A stigmergic approach to indoor localization using Bluetooth Low Energy beacons

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Abstract

Localization of people and devices is one of the main building blocks of context aware systems since the user position represents the core information for detecting user's activities, devices activations, proximity to points of interest, etc. While for outdoor scenarios Global Positioning System (GPS) constitutes a reliable and easily available technology, for indoor scenarios GPS is largely unavailable. In this paper we present a range-based indoor localization system that exploits the Received Signal Strength (RSS) of Bluetooth Low Energy (BLE) beacon packets broadcast by anchor nodes and received by a BLE-enabled device. The method used to infer the user's position is based on stigmergy. We exploit the stigmergic marking process to create an on-line probability map identifying the user's position in the indoor environment.

1. Introduction

Localization of people and devices is one of the main building blocks of context aware systems [1, 7] since the user position represents the core information for detecting user's activities, devices activations, proximity to points of interest, etc. It has proven useful in different scenarios spanning from single and multiple object tracking [16], to human behavior analysis [2], and activity detection and recognition [15]. While for outdoor scenarios Global Positioning System (GPS) constitutes a reliable and easily available technology, for indoor scenarios GPS is largely unavailable. For this reason, several systems have been proposed for indoor localization. Each solution has advantages and shortcomings, which, in most cases, can be summarized in a trade-off between precision, installation complexity (thus costs), and privacy issues. In practice, although indoor localization has been a research topic for several decades, there is still not a *de-facto* standard. Among the possible solutions presented in the last years [12], wireless sensor network- (WSN-) and WiFi-based techniques are the most promising, since they overcome the privacy issues related to vision-based positioning systems.

In the case of WiFi indoor positioning, the so-called fingerprinting method based on WiFi signal strength observations is generally used. It is a two-phases process: in the first off-line phase some characteristics of the environment are measured at different locations and the data is stored along with a spatial reference information, in the second on-line phase the same parameters are measured by an hand-held device and the results are compared to the stored values. This method is very efficient if the environment is precisely surveyed and the devices accurately calibrated. However it presents several disadvantages, mainly due to the required setup time, the costly signal strength system calibration in the off-line phase, and the high data volume to be managed. Furthermore, any change in the configuration such as moving a beacon or modifying the environment, will imply creating a new database [17].

In the case of a mobile WSN-based fingerprinting system, partial to complete updates are frequently necessary. Because of this, when based on WSN technologies, indoor localization systems mostly use range-based localization methods. These systems exploit measurements of physical quantities related to beacon packets exchanged between the mobile and the anchors (devices deployed in the environment whose position is a priori known) [21]. In order to guarantee a high localization precision, these systems require dedicated hardware. This is a major drawback, in particular for applications where low price and unobtrusive hardware are required.

A possible solution, that overcomes the limits related to the off-line phase of WiFi-based systems and the need of dedicated hardware required by WSN-based solutions, is represented by Bluetooth anchors broadcasting their presence in the indoor environment. As WiFi, this consumer technology is largely available in personal and wearable devices and as WSNs, it can be pervasively deployed. In the past years, practical issues mostly related to the lengthy scan procedure, have limited the use of Bluetooth in localization and tracking applications. However, the recent introduction of the Bluetooth 4.0 specification has potentially addressed these problems by means of the Bluetooth Low Energy (BLE, also known as Bluetooth Smart) subsystem [3]. BLE devices are small, inexpensive and designed to run on batteries for many months. It is expected that many buildings will contain a high density of BLE devices in the near future.

For these reasons, we present a range-based indoor localization system that exploits the RSS of BLE beacon packets broadcast by anchor nodes and received by a BLE-enabled hand-held device. The method used to infer the position of the user carrying the device is based on a technique successfully used in the field of motif discovery, called *stigmergy*. This is a term derived from the research on the foraging behavior of ants which communicate with each other exchanging information through the modification of the environment. Several works used this technique in order to infer motifs in time series related to different fields, from DNA and biological sequences [4] to intrusion detection systems [8]. We exploit the stigmergic marking process to create an on-line probability map identifying the user's position in the indoor environment.

The paper is organized as follows: Section 2 surveys related work in the indoor localization area with a focus on Bluetooth-based solutions, Section 3 describes the details of the proposed solution from the hardware and algorithmic point of view, Section 4 shows the performance of our approach, while concluding remarks are presented in Section 5.

