2016 International Conference on Indoor Positioning and Indoor Navigation (IPIN), 4-7 October 2016, Alcalá de Henares, Spain

Towards accurate indoor localization using iBeacons, fingerprinting and particle filtering

Dierna Giovanni Luca
Institute of High Performance Computing and Networking
(ICAR) - National Research Council (CNR)
Palermo, Italy
gl.dierna@pa.icar.cnr.it
gianlucadierna@gmail.com

Machì Alberto
Institute of High Performance Computing and Networking
(ICAR) - National Research Council (CNR)
Palermo, Italy
alberto.machi@cnr.it

***Abstract*—In this paper we present preliminary results of an experimental work aiming to exploit Bluetooth Low Energy technology for accurate indoor localization in highly structured environments.**
In the described experiment 31 iBeacons were placed in a small museum and their fingerprinting was modelled via progressively dense sampling, interpolation and Monte Carlo simulation.
An accuracy of 2 meters was reached at an average density of about 0.3 samples square meter, and further increased with denser sampling in proximity of singularities of structural elements.
Limits of two locate algorithms were analyzed. k-NN takes advantage of presence of near reference points but is fooled by minima of the distance function spatially apart from current location. Particle Filter takes advantage of accumulated evidence of locality but looses accuracy in areas where the distance field has low gradient values.
Optimal beacons positioning is expected to improve accuracy of particle filtering in areas where the field is poorly structured.

Keywords—bluetooth low energy; iBeacons; indoor positioning; fingerprinting, particle filtering.

1. INTRODUCTION

The increasing demand for indoor positioning systems as location based services, has prompted research into positioning schemes comparable to those of outdoor postioning (GPS).

Fingerprint-based indoor positioning, based on Bluetooth Low Energy (BLE) appears an attractive choice, due to low cost and high availability of Bluetooth-enabled devices. BLE is in fact widely available in mobile phones, tablets, computers and headsets and is a low-cost technology. Bluetooth technology is also simpler to install and maintain in respect other technologies, including Wi-Fi, infrared and ultra-sound.

Furthermore, owing to BLE beacon optimized advertising protocol, mobile OS can complete a scan of BLE radio channels in less time than in Wi-Fi case. Android 4.3 spends 1.1 sec. for BLE and 4 sec. for Wi-Fi.

Nevertheless, as analyzed by Ramsey Faragher and Robert Harle in [1], the limited bandwidth of BLE channels is responsible for high spatial and temporal variability of BLE signal in structured areas and for poor reliability of the evaluation of source distance. In [2] Krzysztof Piwowarczyk, Piotr Korbel and Tomasz Kacprzak discuss the effects of improper positioning on the accuracy of the positioning system.

Due to these limitations, BLE has been used so far just for what is called micro-location or proximity, that is, to indicate rough evidence of presence of advertising emitters in the immediate or proximal neighborhood of the user, as described by Shinsuke Kajioka, Tomoya Mori, Takahiro Uchiya, Ichi Takumi and Hiroshi Matsuo in [3] and exploratory work on the usage of BLE beacons for localization in museums has been described by Angelo Chianese, Fiammetta Marulli, Vincenzo Moscato and Francesco Picciali in [4].

An encouraging localization accuracy of 1.5 meters has been reported by Zhu Jianyong, Chen Zili, Luo Haiyong and Li Zhaohui [5], but the latter authors don't specify if their measurements are performed in free or structured space. Similarly, Filip Mazan and Alena Kovarova report results of using a neural network algorithm in a corridor [6].

In the following, we present preliminary results of an experimental work aimed to provide effective localization assistance in structured indoor environments as museums, art galleries, hospitals, universities, office buildings, based on the evaluation of fingerprinting of BLE beacons. The localizations assistant should gently suggest to museum visitors evidence of contextually coherent areas of interest around him [7].

In section 2 we describe the realistic experimental site under study, in section 3 the procedure used to obtain site radiomaps and to evaluate related statistics. In Section 4 we describe two localization algorithms and the Monte Carlo procedure used to simulate tracking along the test path. Section 5, finally, discusses results so far obtained and directions of ongoing activity.

