Localization and monitoring system based on BLE fingerprint method

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Abstract. Among techniques designated for indoor localization, wireless fingerprinting is the most emerging because of the widespread deployment of wireless networks. Moreover, positioning methods based on received signal strength indicator fingerprint are attractive for their accuracy and independence from the radio propagation model. This paper describes an implementation of Bluetooth Low Energy positioning method based on fingerprint technique, according to Wi-Fi localization techniques. Adopting the received signal strength indicator and an accurate model, a localization system with a good accuracy is obtained. The method feature of not limiting the freedom and privacy of users, makes it advisable for elderly behavior monitoring.

Keywords: BLE, indoor localization, Wi-Fi positioning, fingerprint, elderly, monitoring

1 Introduction

Advances in medical diagnostics and treatments have produced lengthening life expectancy and, consequently, rise in elderly people in many nations. In fact, health technology contributes both to disease prevention and to limit the decay of a person functions which corresponds to increase in life expectancy [1-6]. Many elderly live alone in their home because they are creatures of habit. Unfortunately, their deteriorated physical functions severely reduce their mobility and their self-sufficiency. Therefore, elderly are prone to abrupt health problems such as falls, sudden illness, loss of consciousness, etc. Modern advances in the fields of information technology, communication/sensor networks and electronic devices are enabling the development of technological solutions for elderly taking care [7-8]. Many efforts have attempted to monitor the location where old people live by applying intelligent technologies, such as image surveillance, sound detection or vibration sensing for the identification of fall or trip hazards [9, 10]. For this reason, indoor positioning systems have rapidly developed by using new technologies and methods. One of the most popular positioning technologies based on 2D modeling is the fingerprint on Wi-Fi which can be used in both outdoor and indoor environment. Because of Wi-Fi localization system need at least three Wi-

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Fi routers in the monitoring area, it is not advisable for elderly monitoring in their home. Compared with Wi-Fi localization system, Bluetooth Low Energy (BLE) fingerprinting is a low-cost technology in fact it need only to install beacons in the monitoring area that are battery operated cheap devices. Moreover, these systems are characterized by high precision but the algorithm complexity and the computational consumption is relatively high [11]. Like all indoor positioning systems, fingerprint technology is influenced by the environment such as multipath effects, number of access (AP or BC) and reference points (RP), presence of mobile devices, etc.

BLE fingerprinting is characterized by an off-line phase followed by an on-line phase [12]. During the off-line stage fingerprint data are collected to build a model; in fact the location dependent characteristics of a signal acquired at known locations are stored in a database or radio map. For the model development, both accurate and empirical models can be used [11], [13]. Adopting empirical modeling, the measure of the signal strength received from different beacons (BC) at the location of every RP is performed and stored in the database with the information of RP location. This modeling method has a high level of accuracy even if the workload is, often, large for the need of many data samples. For accurate modeling, the accurate position of BCs is necessary. Moreover, for the radio map generation, the signal strength of several important positions is only needed. Because of complexity and limitations of indoor environment which causes scattering, reflection, and refraction of the propagated RF signal, the main task of accurate modeling is to define a channel propagation model able to describe indoor signal fading properly. To remove invalid samples and improve accuracy of the positioning method, the fingerprint database has to be filtered since the acquired signal strength is corrupted by noise generated by the indoor environment. Both deterministic denoising and probabilistic denoising methods can be used.

In the online phase, collected signal strengths are compared to the signal strength at the user location to estimate the user position adopting deterministic or probabilistic positioning algorithms. These type of procedures differ mostly because deterministic algorithms match the signal strength of corresponding fingerprint data by using the positioning algorithm to obtain the final position of the user, while probabilistic algorithms store the probability distribution of the signal strength during a certain time in the fingerprint database and then the probability position of the user location is evaluated by the Bayesian theory system.

In this paper, a monitoring system for elderly people based on BLE technology is presented. The method performs indoor positioning adopting Wi-Fi fingerprinting technique based on Received Signal Strength Indicator (RSSI). After a brief description of the BLE technology, the implemented system for the indoor localization is detailed. The method performance is evaluated and some conclusions are drawn out.