2. Related work

From a technological point of view, in order to build an extensively used indoor localization system, it should exploit technologies largely available on commercial devices. In this context WiFi and Bluetooth are the most promising. Most of existing approaches using WiFi are based on fingerprinting of different statistical features extracted from the received signal strength [13]. This method, however, presents several disadvantages due to long setup time, costly calibration, and high data volume. Bluetooth, instead, can be used for creating different approaches based on the RSSI signal metric exploiting the possibility to deploy a large number of battery-powered devices due to their dimensions and cost.

Positioning systems based on pre-4.0 specification Bluetooth devices used various techniques, from proximity [11, 5] to trilateration [9, 22] and fingerprinting [6, 22]. However, the time taken for a mobile handset to scan the nearby Bluetooth beacons was a limiting factor. The specification allows for a scan each ~10 seconds, during which time the user's position can considerably change. Consequently, positioning using old versions of Bluetooth has not proven popular due to its latency. This problem is not present in the BLE specification. Indeed, the standard itself incorporates the notion of *micro-location* [3], which is an actual proximity feature. To date, the only study based on BLE devices is the one proposed in [10], where authors analyze the application of fingerprinting techniques on BLE RSS values.

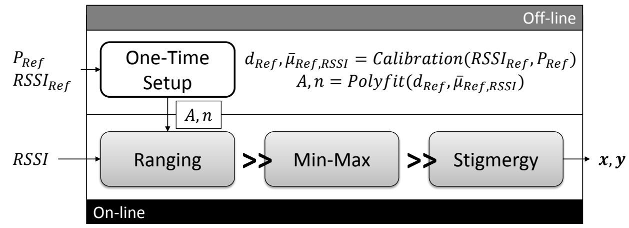

Figure 1: Overall architecture of the proposed localization algorithm.

From an algorithmic point of view, localization techniques can be divided into two categories: range-free and range-based. Range-free localization usually assumes isotropic networks where the hop count between two nodes is proportional to their distance. However, anisotropic networks are more realistic due to the presence of various anisotropic factors in practice, e.g. irregular radio propagation, low sensor density, anisotropic terrain condition, and obstacles which can detour the shortest path between two nodes [23]. Range-based techniques, instead, assume that the inter-node distances can be measured by ranging models. However, these models, usually based on RSS measurements, suffer from the intrinsic ranging noise, which affects the localization accuracy.

In this work we mitigate the noise of the model typically used in range-based RSSI techniques [20] implementing a stigmergic marking process. After a one-time channel characterization, it releases a decaying mark that acts as fading filter. The result of the algorithm is a probability map indicating the position of the user.

3. The localization algorithm

The proposed solution is a modified version of a state-of-the-art localization algorithm, namely Min-Max [14, 18]. It exploits the features of the stigmergic process in order to mitigate the deep multipath fades typical of BLE beaconing technology. Figure 1 shows the various steps performed by the algorithm. Each of these steps will be detailed in the following subsections.

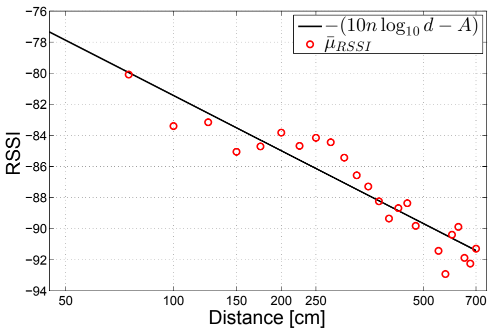

Figure 2: Logarithmic fitting after calibration.

3.1. BLE beacons and One-Time Setup

The BLE beaconing system is a way to detect proximity between BLE devices by means of received signal strength. The first protocol in this sense was introduced by Apple in the mid 2014 and was called iBeacon [1]. iBeacon uses Bluetooth low energy proximity sensing to transmit a universally unique identifier picked up by a compatible app or operating system. Lately, Radius Networks [2] has introduced an open standard compatible with iBeacon technology called AltBeacon [3]. In our experimentation we used RadBeacon X2 [4] devices since their compatibility with both technologies.

