Fusion particle and fingerprint recognition for indoor positioning system on mobile

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Abstract— High accuracy localization is easily obtained in an exterior context with GPS, but the development of indoor positioning systems remains a challenge. The GPS signals, by nature, cannot penetrate walls thus preventing this technology to provide any service indoor. This paper proposes a practical implementation of an accurate Indoor Positioning System based on Bluetooth Low Energy technology to ensure a low power, efficient and easy to setup infrastructure. It is available on any current Smartphone and requires no extra devices for the user. We use a fusion of the inertial sensors available on the device to output a precise and drift-free estimation of the user displacement, leverage this information with iBeacon radio signals used as anchors to readjust the path if needed and process all these inputs in a Particle Filter. We augmented the Fingerprinting-based likelihood calculation of the particles position's with a unique simulation of the particle's theoretical RSSI and also reduced the number of particles to better fit within the bounds of the computational capabilities of mobile devices. The experiment was conducted in a 400m2 open space and yielded positive results as a first attempt in accurate indoor localization and proved to be viable in an indoor context.

Index Terms— Particle Filter, Optimization, Bluetooth Low Energy (BLE), Fingerprint recognition, Fusion Sensor, Indoor Position System (IPS)

1 Introduction

The localization and tracking of moving objects or people has long been an interesting area of research, but is also well addressed in the outdoor case with the Global Positioning System. However, GPS has exhibited limitations in indoor environments because of the absence of line of sight (NLOS) with satellites, and thus is still an on-going field of research. Many approaches have been envisioned from the early ages of indoor positioning systems with a wide variety of technologies and methods. Some tried the approach of acoustic systems [1] whereas others focused on infrared- [2] or ultrasound-based systems [3]. However, the technology that has contributed the most to indoor location systems is the radiofrequency (RF). Wi-Fi [4], [5], is the most popular approach of RF-based systems because it relies on the existing infrastructure of the localization area and can work on any existing mobile device, thus ensuring a large user-base. As an alternative to Wi-Fi-based systems, Bluetooth has also been tested [6] as the deployed infrastructure and ensured a better line of sight between the anchor nodes and the tracked device. Unfortunately the costs of setup and maintenance regarding accuracy and device power consumption concerns didn't make it a reliable solution.

When considering possible use-cases for indoor localization, perhaps the most obvious examples are people navigating shopping malls, convention centers, museums, etc. We cannot expect users to carry a specific device to provide them with localization; even a simple foot-mounted sensor would be an inconvenience. For that reason, high accuracy approaches such as ultra wide band (UWB) [7] or Radio Frequency Identification (RFID) [8] that require both a specific infrastructure or a specific tag for localization cannot be applied in most user-driven contexts.

If we focus on works that rely solely on mobile device capacities and pre-existing infrastructure, we can consider light-based systems [9] that use the camera to detect the information transmitted by LEDs. However, those methods have two major constraints: First, the LEDs need to be installed beforehand, which means supplementary infrastructure costs. Second, constantly using the camera draws the battery faster than Bluetooth or Wi-Fi and would prevent the user from doing anything else with his/her phone than providing localization. Other mobile-only systems like FM-based [10] or GSM-based [11] solutions were envisioned but could only provide room-level accuracy. Magnetic approaches were developed [12], only requiring the use of device sensors, but they only reached room level granularity [13], and required a very long training phase or were not viable in the long term. With regards to accuracy, each has its own definition regard-

ing "high" accuracy, but none were able to surpass the one-meter level without the use of external devices such as sensor extensions, or over-focused use of the mobile device. Since 2010 and the appearance of the Bluetooth 4.0 standard [14], also known as Bluetooth Smart or Bluetooth Low Energy (BLE), a new kind of RF-based indoor positioning system has emerged. This new technology has become very popular with the launch in 2013 of the iBeacon protocol which only broadcasts a unique identifier over BLE. Because BLE was designed as a low-cost and low-energy device, an infrastructure consisting entirely of these beacons can be deployed at a low cost, and provides a proper coverage of the area, thus enabling new studies to be conducted on high accuracy indoor positioning systems [15], [16].

Using only the inertial sensors of a mobile device to determine the position of the user with high accuracy is still a challenge and is known as "pedestrian dead reckoning (PDR)." This method estimates the distance and heading direction of the user, based on the accelerometer, gyroscope and magnetometer of the mobile device. Based on the assumption that PDR could give an accurate estimation of the trajectory of the mobile device, and therefore the user, researches have been attempting to fuse PDR with some, if not all, of the previously mentioned technologies in order to improve both robustness and accuracy of the positioning system. PDR can estimate the path of a user but only over a short time interval; this is due to the drift effect which contains a double integration of acceleration and a single integration of the gyroscope. However, when fused with other methods PDR can increase the accuracy of indoor positioning systems.
The rest of this paper is organized as follows: Section 2 describes the related work that has been conducted over the past decade on indoor localization and section 3 presents our proposed method. Section 4 explains the experimental setup and results and proposes a discussion. Finally, section 5 concludes this paper and presents the future work we are planning, as well as some improvements that can be made based upon our proposed approach.

2 Related Work

In this section we will review the work on indoor localization and focus more so on methodologies rather than on the technologies that were presented in the Introduction.
In [17], indoor positioning approaches are briefly overviewed and classified in two categories: model-based and fingerprinting-based. We chose to add a third group termed "filter-based" which we believe to be important to mention when reviewing indoor positioning methods.

2.1 Model-Based

Model-Based approaches are mainly geometrical methods and use information such as distance, angle or time to process and estimate the position of the mobile node.