2. THE EXPERIMENTAL SITE

The Regional Archaelogical Museum of Camarina, in province of Ragusa (Italy), is located in a nineteenth-century farmhouse, and has 9 exhibition halls with archaeological finds ranging from prehistory to the Middle Age, exposed on

an area of about 670 square meters. It is a confined and structured environment, in which are present many structural elements, several reflective objects (glass display cases) and several objects (stone materials, including marble) that absorbe energy at bluetooth frequencies.



Fig. 1. The Camarina Museum: Hall of underwater archeology.

In the first mapping experiments, two or three BLE beacons were installed in each cultural area, hall, or exposure and in proximity of main display cases and relevant findings or objects of interest. We placed a total 31 BLE beacons, on museum walls, at a height of about 2.5 meters, and selected 224 reference points not uniformely spaced to provide full coverage of site walkable areas. The frequency advertising messages of the beacons was set to 100 ms, and their transmission power was set between -59 dB and -72 dB, according to the size of the exposition area they were put in.

At each reference point signal intensity was sampled at least 30 times. Measurements were taken by an experienced operator holding the tablet at waist height, to simulate real usage. Because the radio signals on the same locations are affected by the orientation of the human body, all measures were taken by orienting both operator's face and the device always in the same direction (north-east).

A complex closed track, traversing any main exposition area and main interest point was designed. Radio field was sampled along the circuit, in about 300 test waypoints, spacing each other between one half and one meter. RSSI values were sampled at least 10 times at each test point.

The RSSI values were acquired using a LG V490 tablet, running the operating system Android v. 4.3 and they were individually stored in a relational Data Base.

3. Site Radiomap and Monte Carlo Sampling

A commonly accepted methodology for indoor localization is fingerprinting [8]. A fingerprint is a set of radio signal components measured at a particular location, in which each signal component is associated with the device from which it is emitted. It is represented as a vector, where element *i* contains the RSSI level received from beacon *i*.

Before tracking, a radiomap of the site is constructed off-line, by sampling radio signal strength intensity in a number of reference points. During on line tracking, the radiomap is used for identifying reference points where the average recorded RSSI is most similar to the currently perceived one.

A raw static reference radiomap was then obtained by averaging RSSI values for each beacon in reference points and by interpolating values on a grid of one meter cell size via triangular linear interpolation. Cartesian metrics was adopted for evaluation of fingerprintings distances.

Local and global statistical probability distributions of distance values among fingerprintings at grid nodes were obtained by Monte Carlo Simulation, as described in the following section.

4. Localization Algorithms

One static indoor positioning algorithm and a non linear filter were used for evaluation of user localization, namely:

1. k-Nearest Neighbor (k-NN), based on detection of most similar fingerprints in the raw radiomap.

2. Particle Filter, based on the statistical evaluation of probability of being in a location, given the statistical knowledge of previous position, a measurement of fingerprint in current position, and the priori distributions of fingerprint distance values.

The first technique (k-NN) is a deterministic algorithm comparing an input vector with the training set, using a distance metrics such as the Euclidean distance. The k instances of the data set most similar to the input are selected. As a crude approximation of fingerprint spatial variability in the site radiomap, fig. 3 shows the interpolated map of maximum RSSI values recorded at reference points.

In our experiment field sampling density varied from 0.7 reference points per square meter in museum halls to 1 point each 4 square meters in the courtyard.

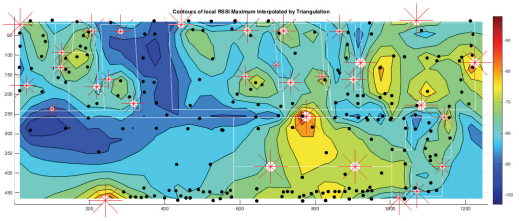


Fig. 2. Interpolated map of maximun fingerprinting component values (reference pionts shown as black dots, beacon pisitions as red stars).