As range-based technique, a one-time off-line calibration phase is performed (*One-Time Setup* in Figure 1). In this phase, we measure the RSSI from a reference beacon at predefined distances with steps of ~25 cm. For each step of distance d_{Ref}, 100 samples are collected, then outliers are removed (any sample that is more than 2 times the standard deviation is considered an outlier) and we compute the mean value $\bar{\mu}_{Ref,RSSI}$ on the resulting dataset. On the obtained couples $(d_{Ref}, \bar{\mu}_{Ref,RSSI})$, a logarithmic interpolation is applied in order to fit data with the nominal distance-power loss law:

$$RSSI = -(10n\log_{10} d - A) \tag{1}$$

From this fitting process, the parameters of the channel A and n are obtained. Figure 2 shows the resulting semi-log plot of the fitting line where n represents the slope and A the intersection with the RSSI axes.

3.2. The on-line stigmergic map

The first step of the on-line phase of the algorithm is the ranging. The proposed solution estimates a position with a frequency of 1Hz. The RSSIs collected from the beacons deployed in the environment are averaged and the computed mean is used to retrieve an estimation of distances between the mobile node and each beacon. This is done using the parameters A and n computed in the off-line phase (inverting the Equation 1).

In the second step, a Min-Max-like algorithm is applied on the extracted distances. MinMax [14, 18] is a very popular localization algorithm, in which the mobile node creates an association between each beacon position and the distances previously estimated. The mobile node draws a pair of horizontal lines and a pair of vertical lines around each beacon, in such a way that the minimum distance between each line and the beacon position equals the estimated node-beacon distance. The node localizes itself in the center of the rectangular area obtained by considering the innermost horizontal and vertical lines (the lowest and highest among all the horizontal lines placed above and below each beacon, respectively), and the leftmost and rightmost among the vertical lines placed on the right and left hand side of each beacon.

In the proposed approach, instead of estimating the output position as the center of the rectangular area obtained, we apply the stigmergic process on the output area from the Min-Max in order to overcome the deep multipath fades typical of the BLE beaconing technology. Experimental results in [10] have shown that BLE beacons present up to 30dB drops in the signal strength received by a mobile node moving towards them across just 10cm. This behavior is present in all the different radio channels used by BLE and at different spatial positions. If the mobile node does not collect enough measurements while computing its position, it will base its estimate on a few sharp-fade readings, resulting in wrong output coordinates. For this reason, we adopt the principles of the marker-based stigmergy, which, in social insect colonies, employs chemical markers (pheromones) that the insects deposit on the ground in specific situations. Multiple deposits at the same location aggregate in strength. Members of the colony who perceive pheromones of a particular flavor may change their behavior. Pheromone concentrations in the environment disperse in space and evaporate over time, because pheromones are highly volatile substances.

In the proposed marking process (*Stigmergy* block in Figure 1), a mark structure is constructed starting from the Min-Max resulting area and it is released in the spatial environment, thus allowing the accumulation of marks. The mark is released with intensity I and has the same size and position of the Min-Max resulting area. At each step, the mark *evaporates* and *diffuses*, meaning that at each step its intensity decreases by a percentage ϵ (called *evaporation*) and becomes wider towards adjacent positions with a constant diffusion rate $d \in [0, 1]$ (in this work we choose $\epsilon = 10\%$ and $d = 0.3$). Hence, an isolated mark after a

[1] https://developer.apple.com/ibeacon/
[2] http://www.radiusnetworks.com/
[3] http://altbeacon.org/
[4] http://store.radiusnetworks.com/products/radbeacon-x2

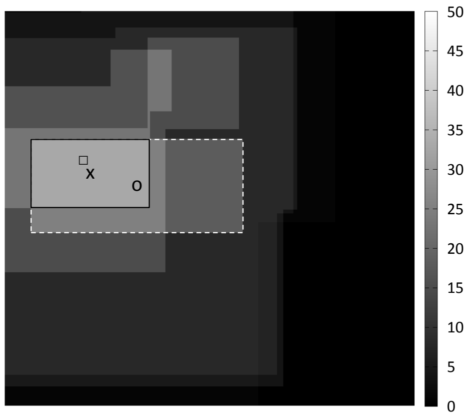

Figure 3: The stigmergic map during the marking process (square: ground truth, cross: stigmergic output, circle: Min-Max output).