In Time Of Arrival method, also called Time Of Flight, the propagation time of a signal (most often RF signal) is measured. Because the precise time of emission and the propagation speed of the signal are known, it is possible to calculate the distance between the emitter and the receiver. Afterward, with the calculated distance of three known emitters, a trilateration algorithm can be performed to estimate the position of the tracked node. One of the major drawbacks of this approach is that it requires a very fine synchronization between all the nodes of the deployed infrastructure and the receivers. Only nanosecond latency can cause an accuracy error of 0.3m when using RF. The speed of a radio-frequency wave is close to the speed of light, $c = 3.0 \times 10^8 \text{m/s}$. Thus if $\partial t = 10^{-9}$ s then $\partial d = c \cdot \partial t = 3 \times 10^{-1} \text{m}$. Another restriction when using direct signal information is that it requires a perfect line of sight between the emitters and the receiver. Furthermore, the deployed infrastructure must be dense enough to properly cover the whole area.

TDOA, Time Difference Of Arrival, is a slight variant of the TOA approach in that it only requires synchronization between the emitters' nodes but it remains the same in the distance estimation from time and position estimation using Trilateration. Hence, the hardware used for the beacons require strong clock accuracy and precise synchronization throughout the network making the infrastructure cost not negligible.

As mentioned in TOA and TDOA methods, the Trilateration is often used in Indoor localization context because of its simplicity. In the two previous methods, the accuracy of the estimated distance from time can lead to a good positioning result but if the Trilateration is used and the distance is estimated based on another parameter it can rapidly become less attractive. This is the case in lot of indoor positioning systems relying on an existing Wi-Fi infrastructure and/or extended with Bluetooth Low Energy beacons. The parameter that has been used widely in those RF-based system is the received signal strength indicator (RSSI), and distance estimation can be obtained with the well-known log-distance path model:

$$\text{RSSI} = -10 \cdot n \cdot \log\left(\frac{d}{d_o}\right) + PN$$

Here, PN is the signal strength at the reference distance d_o and n is the path loss exponent parameter, which usually varies between 2 in free space and 8 in a noisy environment.

The intrinsic characteristics of RF signals are such that there is strong multi-path effect in indoor environment, meaning the attenuation through obstacles

and human bodies make the received RSSI at a fixed position very erratic. If we take the example of a Bluetooth Low Energy beacon, emitting a 2.45GHz RF signal in free space with a -58dBm reference power at 1 meter, a 4dBm differential at close range (received -65dBm and -69dBm) means 1.3 m in distance estimation error but is equal to almost 7m error at medium range (-80dBm and -84dBm) and up to 20m at long range (-88dBm and -92dBm). In an indoor context, using trilateration with RSSI in the case of an RF infrastructure cannot achieve strong accuracy unless with high pre-processing to filter-out the unreliable data, thus reducing the real-time performance.
Finally, one last model-based approach is to estimate the position of a mobile node in a wireless sensor network, and is referred as the AOA, Angle of Arrival (also known as Triangulation). The calculation is very simple and the accuracy achieved is high but it requires a specific hardware on the mobile node that capable of detecting the angle of arrival of the signal from specific hardware infrastructure. Once the angles $\theta 1$ and $\theta 2$ from two beacons are measured and the coordinates of those beacons (x_1, y_1) and (x_2, y_2) are known, it is possible to estimate the position with the simple formula: $yi - xi.\tan(\theta i) = y - x.\tan(\theta i)$. As stated above, the hardware cost of this infrastructure would be non negligible and the hardware that detects the angle of arrival is not available in today's Smartphones

2.2 Fingerprinting-Based

Fingerprinting-Based methods are divided in two steps commonly referred to as an off-line (or training) phase and an on-line (or localization) phase. In the former, a site survey is performed in which signal values are collected and stored in a database along with the coordinate position. The tuple signal-position is called a Fingerprint. In the latter, the signal values observed by the mobile node to track are compared with the ones in the database and the closest match is returned. The position of this Fingerprint is considered as the mobile node position. The great advantage of this approach relies in its simplicity, adaptability to different technologies and its accuracy that is better than model-based methods. Indeed, it is easy to construct a database only made of Wi-Fi fingerprints as most indoor environments are already equipped with Wi-Fi access points, and line of sight is a non-issue; the challenge lies in the reinforcement of the fingerprint database with respect to the diversity of the fingerprints contained within it.

Much work has been done on Fingerprinting, and groups have tried to enhance it by combining multiple signal sources such as Wi-Fi, GSM, RFID or Bluetooth (and most recently Bluetooth Low Energy). Others experienced different methods to look for the best match in the database like the classic k-NN which retrieves the k nearest neighbors based on an Euclidean or Manhattan distance selection criterion, its variant the weighted k-NN or also a classifier like the Bayes' classifier.

However, the main drawback of this approach relies in its off-line site survey and most of all, its maintenance, which can be overly expensive. Constructing a database by collecting data each one or two meters for accuracy sake in a static small room is easy and the radio-map will still be valid one week or one year after. But if we consider an exhibition mall that frequently hosts events over the course of a year, it is easily deducible that its configuration changes with every event. Generating the radio-map for such an environment is extremely time-consuming and costly. Moreover, every 2 to 3 events this radio-map will become invalid and this work would have to be reconstructed.

Recent researchers have attempted to simulate the construction of the radio map, however the resulting accuracy was suboptimal. Others tried to find a compromise by utilizing the on-line phase as a way to crowd source the radio-map. The results show room-level accuracy which is good for small contexts or narrow areas but not for large open indoor spaces. Moreover, there are no explicit measures about the time it takes to create the crowd-sourced radio-map whereas it is the key component of the localization system.

