Improving positioning capabilities for indoor environments with WiFi

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***Abstract*— A framework for positioning and tracking problems in indoor environments using particle filters has been developed and applied to a WLAN location determination technique. The use of Kalman filter or particle filtering represents an interesting way to handle the variations of the signal strength measurements. The second one, being more generic, can also aggregate in a simple way different information like signal strength and the map of a building. This type of information is very useful to obtain correct trajectories without wall-crossings. In this paper, Kalman filter and particle filter are presented, with their performances in indoor environments by combining WLAN signal strength and fingerprinting.**

I. INTRODUCTION

Mobile positioning becomes increasingly an interest for many applications. Many techniques are available to deliver a user his position. If so many positioning techniques exist, it is mainly due to the heterogeneous situations in which the service must be available, and the needs of the users. The European project LIAISON [1] will turn emergent technologies, applications and services into actual business cases in order to allow key European actors to fulfil in a competitive manner the needs of workers in their daily life, for seamless and personalised location services across heterogeneous network. However each positioning technology has its own weaknesses. Fusing all those techniques should lead to no area uncovered by a position service.

Unlike open environments, where high location accuracy can be achieved, indoors settings pose a special challenge for location technologies. Some reports note that even some outdoor areas may hamper GPS positioning (presence of dense foliage or urban canyons). Moreover, locations, such as large commercial,residential buildings, subways or malls, may be difficult or even impossible to cover with traditional wide area location technologies such as AGPS and TDOA. Even if these technologies may provide location fixes in some indoor environments, they do not address 3-dimensional positioning, which is required for pinpointing location in multi-story buildings.

Some other solutions exist but their deployment cost may be significant to cover little area. 802.11b WLAN networks which have begun to take root in residential homes as well as in many public and commercial areas, could potentially provide a solution for local positioning. Such a solution has been proposed to the FCC to improve the ability to locate indoors-wireless E911 callers [2], [3].

Several research systems determine a person's location from signal quality measurements of IEEE 802.11b wireless networking. The RADAR system [4] uses multilateration and pre-computed signal strength maps for this purpose. Accuracy depends on the number of positions registered in the database. However, signal strength fluctuate wildly, and in some cases disappear altogether. Those signal fluctuations over time introduce errors and discontinuities in the user's trajectory.

To minimize the fluctuations of the received signal strength (RSS), some filtering is needed. A simple temporal averaging filter does not give satisfying results. Kalman filtering [5], [6] is commonly used in automatic control to track the trajectory of a target.

However, more information can be available. The map of the building is another one that can be useful to help the filter to deliver a better positioning (like remaining in the corridor for example). Introducing such information in the Kalman filter is not easy. Particle filters [7], [8], [9], based on Monte-Carlo simulations, are interesting tools to solve the problems of position estimation. Though, these techniques seem interesting and merit further study, their complexity may impede their implementation on handheld devices whose processing capabilities are limited.

The main contribution of our paper is to investigate the performances that can be achieved in term of accuracy of the position estimation with a WiFi positioning system. Different filtering techniques will be presented and evaluated.

II. BASIC WIFI POSITIONING

Today, off-the-shelf WiFi equipments are everywhere. In comparison with traditional systems like GPS, WiFi does not propose any timing information describing the ranges between the receiver and the access points. However, access points emit periodically some beacons to allow the mobile device to handle the roaming, and keep the connection with the access point with the best signal to noise ratio. Thus measuring the signal strength of those beacons is possible. Given this consideration, it is possible to get a list of the received signal strength coming from all the Access Points that cover the area where the mobile is, and use them to determine the position of the mobile.