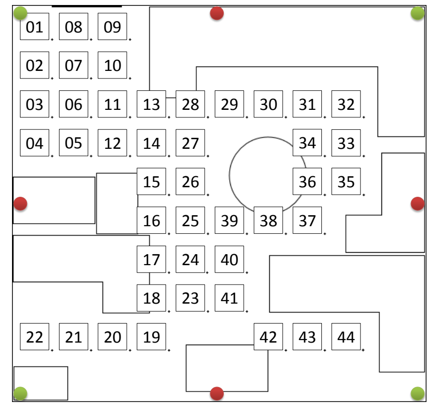

Figure 5: The map of the deployed beacons and the ordered reference points used for the experimentation.

certain time tends to disappear. The time that a mark takes to disappear is longer than the period used by the system to release a new mark. Indeed, if the mobile node is still in a specific position, new marks will superimpose on the old marks, thus increasing the intensity of the stigmergic map in that point. If the node moves to other locations, consecutive marks will be partially superimposed and intensities will decrease with time without being reinforced.

At each step, after a new mark is released, the proposed algorithm creates a stigmergic map that is the sum of all the still existing marks released in the previous steps and the mark released in the current step. Afterwards, the widest area with maximum intensity is computed and the resulting output (x, y) is represented by its centroid. Figure 3 shows the stigmergic map in a generic step of the marking process. The square mark represents the ground truth point, while points marked with cross and circle represent the output of the proposed system and the classic Min-Max algorithm respectively. the figure also shows the corresponding output areas, marked with black solid line for the stigmergic output and with white dotted line for Min-Max. It can clearly be seen how the presence of previous marks in the stigmergic map mitigates the multipath fade effect of the BLE technology that pushes the Min-Max algorithm to estimate an erroneous position.

4. Experimental results

In this section we present the experimental scenario. Since our aim is to evaluate the possibility to use commercially available BLE devices for indoor localization in small environments, we chose to deploy 8 Radbeacon X2 devices in a 6m x 6m office. Figure 5 shows a map of the office with the positions of the deployed sensors and the reference points used for the evaluation.

The presence of office furniture influences the propagation of the beaconing signal as highlighted in Figure 6, where the RSSIs collected from one beacon in the considered reference points are shown. It can be seen that furniture creates noticeable shadow zones that, together with the typical multipath fading effect of the chosen technology, make the localization task non-trivial.

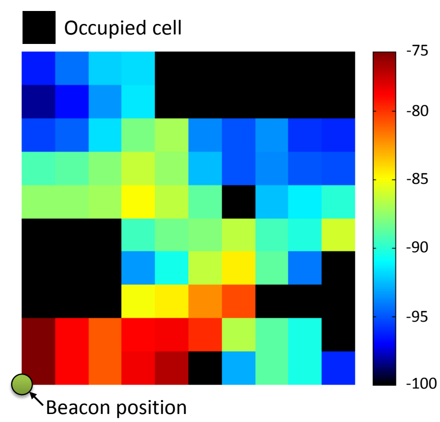

Figure 6: The map of the received signal strengths for one of the deployed beacons.

We performed two measurement assessments in order to evaluate how the performance changes with respect to the number of deployed sensors. For each test, an actor, holding a phone at 1.5m from the floor, performed a walk through 44 reference points numbered and marked on the floor, stopping 5 seconds on each point. This in order to reproduce the experiment in a controlled way. A mobile application was used to collect the ground truth, allowing the actor to mark his actual position during the trajectory performed (numbered reference points in Figure 5). In the first assessment, 4 beacon were used (colored in green in Figure 5), while in

