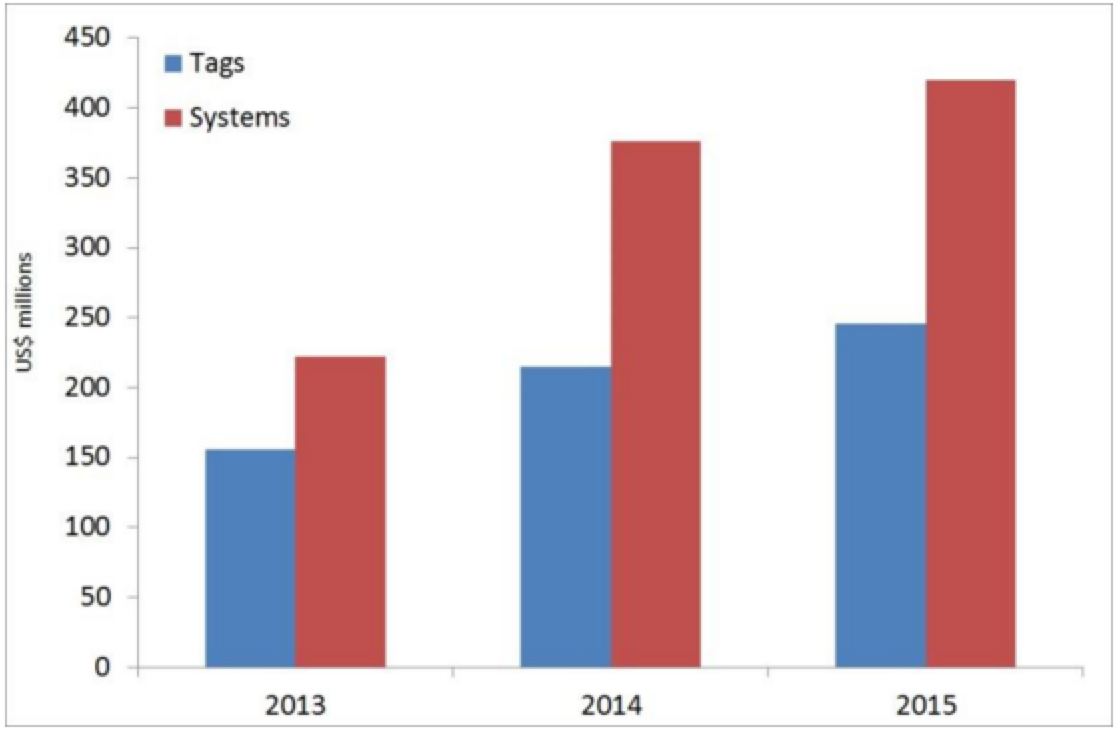
The term Indoor Positioning Systems (IPS) concerns positioning services suitable for mobile devices where GNSS does not work.

The term Real Time Locating Systems (RTLS) concerns positioning services suitable for locating people and things as needed from applications

Location-based services are a primary goal of the Internet of Things (IOT).

Localization accuracy is a key issue.

Forecast of global RTLS market by value in $US millions



Source: IDTechEx

Indoor Positioning main approaches

Positional approaches (suitable for mobile devices)

Reference points Map + Range → **Trilateration**

Reference points Map + Bearing →**Triangulation**

Reference points Map + Short-range detection → **Proximity**

Radio Signals Map → **Fingerprinting**

Inertial Navigation

Computing approaches

The most used approaches are Kalman Filter (**KF**) based:

- To filter **noisy data**
- To fuse data from **cooperating positional approaches** (*reduce ambiguities, control drift*)

SLAM (*Synchronous Localisation And Mapping*) approaches are useful to build a realtime/volatile map dataset, thus avoiding the need for external data.

SLAM alghoritms are also KF-based.

The goal of this work

Evaluation of the positional improvement of a smarthphone with inertial capabilities in a beacon environment

1) Evaluation of the accuracy of a only-INS based positioning in a typical indoor scenario