2 Bluetooth Low Energy technology

Bluetooth low energy technology combines a standardized technology designed for ultra-low-power batteries and a new sensor-based data collection framework. It boomed in the mobile device market and uses devices working at 2.4 GHz and within the Industrial, Scientific and Medical (ISM) band. BLE technology employs a variable connection interval that can be set from a few milliseconds to several seconds depending on the application. In addition, because it features a very rapid connection, BLE technology can normally be in a "not connected" state (saving power) where the two ends of a link are aware of each other, but only link up when absolutely necessary and then for as short a time as possible. Benefits of BLE technology are [14]:

- Low power consumption*:* nowadays, in order to reduce the cost of system infrastructure, the most important requirement for all electronic systems is a low power consumption;
- Indoor positioning*:* BLE technology is designed specifically for this purpose;
- Supported by smartphones*:* this feature is very important in view of trends in the mobile telephone systems;
- Very long life battery*:* this is a very important aspect for all portable systems. A long life battery enables a long life system operation and, consequently, the possibility to replace batteries after a few months of use. As a result, system maintenance costs decrease;
- Low cost*:* cost control is one of the requirement/constraint in designing an electronic system. The adoption of low-cost hardware guarantees cost reduction for system implementation.

3 Adopted method and measurements

The purpose of the implemented system is to localize the positions of one receiver (i.e. smartphone) in the physical area of interest using the BLE technology. In BLE fingerprint technique, the definition of a radio frequency map is necessary which combines geographical coordinates (2-Dimension Cartesian Space) and RSSI values received by the tag and transmitted by several beacons (BC). The location of beacons is a key point because it must be chosen in such a way that at any time the tag is within the radio range of at least one beacon. The generic RSSI vector received by a receiver is denoted as $t = (t_1, t_2,\ldots, t_n)$, where t_j, $(1 \leq j \leq n)$ denotes the RSSI value from the j^{th} beacon and n is the number of beacons in the area of interest. Adopting m RPs in the offline phase, the RSSI vector received at the i^{th} RP $(1 \leq i \leq m)$ is denoted as s_i, where $s_i = (s_{i1}, s_{i2},\ldots s_{in})$.

The implemented method is composed of an off-line phase, in which the fingerprint data base is constructed adopting an accurate model, and an on-line phase in which a deterministic positioning algorithm is implemented to localize the receiver inside the area under test.

In the implemented system, four beacons and a mobile receiver are used inside an indoor environment of about 133 m^2 (fig.1).

In order to reduce the effort dedicated to off-line measurements, a virtual fingerprint database is calculated using the Multi-Wall Multi-Floor indoor propagation model whose effectiveness was investigated [15]. The RSSI database is composed of 250000 elements (m=250000) (fig 1).