As for today, the classic radio-map creation in the training phase remains the most preferable way to achieve high accuracy in a Fingerprinting-based approach and hence our proposed method relies on it.

2.3 Filter-Based

Filter-Based methods rely on statistical computations that aim at estimating the true value state of an unknown variable, most often the hidden state of a Markov Chain, using only observed set of data described by a mathematical model. These filters work in two phases, namely the prediction step and the update step.
The Kalman filter, one of the most well-known algorithms and linear quadratic estimation relies on the Bayesian inference to estimate unknown variables based on the prior knowledge of the variable and a measurement set. It is widely used in robotics and aircraft navigation and guidance systems but requires only linear operators and there is a strong constraint on both noise covariance matrices that must be precisely estimated. As stated above, the estimate of the true state at given time k is only a linear function of the true state at the previous time k-1 and can be written as follows:

$$x_k = F_k . x_{k-1} + B_k . u_k + w_k$$

Here, F_k is the state transition model, B_k is the control-input model applied to the control vector u_k. Finally, w_k is the noise associated with this transition from time k-1 to k and is most often drawn from a zero mean multivariate normal distribution with a covariance Q_k:

$$w_k = N(0, Q_k)$$

To this unknown state of variable at time k we can observe a variable z_k that follows the given equation:

$$z_k = H_k . x_k + y_k$$

H_k is called the observation model and v_k the observation noise. The observation noise is a zero mean Gaussian white noise with a covariance R_k:

$$v_k = N(0, R_k)$$

During the Predict step, the Kalman filter calculates the 'a priori' state estimate $\hat{X}_{k|k-1}$ and its accuracy, also called the 'a priori' error covariance matrix $P_{k|k-1}$. During the Update step the measurement pre-fit residual, its covariance, the optimal Kalman Gain, the 'a posteriori' state, its error covariance and the post-fit residual are calculated.

To apply filter-based methods on RF-Based Indoor Localization Systems, we must find the relation that binds the observation set to the hidden state of the Markov model (i.e. the H_k matrix of the Kalman filter) and the relation between two iteration of the variable to estimate (i.e. the F_k matrix). As we rely on Bluetooth Low Energy Beacons, the main observable signal at our disposal is the RSSI received on mobile device, and the relation that links the RF signal to a distance (and therefore to the mobile device position) is the Log-distance path model mentioned in section 2.1. This obviously is not a linear model thus the Kalman Filter cannot be used in this context. We could use the Extended Kalman Filter or the Unscented Kalman Filter but they are only first and second order estimations respectively.

The Particle Filters, or Sequential Monte Carlo belong to the genetic type branch of Monte Carlo methods and handle non-linear system. Like the Kalman Filter, when using a Particle Filter we need to define the state transition equation f() as well as the observation equation g() but there are no requirements on their linearity. The other parameters involved are only the set of state variable X_t, the state transition noise A_t, the set of measurements Y_t, and the measurement noise N_t. In the Particle Filter, M samples (called particles) are initialized at time t=0 with an equal weight $\{w_0^{(m)} = \frac{1}{M}\}_{m=1}^{M}$ and a random state variable, then each of them is propagated through the state space according to the state transition equation f() :

$$\{x_t^{(m)} = f(x_{t-1}^{(m)} - a_t^{(m)})\}_{m=1}^{M}.$$

After a new measurement has been observed, the particle set is updated, meaning the weight of each particle is calculated using the observation equation g() which is also called the "measurement likelihood function".

In several previous works, the fusion of inertial sensors like the accelerometer and gyroscope of an external device [18] combined with other observations like Wifi signals [18], [19], ultrasounds or infrared [20] have been tested using the particle filter. These solutions, however, only resulted in medium to low accuracy while requiring the processing of several thousands of particles, most often in large buildings with few-to-no open spaces or requiring extra devices to lower the number of particle used. [18], [21] addressed the question of the particle number by proposing a graphed-based solution in order to reduce the degree of freedom the user can move thanks to the map information. This led to some improvements in the calculation process, reducing the number of particles by a factor of 10 but achieving the same accuracy, at the cost of constraining the user movements. That constraint was not such a problem in their experiment as they were testing the model in a building mostly made of corridors but this solution could not be applied in an open space.

3 Proposed Approach

In this section we will explain the unitary models used as part of the fusion particle filter implementation: The inertial model - also called Pedestrian Dead Reckoning (PDR) - The Fingerprinting radio map constructed with Bluetooth Low Energy beacons and its associated weighted k-nearest neighbor algorithm and finally how they fused together into a particle filter

3.1 Inertial Model

In this experiment, we aim at providing a mobile indoor positioning solution that does not require any other external or wearable device other than the beacon infrastructure to provide more information to the system. For this reason, we are going to use the inertial sensors present in all Smartphones currently available, which are a 3-axis accelerometer that measures the accelerations that affect the device, a 3-axis Gyroscope that measure the relative orientation of the user and a 3-axis Magnetometer that determines the heading of the device towards the True or Magnetic North.

To estimate a distance spanned by the user from device-based measurements, we must doubly-

integrate the accelerations that device senses, which is drift-prone in medium-to-long time intervals. This is a result of several factors: device sensitivity, noise induced by the user due to moving the device, and the double integration required to transform acceleration into position. To avoid the cumulative error that could arise and ruin the accuracy of the system, we combine this measurement with the gyroscope measurements and the magnetometer. The latter senses the magnetic fields and is thus very sensitive to other magnetic sources around it which could cause interference. We use this sensor first to initialize the orientation of the device and secondly to correct the drift caused by the double integration of the gyroscope readings to determine accurately the heading of the mobile device.