The following summarizes the accuracy of localization obtained with k-NN (k=3) by averaging 1, 3, 5 or 10 sample fingerprints per track point.

TABLE I.

k-NN accuracy	**Accuracy (224 reference points)**		
n_samples	***Average Error***	***Max Error 80%***	***Max Error 90%***
1	1.72 m.	2.58 m.	3.56 m.
3	1.41 m.	1.86 m.	2.79 m.
5	1.34 m.	2.01 m.	2.76 m.
10	1.28 m.	1.87 m.	2.49 m.

Samples averaging simulates user motion between track points at a speed between 0.5 and 1 meter per second with a stop of 0, 2, 4 or 9 seconds at each waypoint.

Averaging several samples lowers signal variance and increases accuracy, but a static algorithm cannot discriminate local minima geographically apart from current position.

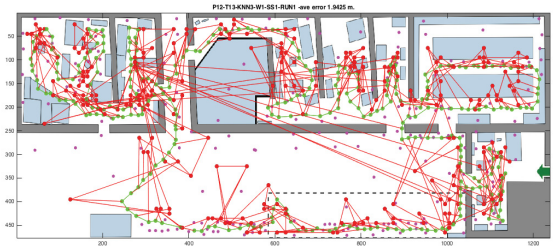


Fig. 3. Localization accuracy at track waypoints using 3 nearest neighbours in k-NN algorithm (average fingerprinting of 1 sample).

Particle Filtering is instead a probabilistic tracking algorithm in which a large number of points represent possible tracks and are assigned relevance weights according to a Bayesian classifier [9-10-11].

In this tecnique a large number of candidate points (particles) are assigned a relevance weight according to the plausibility of being in the correct location. Weights are assigned according to three factors: a model of motion, the instantaneous measurement of a control quantity, and knowledge about the statistical behaviour of the control quantity itself. Weights are updated at each tracking step.

If the global probability of obtaining value z and the local probability of obtaining value z and the probability of being in place are known in form of (a priori) distributions, Bayes theorem espresses the (a posteriori) joint probability of being in y while measuring z as:

$$p(y_i|z_{1:i}) = \frac{p(zi|yi)p(yi|z1:i-1)}{p(zi|zi-1)}$$

In Particle Filter implementations, at each tracking step a motion estimate is performed using the most probable position or the weighted baricenter of relevant particles. Particles are then moved according to estimated motion, and weights are revaluated in the updated positions. Redistribution of particle weights in relevant areas (resampling) takes in account the indeterminacy in the knowledge of a priori probability distributions and allows rapid condensation of weights in a few particles.

In our case, the measured control quantity is the Cartesian distance among RSSI signatures. Because motion smoothness is not guaranteed along the test track, motion was modelled averaging the estimated displacements in the current and previous time interval.

A priori probability distribution of local fingerprint differences was evaluated using Monte Carlo simulation. We generated 30 instantaneous site radiomaps by interpolating on a grid of mesh size 1 meter (672 points) instantaneous samples of signatures at reference points. Each local instantaneous signature was assembled from RSSI values randomly drawn from the population of measures at reference point stored in our DB. For each instantaneous radiomap, distances among signatures of grid points were evaluated and collected in local histogrammed distributions p(zi|yi), using 12 bins resolution.

Finally, the global probability distribution for signature distances was obtained by summing up and normalizing the local distributions p(zi|zi−1).

Random samples of instantaneous field readings along the track were also generated by Monte Carlo simulation, reproducing field perception while moving along the track.

Particles density was set to one per square meter (672 particles). Particle weights were initially set equal, and updated at each step with p(yi|z1:i) evaluated according to Bayes formula.

At each track step importance resampling [8] was used to update particles' weights and locations. The cloud of particles was then moved according to the motion model.

With these settings we obtained an unsatisfactory average accuracy over 2.5 m. using just one fingerprint sample per track point (corresponding to a tracking speed between 0.5 and 1 meters per second).