A. Signal Strength and Motley-Keenan Propagation model

A convenient way to handle those information would be to turn the signal strength into ranges like in the GPS system. Propagation models can be convenient tools as they allow determining the received signal strength given the distance and the propagation that may occur. Motley-Keenan propagation model is often used for its simplicity. This model is presented in [10]. It can be modeled by:

$$P_{received}(d) = P_{received}(d_0) - 10 \cdot \alpha \cdot \log\left(\frac{d}{d_0}\right)$$

with $P_{received}(d)$ the signal strength received by the mobile at the distance d, $P_{received}(d_0)$ the signal strength received

at the known distance d_0 from the access point, and α a coefficient characterizing the propagation in the environment. For example in Free Path Loss environment (in the Fresnel ellipsoid), we have $\alpha = 2$. In indoor environments, this factor will be closer to 3. For indoor environments, this parameter needs to be tuned, as it may vary according to the structure of the building. This parameter is rather important as it may significantly change the estimation of the distance.
This model is presented here in its simplest form, but introducing some wall attenuation factors is possible [11], but some more information is needed to describe more closely the environment (permittivity and permeability of the materials composing the building). Once the ranges are estimated, it is possible to process the position of the mobile with a multilateration algorithm.
Further investigations showed that combining the errors coming from the range estimation using this simple propagation model, with a multi-lateration algorithm, leads to a poor positioning.

B. Signal Strength and Fingerprinting

Fingerprinting positioning is a quite different technique. It consists in having some signal strength footprints or signatures that characterize the WiFi radio coverage at different positions in the environment. These signatures are made of the received signal strength from different access points that can be collected at those positions in the environment.
The Motley-Keenan model showed that the received powers change regarding to the distance separating the access points from the mobile and the propagation. Fig. 1 ,based on real measurements, illustrates this phenomenon. Thus, overlapping the information of different power coverage maps shows that it is possible to find a unique position when a tuples of signal strength is received. The access points are represented on the maps with the green star.
Power maps are an alternative to the Motley-Keenan propagation model. They allow transforming some tuples belonging to the received signal strength space, into positions belonging to metric space
This database is convenient because it really takes into account the local complex propagation, as it is built with real measurements.
Thanks to the reverse operation, given a tuples of received signal strength, it is possible to find the received signal strength tuples in the database that match the instantaneous one received. Different algorithms can be used to achieve this operation. The closest neighbor algorithm or k closest neighbors algorithm [4] can be used. They consist in searching in the database either the closest neighbor or the k closest neighbors given the following criterion:

$$X = \underset{x_k, y_k}{argmin} \left(\sum_{l=1}^{N} \left(P_{r_l}(x, y) - P_{r_l}(x_k, y_k) \right)^2 \right)$$

with "l" representing the index over the received APs, and $(x_k,\ y_k)$ the positions referenced in the database.
A probabilistic approach exists too [12], [13], but it will not be described in this paper.

C. The limitations of this technique

This method suffers from the fluctuations of the received signal strength. Indeed, the signal strength fluctuates over the time due to the non stationarity of the channel and the RF impairments. Fig. 2 presents some measurements recorded over 2 hours for two positions in the building. Those fluctuations also have an impact on the fingerprinting method. In dense database, those signal strength fluctuations will induce the closest neighbor algorithm to continuously choose a different position for the user even if he is not moving. This may be striking for the user. The delivered position could be in the vicinity of the real position (within 2 to 3 metres or even worse if the signal strength are greatly different from the recorded mean values), so reducing the effect of those instantaneous fluctuations is necessary to improve this rough positioning.

III. The Kalman filter

The Kalman filter is often used in many automatic control problems [5], [6]. It implements a predictor-estimator type estimator that is optimal in the sense that it minimizes the estimated error covariance when some presumed conditions are met. The problem can be modeled by the following linear state-space models, where Eq. 1 is the typical process model that models the transformation of the process state.