We can formulate the position of the user at time t with the following equation:

$$\begin{cases} x_t = x_{t-1} + d_t * cos\theta_t + v_t \\ y_t = y_{t-1} + d_t * sin\theta_t + v_t \end{cases} \quad (1)$$

Here, d_t is the distance travelled between time t-1 and t, $\boldsymbol{\theta}_t$ the orientation of the user between time t-1 and t and v_t a Gaussian white noise with zero mean and known standard deviation.

Unlike most of the related work related to PDR, we do not rely on step detection to estimate the distance because in the case of a hand-held device, the step detection would fail with the lack of significant accelerations peaks. Moreover each person is unique and has a different step stride that would need to be either estimated, or calculated with another filter like the Kalman Filter, which would ultimately add unnecessary processing overhead. We would rather use the double integration method and use BLE information to reset the drift caused by this method as the device is anchored. Furthermore, we can strongly assume the mobile device is placed under a Bluetooth beacon.

3.2 Bluetooth Low Energy Model

As in all traditional Fingerprinting-based systems, a radio map is created. Here we propose to associate the Cartesian coordinates of the location fingerprint with an array filled with Θ vectors of N RSSI values corresponding to the N beacons deployed in the area. The number Θ here is used to inject diversity into the database and thus compensate for the multipath effects of the RF signal. Indeed in an indoor environment the signal coming from a given beacon should flow all across the area and hit the mobile device in a line of sight manner (LOS). But as a radio frequency signal bounces on obstacles, it can reach the same mobile devices after a random number of bounces and with an attenuated RSSI. In a similar way, a signal flowing through something as common as a human body will reach the mobile device attenuated by several dB. The diversity introduced in the database is made by collecting the N RSSI values of the beacons with Θ different orientations.

Once the database is created, the online phase consists of a real time observation of the radio environment and a comparison over the training set. We apply a K nearest neighbors algorithm based on a simple Euclidean distance to find the best location fingerprint (LF):

$$Euc^i = \sqrt{\sum_{n=1}^{N}(RSSI_n^i - RSSI_n)^2}, i \in [1..M] \quad (2)$$

In this equation, M represents the number of entries in the database.

In case of a missing $RSSI_n$ or $RSSI_n^i$ value, due to infrastructure noise during either the radio-map construction or the on-line phase, we decided to consider such a missing value as the sensitivity limit of the Bluetooth chip used in the Smartphone. Most Bluetooth chips of current Smartphones have sensitivity approaching -100dB, which is why we choose a limit of -99dB (see section 4 for further explanation).

3.3 Fusion Particle Filter

We break up our particle filter into one initialization step and four loop steps that are Prediction, Correction, Re-Sampling and Estimation.

In order to avoid injecting a bias we choose an initial uniform sampling of the particles across the state space, but such a method would slow down convergence. Because we can have an a priori estimation of the mobile device position on the state space with the Beacons radio frames we decided to sample all the particles following a Gaussian distribution over this first estimated position. Two cases arise for this setup: The first corresponds to when the mobile device is right under a Beacon, and in this case we 'anchor' it by setting its position to the beacon's location. In the second case, when no strong signal has been detected, we set the mobile device's position to an initial Fingerprinting estimation.

We then predict the user location based on the inertial measurements sensed by the Smartphones. Each particle's position is updated using (1) where v_t is random for each one of them.

Correction is what comes after with the likelihood calculation of the particle's position given the observations made by the Smartphones and the Bluetooth Low Energy Fingerprinting database. The following algorithm describes the calculation that is performed for each particle p ∈ [1..P]:

For each visible AP_n, n∈ [1..N]
For each close LF_j, j∈ [1..K]
Calculate $n_{AP_n}^{LF_j} = \frac{(RSSI_{AP_n}^{LF_j} - PN)}{-10*log\,(d_{AP_n}^{LF_j})}$
End For.
Calculate $n_{AP_n} = \frac{1}{K}\sum_{j=1}^{K} n_{AP_n}^{LF_j}$.
Calculate $RSSI^p = -10 * n_{AP_n} * \log(d_{AP_n}^p) + PN$.
End For.

We now have a set of simulated RSSI for each particle that we can compare to the observed set. The Euclidean distance Euc^p is calculated between the observed set and the simulated set which yields the new weight for the particle:

$$w_t^p = w_{t-1}^p * \frac{1}{Euc^p}. \quad (3)$$

Finally, all the weights are normalized following:

$$\overline{w_t^p} = \frac{w_t^p}{\sum_{p=1}^{P} w_t^p}. \quad (4)$$

Before the estimation takes place, we need to identify the number of particles that genuinely participate in the position estimation based on their weights. If too many particles have a negligible weight the filter is considered as degenerating and a resampling must be done. Indeed, because this process is recursive, after multiple iterations some weight may become unimportant and can cause a severe lack of diversity resulting in only few particles with high weight. The key indicator of this phenomenon is the effective sample size that we calculate as follows:

$$Neff_t = \frac{1}{\sum_{p=1}^{P} \overline{w_t^{p^2}}}. \quad (5)$$

Whenever this value falls below a threshold N_{Th} the weak particles are removed and the strong ones are duplicated. For this process we construct the cumulative probability array of the particles, sample randomly P new particles from [0..1] Into a second array, and for each value from this array, find the corresponding particle in the cumulated probability array and set the weight of all the new particles to $w_t^p = \frac{1}{P}$.