From theoretical considerations we expected low accuracy in areas with insufficient field sampling density, where fingerprinting is flat or spatially stable, and outside beacon line-of-sight areas, where reflection, shadowing and multipath are dominant. In effects, figure 4 highlights poor field reconstruction at some grid points showing the distance between signatures of track points and their first neighbour on the reference interpolated grid.

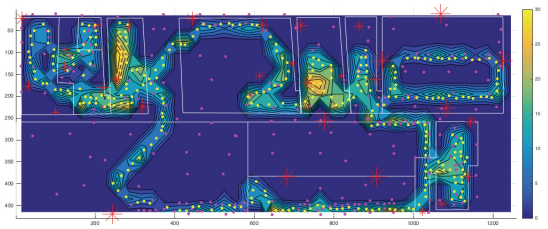


Fig. 4. Fingerprinting distances between track points and their first neighbour on the reference interpolated grid. High distances can be noticed inside walls or in proximity of corners, doors or walls.

In a second experiment, we increased sampling density in proximity of structural points and obtained a significant improvement of accuracy for both algorithms, using 239 reference points. In table II average accuracy on 10 runs.

TABLE II.

	Accuracy (239 ref. points, 1 sample, 10 runs)		
	Average Error	***Max Error 80%***	***Max Error 90%***
3-NN	1.70 m.	2.34 m.	3.14 m.
PF	1.80 m.	2.65 m.	3.20 m.

Figures 5 and 6 show the final accuracy of localization accuracy at track waypoints using 3-NN (average of 1 sample) and Particle Filter (one sample).

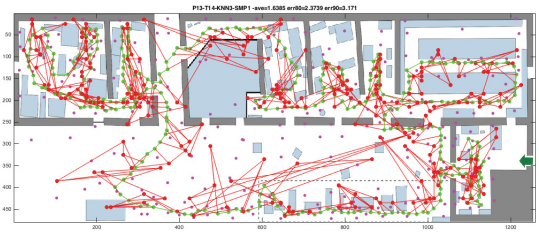


Fig. 5. Localization accuracy at track waypoints using 3 nearest neighbours in k-NN algorithm (attraction from far local minima using one sample per point).

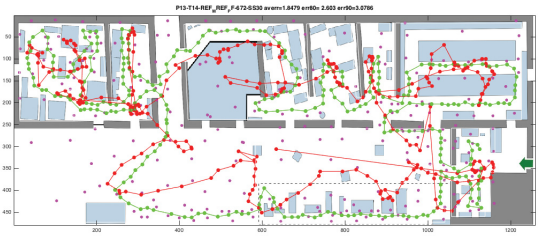


Fig. 6. Monte Carlo Simulation of tracking using Particle Filter with 672 particles. Dot clouds show waypoints position estimates.

In respect to spatial dynamics of fingerprint, figure 7 represents the interpolated map of fingerprint spatial derivative in the museum BLE field. It shows the average value of distances between fingerprint at each grid point on and ones in its spatial neighbourhood. Where spatial gradient is low, space is poorly structured and Particle Filter can be expected to loose accuracy (compare with fig 4).

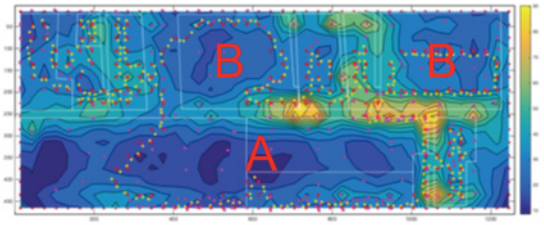


Fig.7. Interpolated map of fingerprint spatial derivative in the museum BLE field. In the lower part of the site (courtyard, indicated with the letter A) and in largest halls space (indicated with the letter B) is poorly structured and Particle Filter performs worse.

5. Results Discussion

This paper has presented an exploration study of the use of Bluetooth Low Energy (BLE) beacons for fingerprint based positioning as well as a field modelling methodology supported by Monte Carlo simulation techniques.