2) Implementation of a simple EKF-SLAM solution in a RF (BLE) beacon environment

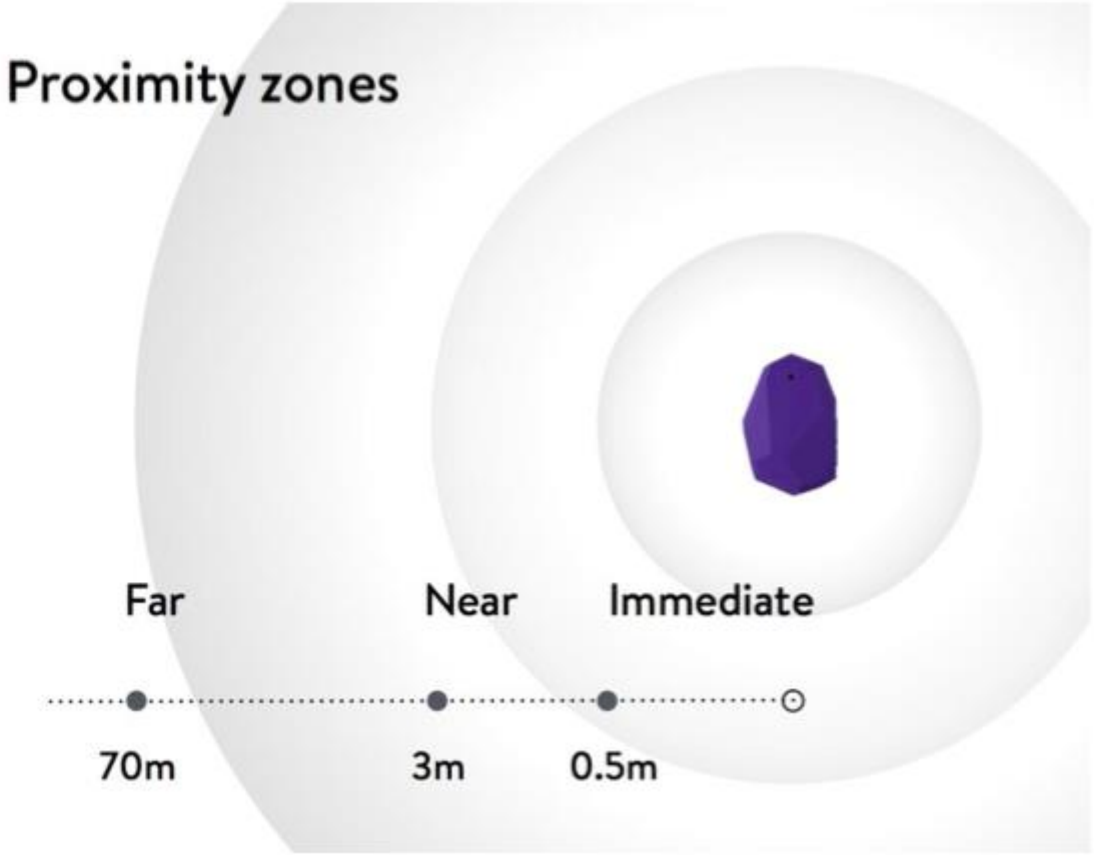
3) Implementation of a simple coupling filter

4) Evaluation of the positional improvement

Experimental steps

1 - Set up space with BLE Beacons (Estimote Beacons)

Why **BLE Beacons?** BLE are **low-cost** devices with very **long-lasting battery** (2-5 years), are **small as the battery** (flexible positioning, good density of beacons). BLE RF field is subject to deep **multipath** fades: this is not an issue (as in GNSS contest) because determines variations of the RF field over a spatial range that is often **smaller than the expected positioning accuracy** → the variaton is useful in a fingerprinting perspective (so the multipath effects are a resource)