At the end of the process the mobile device's position is estimated simply with:

$$S_t = \begin{cases} x_t \\ y_t \end{cases} = \sum_{p=1}^{P} S_t^p * \overline{w_t^p} \quad (6)$$

Here, S_t is the state of the mobile device at time t and S_t^p the state of particle 'p' at time t represented by:

$$S_t^p = \begin{cases} x_t^p \\ y_t^p \end{cases} \quad (7)$$

$\overline{w_t^p}$ represents the normalized weight of particle 'p'

4 EXPERIMENTAL SETUP AND RESULTS

4.1 Setup

The experimental area is represented in Figure 1 with dimensions of 23m by 18m, which represents more than 400m² of complete open space with no walls inside to make the system benefit from tunnel effects that allows it to reduce the degree of freedom the user can move. On the other hand the intrinsic configuration of the environment is multipath prone, so the tests will reflect the performance in a noisy environment. Moreover as we will see in the results the noise was also brought by some of the 6 beacons that compose the BLE infrastructure.
Figure 2 represents a beacon from Kontakt.io that compose the BLE infrastructure and their disposition is shown in blue on Figure 1

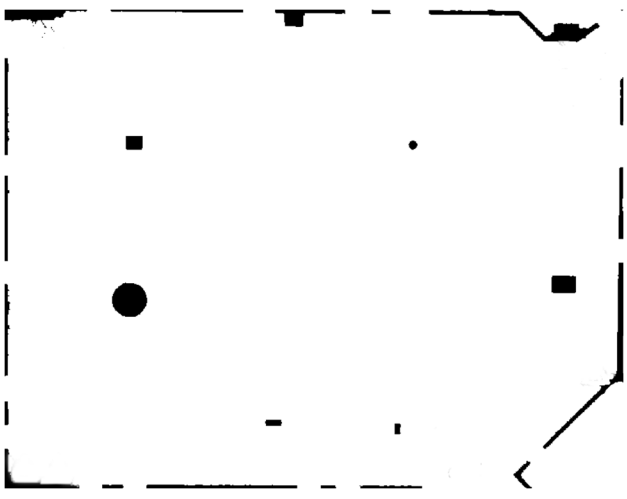

Fig. 1. Test Area

Fig. 2. Beacon Kontakt.io

The software was developed on IOS (version 8) and the Smartphone used throughout the experiment was an iPhone 6+. The mobile application looks for the beacons associated with the current environment using Kontakt.io web services, which ensures a quick and simple deployment and app configuration for additional places. For the entirety of the experiment, the Smartphone is considered to be hand-held and other orientations are currently a work in progress to further improve the robustness and usability of the system.

The Particle Filter outputs estimated position at a configurable frequency selected to 1Hz here and the number of particles selected is 100. The value of K in the Fingerprinting Model is commonly selected as the square root of the number of fingerprints. Considering about 45 Location Fingerprint, each with 8 measurements corresponding to 8 different orientations, we chose a value of 5 for K that is little less than the exact square root because of the low density of the LF constituting the radio map.

4.2 Teoretical Analysis

In this section, we discuss the time complexity of the proposed algorithm. Let us first express some basic variable definitions.

- $\boldsymbol{S}$ is the test Area in m² (414m² in this experiment)
- LF is the maximum number of Location Fingerprints (45 in this experiment). This value is related to the test area and should be equal to $\boldsymbol{S} * c_1, c_1 \in]0..1]$
- N is the maximum number of Access Points (6 in this experiment). This value is also dependant on the test area and is equal to $\boldsymbol{S} * c_2, c_2 \in]0..1]$ and $c_2 < c_1$
- M is the maximum number of database fingerprints (360 in this experiment). Each LF has been measured 8 times corresponding to 8 different heading orientations such as Nort, North-East, East, South-East, South, South-West, West and North-West. This value is also dependant on the test area and is equal to $\boldsymbol{S} * c_3, c_3 = 8 * c_1$
- K is the value for the K-NN algorithm (5 in this experiment). This value should usually be chosen as the closest integer to $\sqrt{LF}$
- P is the maximum number of particles for the Particle Filter algorithm (100 in this experiment). This value is one of the set-by-design variables of our proposed approach.

The time complexity is, in the worst-case scenario, the combined time complexity of the init step and the four run steps: Initialization, Prediction, Correction, Re-Sampling, Estimation. At start, the algorithm scans for every Access Points in range, N in the worst case, and if no access point can be designated as an anchor, a Fingerprint estimation is performed. The complexity for the scan is as $\Theta(N)$ and the complexity for the Fingerprinting estimation is $\Theta(M * (K + N))$. Thus, the time complexity for the initialization step is

$$C_{INIT} = \Theta(N) + \Theta\big(M * (K + N)\big)$$
$$C_{INIT} = \Theta(\boldsymbol{S} * c_2) + \Theta\big(c_4 * \boldsymbol{S} * \sqrt{\boldsymbol{S}} + c_5 * \boldsymbol{S}^2\big)$$
$$C_{INIT} = \Theta(\boldsymbol{S}^2), with\ c_4 = c_1 * c_3\ and\ c_5 = c_2 * c_3$$

The Prediction step has a complexity of:

$$C_{PRED} = \Theta(P * K) = \Theta(P * \sqrt{\boldsymbol{S}})$$

The Correction step simulates for every particle the RSSI at the particles's position given the Access Points in range and the K nearest Fingerprints of the particle's position. In the worst-case this results in a time complexity of:

$$C_{CORR} = \Theta(\mathrm{P} * \mathrm{N} * \mathrm{K}) = \Theta(\mathrm{P} * \sqrt{c_1 * \boldsymbol{S}} * c_2 * \boldsymbol{S})$$
$$C_{CORR} = \Theta(P * \boldsymbol{S} * \sqrt{\boldsymbol{S}})$$