Preliminary results suggest that despite the high spatial and temporal variability of the BLE beacon signal intensity, RSSI fingerprinting can be used for indoor localization in a structured environment as a museum, with an average accuracy better than 2 meters with approriate sampling, more dense in proximity of structural elements. Accuracy is worse in areas where fingerprint spatial variation is low.

Being dense sampling a not economic procedure, one stream of current research work is oriented to experiment smart iterative strategies of not uniform sampling.

Perspective topics of activity are the definition of best practices for beacon positioning in order to optimize proper spatial structuring of fingerprint and modeling of the perturbative effects of visitors on the BLE field.

Acknowledgment

The authors thankfully acknowledge the precious cooperation of G. Distefano, director of the Museum of Camarina.

References

[1] Ramsey Faragher and Robert Harle, *An analysis of the Accuracy of Bluetooth Low Energy for Indoor Positioning Applications*, Proceedings of the 27th International Technical Meeting of the Satellite Division of the Institute of Navigation (ION GNSS+ 2014), Tampa Florida, September 2014, pp. 2011-210.

[2] Krzysztof Piwowarczyk, Piotr Korbel and Tomasz Kacprzak, *Analysis of the influence of radio beacon placement on the accuracy of indoor positioning system*, Proceedings of the 2013 Federated Conference on Computer Science and Information Systems, Kraków, Poland, 8 - 11 September, 2013, pp. 889–894.

[3] Shinsuke Kajioka, Tomoya Mori, Takahiro Uchiya, Ichi Takumi and Hiroshi Matsuo, *Experiment of Indoor Position Presumption Based on RSSI of Bluetooth LE Beacon*, IEEE 3rd Global Conference on Consumer Electronics (GCCE) 2014, 7-10 Oct. 2014.

[4] Angelo Chianese, Fiammetta Marulli, Vincenzo Moscato and Francesco Picciali, *A 'smart' multimedia guide for indoor contextual navigation in Cultural Heritage applications*, 2013 IEEE International Conference for Indoor Positioning and Indoor Navigation (IPIN), Motbeliard-Belford, France, pp. 1-6.

[5] Zhu Jianyong, Chen Zili, Luo Haiyong and Li Zhaohui, *RSSI Based Bluetooth Low Energy Indoor Positioning*, IEEE 2014 International Conference for Indoor Positioning and Indoor Navigation (IPIN), Busan, South Korea, pp. 526-533.

[6] Filip Mazan and Alena Kovarova. *A Study of Devising Neural Network Based Indoor Localization Using Beacons: First Results*. CISJ Vol19 No1 2015.

[7] Giovanni Luca Dierna and Alberto Machì, *From proximity to accurate indoor localization for context awareness in mobile museum guides*, Mobile-CH 16: Workshop on Mobile access to Cultural Heritage, September 6th-9th, 2016, Florence (Tuscany), Italy, in press.

[8] Christos Laoudias, George Constantinou, Marios Constantinides, Silouanos Nicolaou, Demetrios Zeinalipour-Yazti and Christos G. Panayiotou, *The Airplace indoor positioning platform for Android smartphones*, 13thth IEEE International Conference on Mobile Data Management (MDM), 2012, pp. 312-315.

[9] M. Sanjeev Arulampalam, Simon Maskell, Neil Gordon and Tim Clapp, *A tutorial on Particle Filters for Online Nonlinear/Non-Gaussian Bayesian Tracking*, IEEE Transactions on Signal Processing, Vol 50, No 2, February 2002.

[10] Fredrik Gustafsson, *Particle Filter Theory and Practice with Positioning Applications*, 2010, IEEE Aerospace EROSPACE AND ELECTRONIC SYSTEMS MAGAZINE, (25), 7, 53 – 81.

[11] Zafari and Ioannis Papapanagiotou, *Enhancing iBeacon based Micro-Location with Particle Filtering*, 2015, IEEE Global Communications Conference (GLOBECOM), San Diego CA, 16 Dec 2015.