$$x_k = A \cdot x_{k-1} + \omega_k \qquad (1)$$

where matrix $A \in \mathbb{R}_{n \times n}$ represents the relationship between the previous position and the predicted position of the mobile. This matrix can change at each step but here it will be considered as constant. The move of the mobile can be modeled by $p_t = p_0 + v_0 \cdot t$. Thus the matrix A can be expressed as follow:

$$A = \begin{bmatrix} I & T \cdot I \\ 0 & I \end{bmatrix}$$

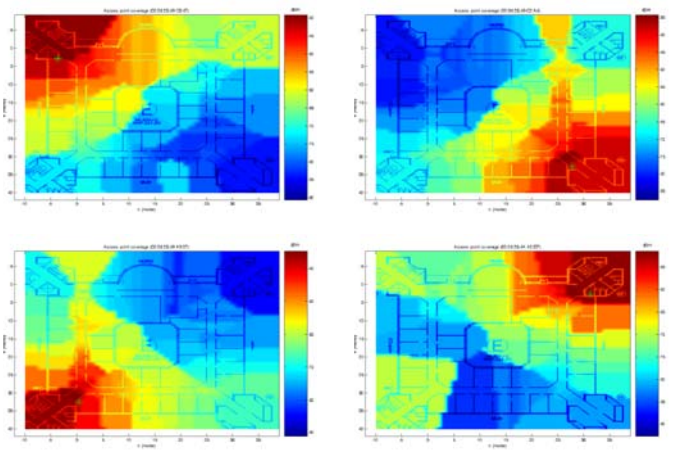


Fig. 1. Access points coverage

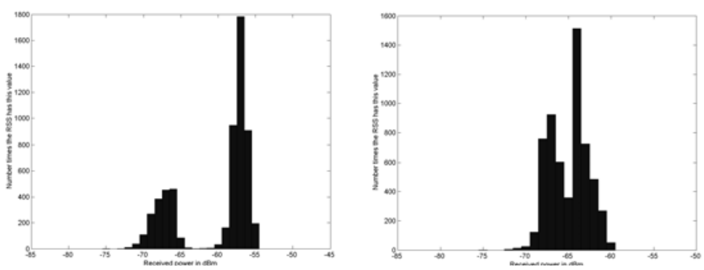


Fig. 2. Signal fluctuations over the time

where I is the identity matrix and T the time between two signal strength measurements. This last equation represents the prediction stage of the filter. This predicted position is then corrected when a measurement is available. The measurement model that describes the relationship between the process state and the measurements can be represented with the following linear expression:

$$z_k = H \cdot x_k + \nu_k$$

where z_k is the position returned by the closest neighbor algorithm for the received signal strength measurement. The following matrix H was chosen to model this relationship:

$$H = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \end{bmatrix}$$

In those equations, x_k is the state vector of the mobile and is defined by $x_k = [X \ Y \ V_X \ V_Y]^T$. ω_k and ν_k are random variables representing the process and measurement noises. The Kalman filter leads to the attenuation of the leap-frog phenomenon but it cannot avoid that the mobile crosses the walls all the time what is quite disturbing when the final trajectory is observed. To reduce this phenomenon, another information is needed. A map of the building is then required but introducing such an information in this Kalman filter doesn't not seem easy. The particle filter seems to be more adapted for taking into account this map information.

IV. Particle filter and positioning

Nowadays, the maps of all the public or company buildings are available in digital format. The key idea is to combine the motion model of a person and the map information in a filter in order to obtain a more realistic trajectory and a smaller error for a trip around the building. In the following, it will be considered that the map, which is available, is a bitmap. So no information is available except the pixels in black and white that model the structure of the building. The particle filter represents the density function of the mobile-position by a set of random samples with associated weights (i.e. a particle). Each particle explores the environment according to the motion model and map-information. Their weights are updated each time a new measurement is received. It is possible to forbid some moves like crossing the walls by forcing the weight at 0 for the particles having such a behavior.

The particle filter tries to estimate the probability distribution $Pr\left[x_k|z_{0:k}\right]$ where x_k is the state vector of the device at the time step k, and $z_{0:k}$ is the set of collected measurements until the $(k+1)^{th}$ measurement. When the number of particles $\left(\text{position } x_k^i, \text{weight } w_k^i\right)$ is high, the probability density function can be assimilated to:

$$Pr\left[x_k|z_{0:k}\right] = \sum_{i=1}^{N_s} w_k^i \delta\left(x_k - x_k^i\right)$$

This filter comprises two steps:

- Prediction
- Correction

A. Prediction

During this step, the particles propagate across the building given an evolution law that assigns a new position for each particle with an acceleration governed by a random process:

$$\begin{bmatrix} x_{k+1} \\ y_{k+1} \\ V_{x_{k+1}} \\ V_{x_{k+1}} \end{bmatrix} = \begin{bmatrix} 1 & 0 & T_s & 0 \\ 0 & 1 & 0 & T_s \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} x_k \\ y_k \\ V_{x_k} \\ V_{x_k} \end{bmatrix} + \begin{bmatrix} \frac{T_s^2}{2} & 0 & 0 & 0 \\ 0 & \frac{T_s^2}{2} & 0 & 0 \\ 0 & 0 & T_s & 0 \\ 0 & 0 & 0 & T_s \end{bmatrix} \begin{bmatrix} \nu_{x_k} \\ \nu_{y_k} \\ \nu_{x_k} \\ \nu_{y_k} \end{bmatrix}$$

where $[x_k, y_k, V_{x_k}, V_{y_k}]^T$ denotes the state vector associated to each particle (position and speed), T_s the elapsed time between the $(k-1)^{th}$ and the k^{th} measurements. $[\nu_{x_k}, \nu_{y_k}, \nu_{x_k}, \nu_{y_k}]^T$ is a random process that simulates the acceleration of the k^{th} particle. This last equation is often called the prior equation. It tries to predict a new position for all the particles. Here the used process is a zero mean Gaussian noise with a 0.1 m/s^2 variance which is a realistic model of pedestrian movement.

When the new position of a particle is known, it is possible to include the map information, in order to remove the particles having an impossible move, like crossing a wall. An algorithm, using the previous known position of the particle, its new one, plus the map of the building, checks all the pixels between those positions to see if a wall has been crossed. This processing is time consuming as it must be done for each particle at each time step. When this checking is finished, it is possible to assign a weight $Pr\left[x_k|x_{k-1}\right]$ as follows:

$$Pr\left[x_k|x_{k-1}\right] = \begin{cases} P_m & \text{if a particle crossed a wall} \\ 1 - P_m & \text{if a particle did not cross a wall} \end{cases}$$

As crossing a wall is impossible for a normal user, it has been decided to take $P_m = 0$. Then the particles disappear when they cross a wall. A common problem with the particle filter is the degeneracy phenomenon: after a few iterations, many particles will have a negligible weight. A re-sampling step will occur when the degeneracy is too severe (see IV-D).

B. Correction

When a measurement (tuples of RSS) is available, it must be taken into account to correct the weight of the particles in order to approximate $Pr\left[x_k|z_{0:k}\right]$. As the measurement is signal strength and given that particles are characterized by their position, the RSS tuples is transformed into a position with the technique presented in section II-B. Then it is possible to estimate $Pr\left[z_k|x_k\right]$. In the case of our movement model, the following law has been retained:

$$Pr\left[z_k|x_k\right] = \frac{1}{\sqrt{2\pi}\sigma} exp\left[-\frac{\left(X_{z_k} - X_{x_k}\right)^2}{2 \cdot \sigma^2}\right]$$

with X_{z_k} the position returned by the database, X_{x_k} the position of the k^{th} particle and σ the measurement confidence. The smaller σ is, the more confident the user is in the measurement. That would mean that there is very little variations in the measurements for the same position. Here, given the variations of the RSS, $\sigma = 5m$ was chosen. Now, all the necessary probabilities to update the weight of a particle are defined. Their combination will lead to find the new posterior distribution.

C. Particle update

The weight update equation is given in [7], [8]:

$$w_k^i = w_{k-1}^i \cdot Pr\left[x_k|x_{k-1}\right] \cdot Pr\left[z_k|x_k\right]$$

To obtain the posterior density function, it is necessary to normalize those weights. After a few iterations, when too many particles crossed a wall, just a few particles will be kept alive (particles with a non zero weight). To avoid having just one remaining particle, a re-sampling step is triggered.