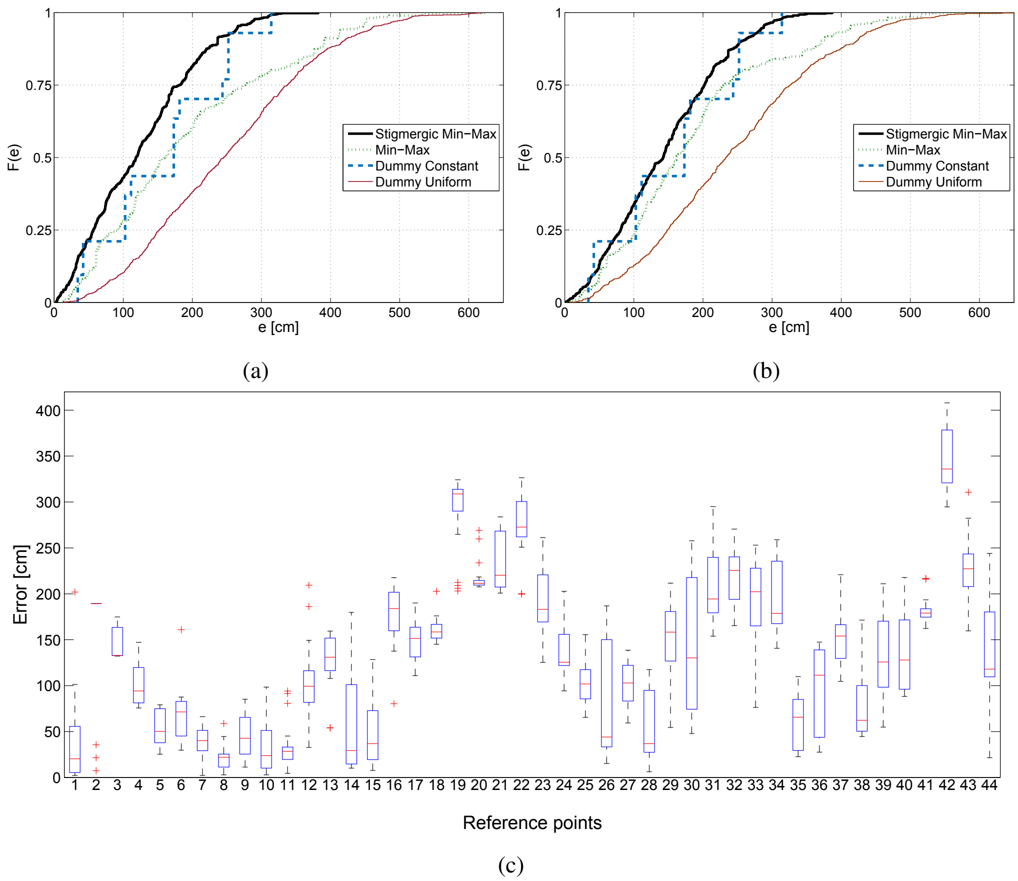

Figure 4: The resulting CDF for the a) 4 beacons setup and b) 8 beacons setup. c) The box-and-whisker plot of the errors' statistics for each reference point.

the second one all the 8 beacons were used. The beacons were placed at 3m from the floor and set-up with a transmit power of -16dBm and an advertisement rate of 3Hz in order to reduce the power consumption (battery life up to 18 months with the current settings). Figures 4a and 4b show the obtained results in terms of accuracy. This is the classical performance measurement for localization systems, it is based on samples of the distance between the point where the system thinks the user is and the point where the user really is [19]. We define the error ϵ (equation 2) as the euclidean distance (in two dimensions) between the ground truth point (x_r, y_r) and the coordinates estimated by the system (x, y).

$$\epsilon = \sqrt{(x_r - x)^2 + (y_r - y)^2} \tag{2}$$

The Cumulative Distribution Function (CDF) of ϵ is the probability that the localization error takes a value less than or equal to e meters and it is defined in equation 3.

$$F(e) = P(\epsilon \leq e) \tag{3}$$

We compared our system with the original Min-Max algorithm and with two "dummy" systems, the first one giving as constant output the center of the room, and the second one implemented as a random position estimator (uniform distribution of estimates over the entire area). Results show that in 75% of the cases the localization error is lower than 1.80m compared with the 2.75m of error obtained with Min-Max, the 2.43m of error with first dummy system (constant), and the 3.37m of error with the second dummy system (uniform). This can be considered a promising result, taking into account the difficulties related to small environments and the presence of obstacles. Indeed, as shown in the box-and-whisker plot in Figure 4c, the results are strongly influenced by the errors obtained in the points most affected by the shadowing effect shown in Figure 6 (see points 19 and 42 as good examples). Another outcome is that, increasing the number of beacons, the overall results of our algorithm slightly degrade. This is due to the increased number of signal received by the mobile node together with their multipath fadings. Increasing the number of beacons in such a small area does not represent a scalability factor, since we are interested in reducing the required number of beacons. The Min-Max algorithm, instead, improves his performance due to its well known tendency to shift position estimates towards the center of the network [18], thus limiting the estimation error to half of the room side (it behaves as the first dummy system). In this case we obtain a third quartile of 2.01m compared with the 2.31m of third quartile error obtained by Min-Max.

5. Conclusions

In this paper we propose a range-based indoor localization technique that uses the received signal strength of Bluetooth beacons. We investigate the possibility to opportunistically exploit the presence of BLE beacons for localization purposes, since their presence is supposed to become more and more pervasive in the near future. In this regard, we show that the technology is ready to be further used. We also prove that the stigmergic approach presented is a promising solution to mitigate multipath fading and shadowing effect of BLE beaconing.

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