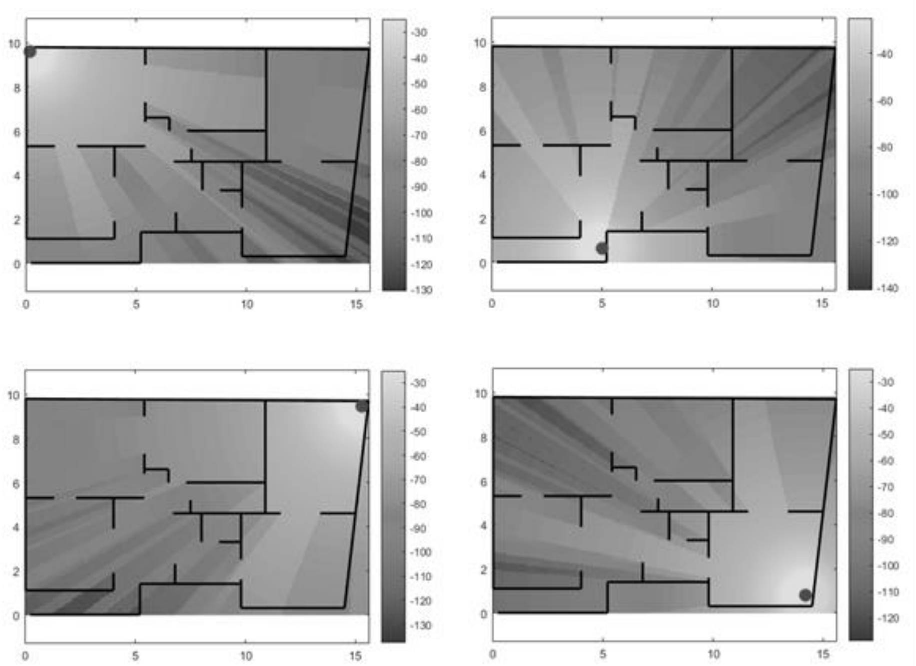


Fig.1 RadioMap of beacons positionated inside the indoor area under study

To simulate the RSSI signals measured by the receiver if it is at the j^{th} RP, the s_j vector was corrupted by random values (noise) which are different for all its components.
As previously mentioned, the signals read by the receiver is called t, where t = (t_1, t_2,…, t_n) and $t_{i,}$ = s_{ij} +$c_{ij.}$
This assumption is justified because errors can corrupt the RSSI values measured by the receiver. The Mersenne Twister algorithm is adopted for the generation of random values. In particular,

$$c_{ij} = (b-a) \times rand\ (1) + a \qquad (1)$$

where a and b are the boundary of the signal corrupted by the error

$$a = s_{ij}-MaxErr \times MSV \qquad (2)$$

$$b = s_{ij+}\ MaxErr \times MSV \qquad (3)$$

and Maximum Scale Value(MSV) is the maximum signal value assumed to be -25dB. MaxErr is in the range [0,1], assuming that 100% is the maximum read error that can be done by the receiver.

For software implementation (online phase), all the s_j points are evaluated with the aim to determine if the s_j point is a probably matching point or not.
The criteria adopted is based on the successful condition that each value of t is in s_j range that is for each sj, t_i has to be in s_{ij} range. The range s_{ij} is a window of size equal to 50% of the t_i value and centered around s_i value.
For j=1..m , s_j is a matching point for t if:

$$\begin{cases} s_{1j} - 0.5 \times t_1 \leq t_1 \leq s_{1j} + 0.5 \times t_1 \\ s_{2j} - 0.5 \times t_2 \leq t_2 \leq s_{2j} + 0.5 \times t_2 \\ \dots \\ s_{nj} - 0.5 \times t_n \leq t_n \leq s_{nj} + 0.5 \times t_n \end{cases}$$

The implemented procedure localizes all the s points inside the area under test which should represent the receiver position.
In fig.2, the receiver real position is indicated by a circle while the gray areas represent the receiver localizations obtained by the implemented procedure. In the figure is easily identify k cluster of probable points.

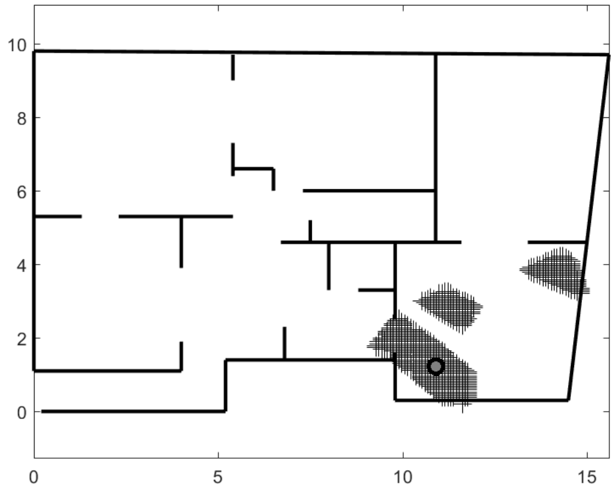


Fig.2 Coarse procedure outputs

The second step consists to evaluating the numerical consistence of each cluster. Only the cluster with the maximum point consistence is considered in the next step.
The third step is the evaluation of the cluster centroid.
For an accurate positioning of the receiver, the k-means clustering algorithm with the Euclidean distance measurement technique, is adopted. The used procedure partitions a set of n objects into k clusters so that the resulting intra-cluster similarity is high but the inter-cluster similarity is low. The procedure defines one centroid for each cluster. Generally speaking, a centroid is an artificial point in the space of records which represents an average location of the particular cluster. Its coordinates are averages of attribute values of all examples that belong to the cluster.
The k-means algorithm uses an heuristic method to find centroid seeds for *k*-means clustering. Assuming k different clusters, the algorithm chooses the seeds as follows:

1. It selects an observation uniformly at random from the data set, *X*. The chosen observation is the first centroid, and is denoted with c_1.