During resampling, the creation of the cumulative probability array has a complexity of $\Theta(P)$, the creation of the index array in the worst case needs to go through both arrays and thus the time complexity is as $\Theta(P^2)$ and finally the creation of the new particle array is as $\Theta(P)$. This results in a Resampling time complexity of:

$$C_{RESAMP} = \Theta(P) + \Theta(P^2) + \Theta(P) = \Theta(P^2)$$

The estimations process is as equation (6) states the sum of the weighted particles positions.

$$C_{EST} = \Theta(P)$$

To sum this up, the total worst-case complexity of this algorithm is composed of the partial worst-case complexities and is:

$$C_{TOT} = C_{INIT} + C_{PREd} + C_{CORR} + C_{RESAMP} + C_{EST}$$
$$C_{TOT} = \Theta(\boldsymbol{S}^2) + \Theta\big(P * \sqrt{\boldsymbol{S}}\big) + \Theta\big(P * \boldsymbol{S} * \sqrt{\boldsymbol{S}}\big) + \Theta(P^2) + \Theta(P)$$

As we stated in this research, the aim was to keep a Particle number as small as possible and as such a fix number. As the experimental area grows, the term that remains dominant is the initialization complexity $\Theta(\boldsymbol{S}^2)$ and in a run condition where there is no need to re-initialize the algorithm, the final complexity is $\Theta\big(P * \sqrt{\boldsymbol{S}}\big) + \Theta\big(P * \boldsymbol{S} * \sqrt{\boldsymbol{S}}\big) + \Theta(P^2) + \Theta(P)$. In practice, this complexity is even further reduced as $\Theta(P^2)$ is only present when resampling which is not the nominal case.

Moreover, as the proposed approached aimed at providing a mobile only solution, the number of beacons that can be scanned by a Smartphone at any time is really small. Indeed, as a design, the beacons are chosen to be one for 100 square meters and the effective line of sight of the beacon radio message doesn't exceed few tens of meters in range. Thus said, the number of concurrent beacons scanned won't exceed 10 even if the test area covers thousands of square

meters which implies that the complexity will be not more than $\Theta(P * \sqrt{S}) = \Theta(\sqrt{S})$ as P becomes negligible in front of S.

4.3 Results

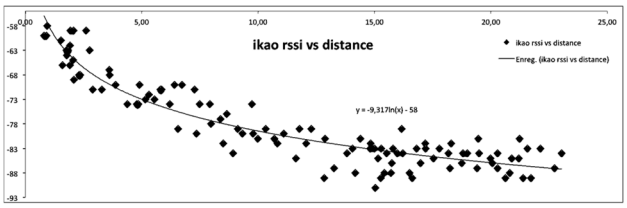

Fig. 3. Path loss model of beacon 1

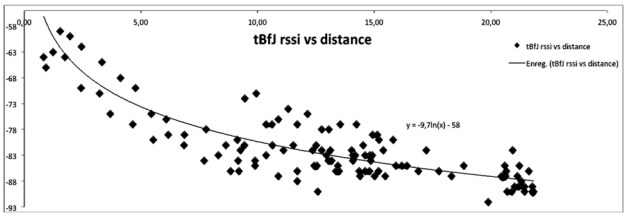

Fig. 4. Path loss model of beacon 2

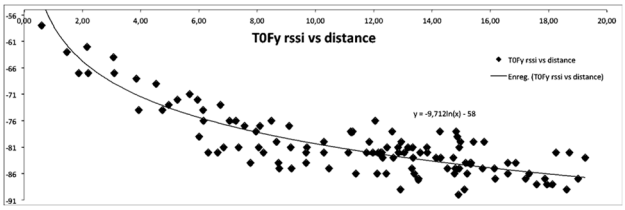

Fig. 5. Path loss model of beacon 3

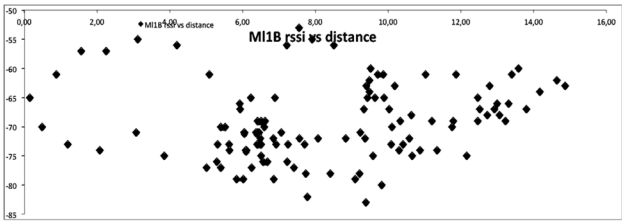

Fig. 6. Path loss model of beacon 4

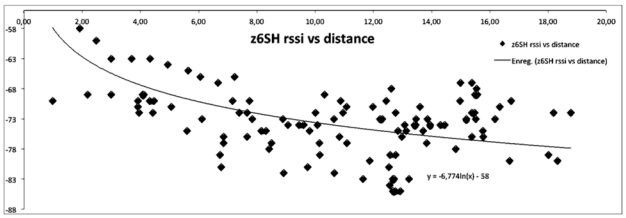

Fig. 7 Path loss model of beacon 5

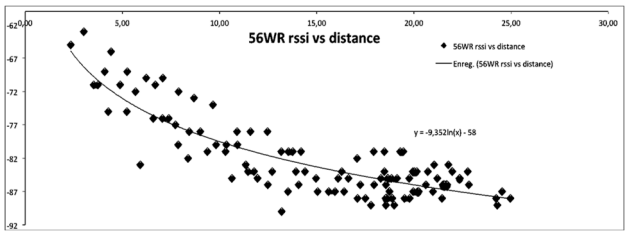

Fig. 8 Path loss model of beacon 6

As we can see from Fig. 3 to 8, the propagation of the beacon's radio signal across the test area follows nicely the path loss model with a path loss coefficient n close to 2.2, which defines a quasi-clear propagation. Nonetheless, two beacons outstand from this model as one completely ignores it and the other follows it with a high spread. The reason for this behavior is easily explainable by the infrastructure of the beacons. Indeed the two-centermost beacons are not placed in the same orientation as the others, causing significant perturbations.