Experimental steps

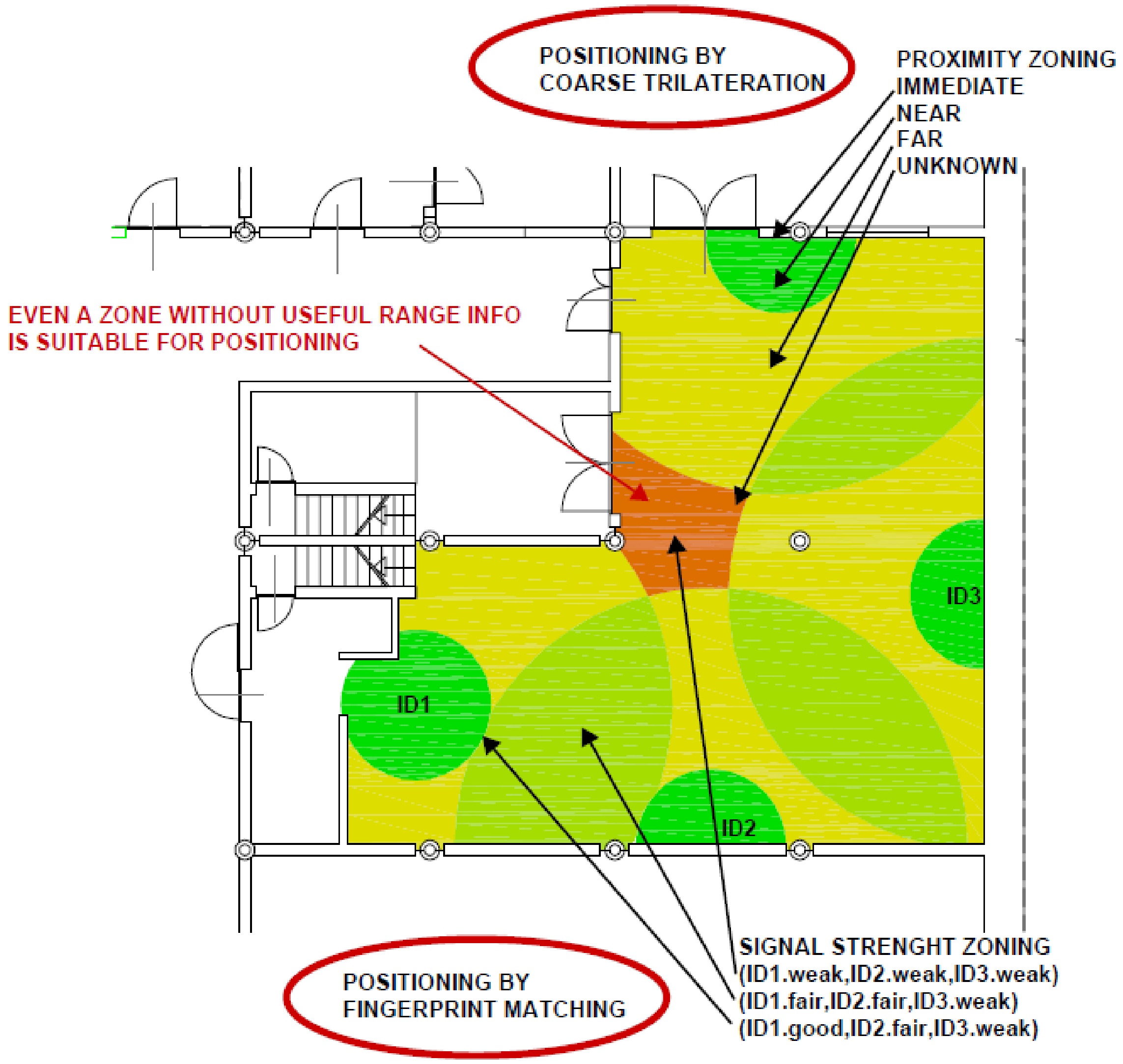
2 - Evaluation of the positional field

Two positioning approaches are possible, relying on the Received Signal Strenght Indicators (RSSI):

1) If the beacons map is known, a coarse trilateration is possible. This rely on «pseudo-ranges» computed using the best RSSI measurements (with apriori knowledge of the signal loss law). This is really useful only for «Immediate» and «Near» proximity zones, with accuracy of 0,5-3 m with good DOP

2) If the RF field map is known, a grid positioning is possible. This rely on the uniqueness of the RF fingerprint (defined as <ID,RSSI> list) and the accuracy is related to map grid (2-4 m)

This defines the maximum theoric accuracy.