2. It computes the distances from each observation to c_1 and denotes the distance between c_j and the observation m with d(x_m, c_j).
3. It selects the next centroid c_2 at random from *X* with probability

$$\frac{d^2(x_m, c_1)}{\sum_{j=1}^{n} d^2(x_j, c_1)}$$

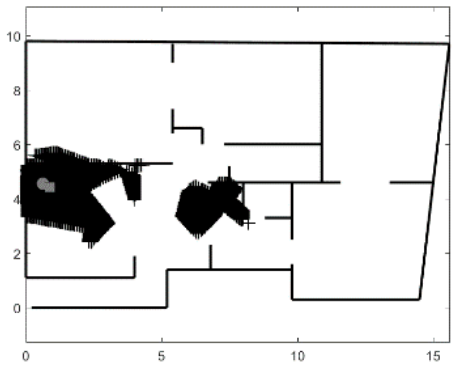
4. For the choice of center *j*, the procedure*:*
   a) Computes the distances from each observation to each centroid and assigns each observation to its closest centroid.
   b) Selects centroid j at random from *X* with probability

$$\frac{d^2(x_m, c_p)}{\sum_{\{h, x_h \in C_p\}} d^2(x_h, c_p)}$$

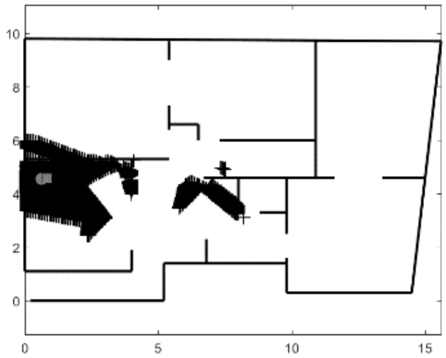
   for *m = 1, …, n* and *p = 1, …, j-1*
   where C_p is the set of all observations closest to centroid c_p and x_m belongs to C_p. That is, the algorithm selects each subsequent center with a probability proportional to the distance from itself to the closest center already chosen.

5. Repeat step 4 until *k* centroids are chosen.

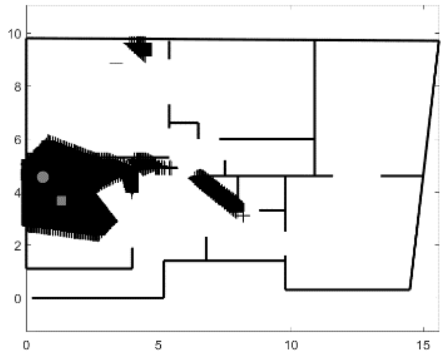
The estimated localization point is considered the cluster centroid.
For the evaluation of algorithm robustness towards noise (such as effects of building layout, construction material, moving objects, reflecting surfaces, temperature changes day, electromagnetic field interference, etc.), several simulations were carried. Assuming a transmission power level of each beacon equal to -25dBm, average error distance values less than 1,4m are obtained for noise values not exceeding 20% of maximum scale value (MaxErr=0.2) (fig.3).



a)



b)



c)

Circle = real position
Square= simulated position

Fig.3 Results obtained with a noise level of 5% (a), 20% (b) and 40% (c) of the maximum scale value (MaxErr=0.05, 0.2, 0.4).

4 Conclusion

In this paper, a BLE fingerprint method using Received Signal Strength Indicator for indoor localization is presented. In the off-line phase an accurate model is adopted for the radio map construction, in the on-line phase a deterministic positioning algorithm is implemented to localize the receiver inside the test area. The obtained results show the method validity.

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