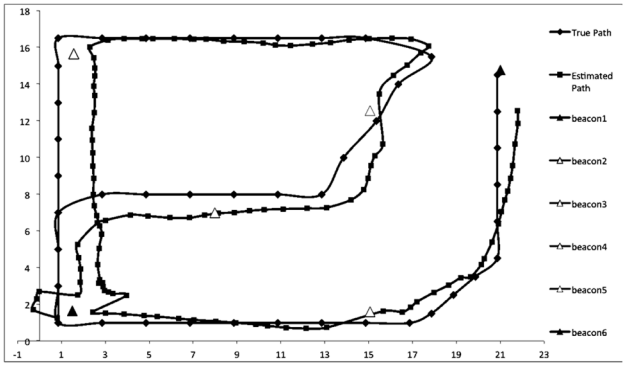

Fig. 9. Trajectories of True and Estimated path of the proposed approach

From Fig. 9 we can see that our method of particle filter aided by inertial measurements and enhanced with a BLE infrastructure can accurately position a mobile device in a wide-open space with as little as 100 particles and as few as 1 fingerprint for 10m^2. Our anchor system also helps in staying close to the true path by readjusting the estimation as we see it on Fig. 9 near the beacons positions.

"The tests were performed in this open-space area were allowed by the direction of the company this experiment was conducted by, and as a confidential R&D study, this was the only available test area at our disposal. Moreover, this space was used as a workplace for other employees and the degree of freedom that was given to us to test the proposed approach, without disturbing the ongoing work of everyone else, was hence limited".

The method used to estimate the error of our proposed Indoor localization system is the root mean square error or RMSE which was computed over all the iterations of the particle filter when a comparison to a true position was available. The accuracy of our system is 1.4m in this experiment

5 CONCLUSION AND FUTURE WORK

Throughout this experiment, we proved that a high accuracy indoor localization system is feasible only relying

on a Smartphone capability and with a simple and cost-efficient deployment of a Beacon infrastructure.

The proposed approach as we just saw, allows a real time Indoor Positioning System to be ran on any Smartphone available on the market and without the need for a 4G cellular connection which would be impossible to ensure in a place such as a Convention Center. Finally, we are able to provide this solution, and have it run on any Smartphones thanks to the reduced time complexity of the proposed approach.

Indeed, we managed such a solution to be viable by leveraging the Fingerprinting algorithm with a Fusion of Motion sensors from the Smartphone and a Particle Filter Algorithm of our own that reduced the run complexity of the process from $\Theta(S^2)$ that can become rapidly huge in wider areas, to $\Theta(\sqrt{S})$.

There are a lot of reflections on our system that could lead to accuracy improvements. The most recent work in progress is in regards to mobile device orientation, which could provide a better estimation of the travelled distance between iterations. The 'anchor' system also could be improved as we can observe on the first iterations on Fig. 9; the readjustment was along the X-axis whereas the movement was along the Y-axis. The two aforementioned beacons at the center of the area that are not well placed and inject too much noise in the system could also be removed, gaining 1/3 less infrastructure cost as a side effect. The map information of the building could also be used even if in the case of such an open space it would not greatly improve the performance of the system. However, as we transition from one open space to another, or when the user enters different rooms, walls and doors will give information on path that otherwise couldn't be inferred.

The main disadvantage of the proposed solution still remains the initial procedure to build the radio map that is used in the Fingerprinting algorithm. Such a procedure requires a manual construction of the map by scanning in every 8 directions for each Location Fingerprint LF of the test Area.

This drawback is to be addressed in future work where we plan to simulate the initial radio-map to get rid of the manual process and then correct it with all the data collected during run time by the Smartphones. Indeed, the Feature of gathering the data and sending it to a dedicated server afterwards for analytics is already implemented in the mobile application.

Finally, the overall system that is currently only running on a Smartphone could benefit from server-sided work to analyze the entire inputs and outputs that several devices processes in order to find corrections to apply to the initial radio-map for instance or the most frequent path.

The described system is an intelligent fusion of a particle filter, motion sensors and a fingerprint radio map that enables precise real time location in a wide indoor area, but the expected performances are however limited by the following factors. The granularity of the constructed radio map and its accuracy mostly depend on the comprehensiveness of the gathered data and the situation during measurement. Indeed, a measurement in an empty space would not reflect exactly a crowded environment.

This is however the main purpose of this study, to leverage the fingerprint by reducing the impact of the inaccuracy of a radio map with motion sensors and a particle filter fusion. In this situation the main limitation is the said motion sensors and the distance estimation as the mobile device can be held in a multitude of positions often changing orientation by being used and stowed regularly by the user.

The impact of this parameter is taken into account in this paper as a white noise injected in the inertial model and is further used by the particle filter. In fact, the crucial point is the deviation that this white noise can cause. But at the same time, it is also feeding the particle filter with a wider diversity of particles positions which is also an important criterion for this filter.

As a last limitation, the overall performance can be achieved after everything is processed and movements are being computed which bring us to the case of a user only using the system sporadically. In this situation the performance would be limited by the precision of the radio map enhanced by the anchor feature and would be tightly linked to the quality of the signals received from the beacons.