D. Re-sampling

The re-sampling is a critical point for the filter. The basic idea behind the re-sampling step is to move the particles that have a too low weight, in the area of the map where the highest weights are. This leads to a loss of diversity because many samples will be repeated. The criterion to trigger a re-sampling is given by:

$$\frac{1}{\sum_{i=0}^{N_s}\left(w_k^i\right)^2} \leq Threshold$$

Various re-sampling algorithms were proposed. We did not choose the simple SIS (Sequential Importance Sampling) particle filter [7], but the re-sampling approach presented in [14], Regularized Particle Filter (RPF). The RPF adds a regularisation step. This approach is more convenient because it locally introduces a new diversity after the re-sampling. This may be useful in extreme situations when all the particles are trapped in a room whereas the device is still moving along a corridor. This method of re-sampling adds a small noise to the particle position and avoids this phenomenon.

The main stages of the particle filter used in indoor environments have been presented. To run it, 10,000 particles were used. This makes the filter very heavy to process at each time step as every particle must be checked for a wall crossing. Due to the large number of particles, the algorithm is too complex to be implemented on handheld devices. A way to cut down this number of particles is proposed in [15].

V. Experimental results

A. Complexity reduction of the particle filter

This kind of filtering suffers from a main weakness. It is very heavy to be run due to all the processing required to update the particles. Reducing the number of particles to take into account, seems interesting. However cutting down the number of particles will probably degrade the performances of the filter. Indeed, fewer solutions (or area) will be explored and a risk that the remaining particles be trapped in a room is higher if a too low number of particles is used.

Fig. 3 shows some performances obtained depending on the number of particles to use. As it was explained earlier, the particle filter is based on the random move of the particles in the building. This must lead from slightly to very different trajectories at the end of the path, even if the information collected along a path are exploited several times to try to predict the trajectory of the user. To get this last figure, data collected along a path were used to see the impact of the number of particles on the evaluation of the position of the mobile. For each simulation step (choice of a number of particles), the path is predicted 100 times. It becomes possible to plot the cumulative distribution function of the mean errors. It seems that at least 8000 particles are required to achieve some acceptable performances. Moreover, it can be noticed

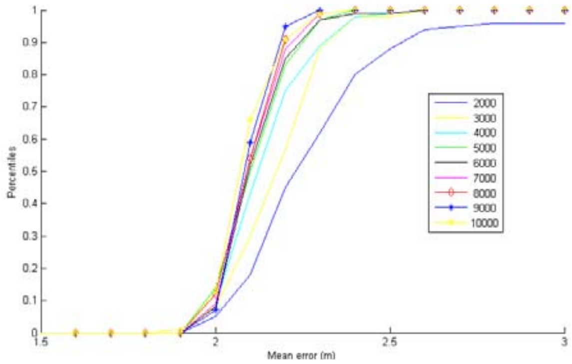


Fig. 3. Study of the influence of the number of particles

that the result of this positioning is not guaranteed. In fact, sometimes, the filter can collapse, mainly because the particles remain trapped in a room.

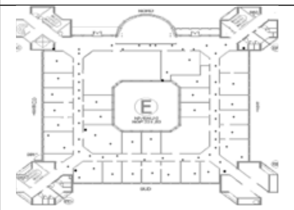
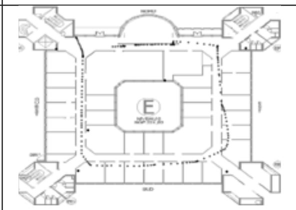
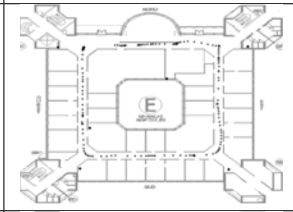
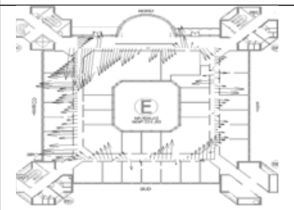
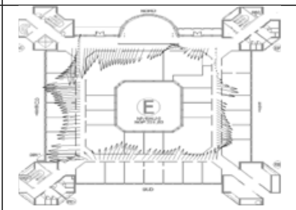
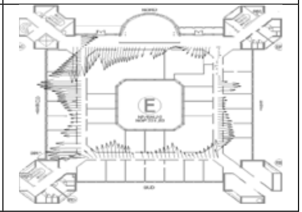
B. Positioning performances evaluation