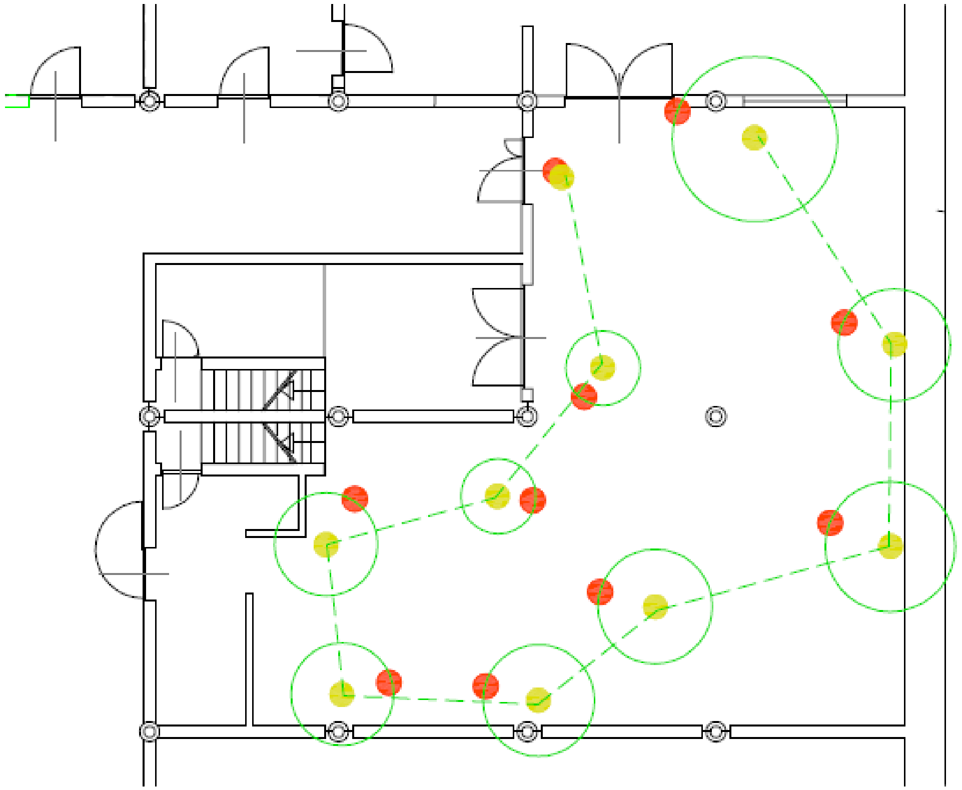


Experimental steps

3 – Evaluation of the INS-only performance

This is done setting up some waypoints (*in orange in the picture*) and walking across while recording the smartphone's IMU data. The raw IMU data are then post-processed and the result is represented (*in yellow in the picture*). The positional error is roughly evaluated as distance from actual and computed waypoint.

The walked distance is about 40 m and the CEP at the endpoint is about 1,40 m. The walking time is about 1 min (because of some stop at the waypoints). *To process the IMU data, a Octave (Matlab) code derived from the **Zero-Velocity-Update Kalman Filter** published in the **OpenShoe** Project is used.*



Experimental steps

4 – SLAM

To test the realtime capability of the proposed approach, **no apriori knowledge of the BLE RF field is assumed**. Instead, a **simplified SLAM approach**, as proposed by Faragher and Harle (2012) is used.

The code used is derived from the **FEKFSLAM** algorithm.

As outlined by Authors, the SLAM is effective after 30-40 steps from start and the measurement model parametrs are well estimated within the first 100 steps.

FEKFSLAM is also interesting because is computed in O(N), where N relates to walked distance.

F-EKF-SLAM basics

→ For each two positions P_n, P_m is defined a «normalised Euclidean distance» $D_{n,m}$ computed upon RF-RSSI fingerprint W_n, W_m at each position. The «distance» increases linearly with the spatial separation: so the value may be predicted

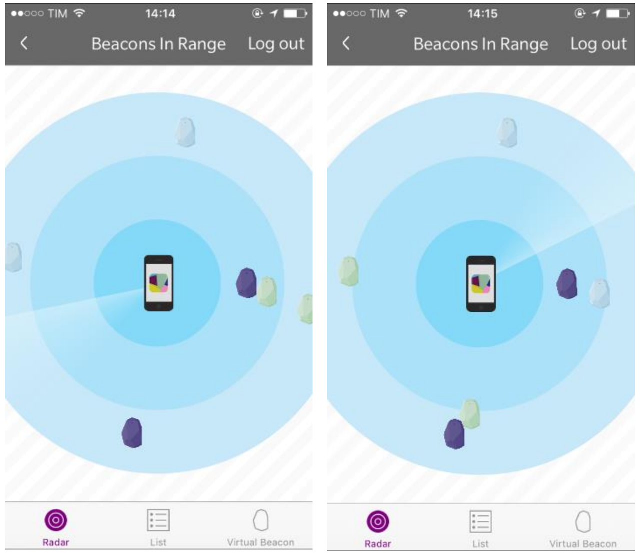
→ If a position P_p computed in the past lies within the covariance ellipse of the current position P_c, then «measure» $D_{p,c}$ upon W_p, W_c

→ Compare the predicted and measured $D_{p,c}$ and do a Kalman Filter update optaining the current best estimates for position and fingerprint

Experimental steps

5 – Overall performance evaluation

The proposed approach has demonstrated to be able to limit the growth of the INS error over time. In the test bed the **filter becomes effective as the INS error raises over 1,5 m**.



RSSI radar working

A beacon in place

A waypoint

Further works

The proposed approach needs to be validated in spaces with variable density of furnitures and variable beacons density and casual walking paths.

The performance of the F-EKF-SLAM filter may be raised introducing the evaluation of the «immediate» proximity of a beacon, when the mobile device is in place.

The coarse trilateration approach also may help; it needs some more investigations and tests.

End

Thank you!