All in all, the random parameters in use in our system are tied to the inertial model and we manage to somehow reduce the importance of this limitation by having the particle filter as the last layer that handles it as well as the variability of the received signals from the beacons.

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REFERENCES

[1] N. Priyantha, A. Chakraborty and H. Balakrishnan, "The Cricket location-support system", in international conference on Mobile computing and networking, 2000, pp. 32-43.

[2] R. Want, A. Hopper, V. Falcão and J. Gibbons, "The active badge location system", ACM Transactions on Information Systems, vol. 10, no. 1, pp. 91-102, 1992.

[3] A. Ward, A. Jones and A. Hopper, "A new location technique for the active office", IEEE Personal Communications, vol. 4,

no. 5, pp. 42-47, 1997.

[4] P. Bahl and V. Padmanabhan, "RADAR: An in-building RF-based user location and tracking system", in INFOCOM 2000. Nineteenth Annual Joint Conference of the IEEE Computer and Communications Societies. Proceedings. IEEE, Vol. 2, Tel Aviv, 2000, pp. 775-784.

[5] M. Youssef and A. Agrawala, "Continuous space estimation for WLAN location determination systems", in Computer Communications and Networks, 2004. ICCCN 2004. Proceedings. 13th International Conference on, Chicago, IL, USA, 2004, pp. 161-166.

[6] L. Pei, R. Chen, J. Liu, T. Tenhunen, H. Kuusniemi and Y. Chen, "Inquiry-based bluetooth indoor positioning via rssi probability distributions", in Advances in Satellite and Space Communications (SPACOMM), 2010 Second International Conference on, Athens, Greece, 2010, pp. 151-156.

[7] C. Zhang, M. Kuhn, B. Merkl, A.E. Fathy and M. Mahfouz, "Accurate UWB indoor localization system utilizing time difference of arrival approach", in Radio and Wireless Symposium, 2006 IEEE, San Diego, CA, USA, 2006, pp. 515-518.

[8] L. Ni, Y. Liu, Y. Lau and A. Patil, "LANDMARC: Indoor Location Sensing Using Active RFID", Wireless Networks, vol. 10, no. 6, pp. 701-710, 2004.

[9] M. Azizyan, I. Constandache and R. Choudhury, "SurroundSense: mobile phone localization via ambience fingerprinting", in international conference on Mobile computing and networking, Beijing, China, 2009, pp. 261-272.

[10] Y. Chen, D. Lymberopoulos, J. Liu and B. Priyantha, "FM-based indoor localization", in international conference on Mobile systems, applications, and services, Low Wood Bay, Lake District, UK, 2012, pp. 169-182.

[11] M. Beigl, S. Intille, J. Rekimoto and H. Tokuda, "Accurate GSM indoor localization", in International Conference on Ubiquitous Computing, Tokyo, Japan, 2005, p. 903.

[12] G. Berkovich, "Accurate and reliable real-time indoor positioning on commercial smartphones", in Indoor Positioning and Indoor Navigation (IPIN), 2014 International Conference on, Busan, South Korea, 2014, pp. 670-677.

[13] D. Vandermeulen, C. Vercauteren and M. Weyn, "Indoor localization using a magnetic flux density map of a building", in The Third International Conference on Ambient Computing, Applications, Services and Technologies, Porto, Portugal, 2013, pp. 42-49.

[14] R. Heydon, Bluetooth low energy: the developer's handbook. Upper Saddle River N.J.: Prentice Hall, 2013.

[15] R. Faragher and R. Harle, "Location Fingerprinting With Bluetooth Low Energy Beacons", IEEE Journal on Selected Areas in Communications, vol. 33, no. 11, pp. 2418-2428, 2015.

[16] P. Martin, B. Ho, N. Grupen, S. Muñoz and M. Srivastava, "An iBeacon primer for indoor localization: demo abstract", in Proceedings of the 1st ACM Conference on Embedded Systems for Energy-Efficient Buildings, Memphis, Tennessee, USA, 2014, pp. 190-191.

[17] H. Zou, X. Lu, H. Jiang and L. Xie, "A Fast and Precise Indoor Localization Algorithm Based on an Online Sequential Extreme Learning Machine", Sensors, vol. 15, no. 1, pp. 1804-1824, 2015.

[18] O. Woodman and R. Harle, "Pedestrian localisation for indoor environments", in UbiComp '08 Proceedings of the 10th international conference on Ubiquitous computing, Seoul, Korea, 2008, pp. 114-123.

[19] F. Li, C. Zhao, G. Ding, J. Gong, C. Liu and F. Zhao, "A reliable and accurate indoor localization method using phone inertial sensors", in UbiComp '12 Proceedings of the 2012 ACM Conference on Ubiquitous Computing, Pittsburgh, Pennsylvania, USA, 2012, pp. 421-430.

[20] N. Davies, E.D. Mynatt and I. Siio, "Particle filters for location estimation in ubiquitous computing: A case study", in 6th International Conference, Nottingham, UK, September 7-10, 2004. Proceedings, Nottingham, UK, 2004, pp. 88-106.

[21] S. Hilsenbeck, D. Bobkov, G. Schroth, R. Huitl and E. Steinbach, "Graph-based data fusion of pedometer and WiFi measurements for mobile indoor positioning", in UbiComp '14 Proceedings of the 2014 ACM International Joint Conference on Pervasive and Ubiquitous Computing, Seattle, Washington, USA, 2017, pp. 147-158.

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methods and their applications in various fields of IT engineering, Security, Communication, Internet of things.