To experiment with all those techniques and estimate their capabilities and accuracy to localize a device, a demonstrator has been built with a set of four access points placed at each corner of the 35×35 m square building. The mobile device (laptop) is evolving in an indoor office environment. The database is built with one measurement in each room, and a measurement every two meters in the corridor. The single floor problem is considered. The criterion to define the error is the mean error over a trip in the building ($\overline{e(m)}$ in meters). A walk around the building is taken for the test. Some real measurements are collected along this path and then reused to estimate the performances of each technique (Table I).

A large improvement may be noticed when filters are applied. When the database is used without any filtering algorithm, it is impossible to determine the trajectory followed by the device. Moreover many jumps between two measurements are observed. The accuracy with a full database is previously described (Table I). A temporal averaging filter (five samples sliding average) is also used to smooth the variations of the instantaneous received signal strength. The Kalman filter removes that leap-frog phenomenon. It builds a coherent trajectory that the device may have followed. It is easier to guess the path through the building. In comparison with the database method, this leads to a better accuracy: 2.29m for the Kalman filter versus 3.50m for the database localization. As it was seen earlier in this paper, the Kalman filter does not take into account the fact that a device cannot cross a wall. It can be noticed that with the Kalman filter, the user often seems to go through the walls. Those wall crossings are mainly due to the signal strength variations. The particle filter tends to attenuate this effect. This can be noticed by observing the trajectory obtained when this kind of filter is used. Some few wall crossings may still be visible because it has been considered that the delivered position of the device would be the barycentre of all the particles. A drawback of the particle filter is that they are non deterministic. The filter can collapse after a re-sampling step if all the particles are trapped in a part of the building and always bump into a wall after then. Fig. 4 gives more information about the performances of the filters. It provides the cumulative distribution function of the root mean square errors over the trajectory.

TABLE I

COMPARISON OF THE DIFFERENT FILTERS

	Database	Kalman filter	Particle filter
Trajectory			
Error vectors (m)			
$\overline{e(m)}$	3.50	2.29	1.99

It can be noticed that in 80% of the time the performances of the particle filter are better than the Kalman ones. The particle filter seems to give a better positioning. But due to the random part of this filter, the results are different from one simulation to the other. Sometimes, some big errors can be obtained. This means that particles have been trapped in a room, when too many particles explore a wrong part of the building and a resampling was triggered. Those collapsing state can be removed by increasing the number of particles.

VI. CONCLUSIONS

In this paper, we have presented a comparison of different positioning and tracking systems in indoor environment. The use of a particle filter which takes into account the human motion, the map information and the received signal strength, leads to a positioning accuracy of 1.8m. Particle filtering with a good motion model seems to be a good choice to improve the accuracy of a rough position given in our case by the signal strength and the database. Particle filters can easily take into account the environment in which the device is evolving to improve the mobile tracking. It also appears to be a valuabe tool to introduce information coming from several other sensors, like Inertial Navigation Sensors for example. Sensor fusion is probably the next step to bypass this accuracy limit.

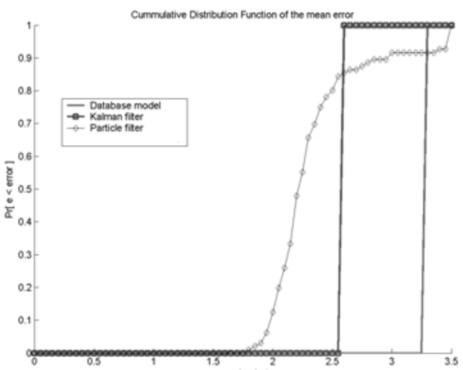


Fig. 4. Cumulative Distribution Function of the mean error for the different filters

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