Sensor fusion for UWB and Wifi indoor positioning systems

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Abstract

This paper advocates the application of sensor fusion for location. More and more sensors, like video, RFID, Wifi, are available in those environments. Fusing all those information is becoming a major task in indoor positioning as all the measurements coming from the sensors are noisy. This noise introduces positioning errors that may vary from one technological system to another. Besides, the coverage area of each single system may not be well adapted for all the application so a multi-scale coverage area system may be defined. This paper presents a reliable mobile positioning system taking advantage of the Wifi and the Ultra Wide Band positioning systems. The first may provide a rough position whereas the second is expected to achieve sub-centimeter position in restrained area. Fusing those two systems should lead to a more accurate system enabling to track a device in a building with different scales of accuracy along the path.

I. Introduction

Mobile positioning becomes increasingly an interest for many applications. Many networks are deployed in public and private area. They become some very interesting sources of information for mobile positioning. Each one can provide the position of an equipment but with a certain accuracy. As no location sensor takes perfect measurements or work well in all situations, it becomes interesting to fuse live measurements from multiple location technologies. To achieve optimal performance, a tracking system must exploit all the information in order to compensate the weaknesses of the other sensors. Wifi positioning has recently been a point of interest. Many buildings are equipped with WLAN Access Points (shopping malls, museums, hospitals, airports, ...). The positioning method is based on the fingerprinting [1], [2] to localize the equipment. As the Access Points have a wide coverage area, it is possible to localize a mobile with little equipment. But the received signals fluctuate over time what introduces errors in the positioning.

Some other sensors, like ultra sound or infra red sensors have already been used for short positioning. UWB technology is now widely investigated in order to estimate the accuracy that can be awaited from this technology. Many experiments have been carried out in ranging in dense multipath environment. They have shown the importance of direct-path finding algorithm [9], [10]. But the accuracy of a positioning system based on this technology have not been investigated yet.

Fusing those two-scale positioning systems becomes interesting. When the UWB tracking system may lose the track of the object due to off-range position, the Wifi tracker could continue tracking the object by using its fingerprinting database. Conversely, UWB could help improving the Wifi positioning accuracy where this technology is available.

The main contribution of our paper is to investigate the performances that can be achieved in term of accuracy of the position estimation and coverage area. Then a multi-scale positioning infrastructure based on particle filters will be studied to fuse data coming from Wifi sensors for a wide area coverage technology, with the short range positions provided by a TDOA based UWB system.

This paper presents in a first section the two positioning systems, on one hand based on a Wifi sensor using fingerprinting, on the other hand on a TDOA based UWB system. Then a tracking particle filter will be discussed and modified to lead to a sensor fusion system fed by the data coming from the two previous systems. Finally, some results using physical measurements will illustrate an unprecedented scaling capability to indoor positioning.

II. Indoor mobile location

A. A fingerprinting Wifi based system

Many outdoor systems are based on time measurements, i.e. the mobile equipment and the network are synchronized, thus the mobile can calculate the distance that it is separated from the Access Point (AP).

However getting this kind of information with commercialized WLAN products is almost impossible. The only available information is the signal strength received from each AP. With such information, it is necessary to find a way to estimate the distance. Using a propagation model $(P_s = f(d))$ might be practical. However, it is really difficult to find an accurate indoor propagation model due to complex RF waves propagation. Simple model (Motley Keenan) [8] has been tried out but lead to bad accuracy. The main source of error is the fluctuation of the RSS over the time.

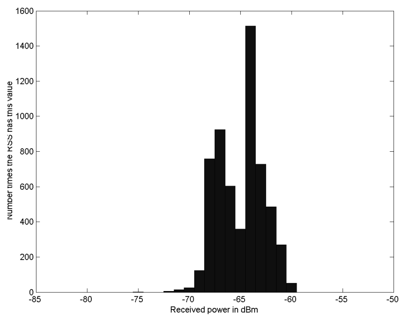


Fig. 1. RSS variations over the time

Finally, we opted for an on-site training to have a mapping between the position and the RSS database. This method was introduced in [1] and consists of two steps. The first step creates a database of the RSS over the building. At some positions in the building is associated an n-uplet of power measurement. The kept value for each AP, is the mean of the RSS over 100 measurements.

During the second step, the device samples the signal strength from each access point and finds its position by comparing its RSS to the ones recorded in the database. It looks for the n-uplet of RSS which is the closest to the instantaneous power measurement.

In comparison with the use of the propagation model, constructing a database is a constraint for the system. However, the fluctuations in the measurements often lead to choose the wrong point in the nearest-neighborhood algorithm. For example the user's position can change even if the user stops or the trajectory of the mobile can become discontinuous. This kind of problems may be avoided with the use of estimating filters like the Kalman filter [3] or the particle filter [5]. A location based on a Kalman filter has been tested in spite of the restrictions on the linear laws that match the prediction and the correction by a measurement. The Kalman filter delivers a continuous trajectory but cannot take into account the other information which are available like the map of the environment. The particle filter is a more generic filter and allows the use of different kinds of information. The price to be paid is a higher complexity of the implementation.

B. *An UWB positioning system*

1) Overview of the system: A 2D location experiment was constructed, consisting of four receivers and one mobile transmitter that should be localized. Fig. 2 shows a high level block diagram of our UWB location experiment. The transmitter consists of a high speed pulse generator which generates a 300 ps width UWB pulse triggered by a pseudo random code generator designed on a FPGA. This code is modulated onto the pulse train using an on-off keying modulation. Then the signal is amplified and broadcasted through a transmitting diamond antenna [12]. The same kind of antenna is used at reception. A synchronous acquisition of the four received signals is made by using a digital sampling oscilloscope (4-channel Lecroy Wavemaster 8620A) after signal amplification.

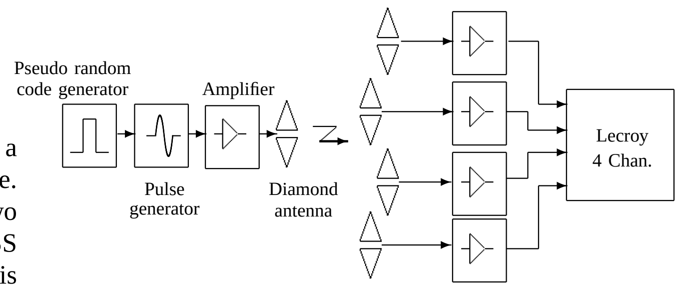


Fig. 2. High level block diagram of Ultra-Wideband location experiment

The sampling rate of the measured signal is 10 GS/s. No sweep averaging is used. The 8-bit pseudo random code is constructed from a 7-bit Barker sequence and has been chosen according to its good autocorrelation properties and shortness. The chip time is set to 200 ns to avoid ISI due to channel delay spread. The length of an acquisition is 5 μs and enables the capture of about 12 UWB pulses (i.e. 24 chips). The pseudo random code is known at reception but there is no synchronization between the transmitter and the receivers. Using four synchronous receivers completely resolves a 2D location of the transmitter thanks to the TDOA algorithm [13].

2) TDOA algorithm: The measurements consist of observing differences in the times of arrival of signal from the transmitter to the four receivers whose locations are known. Each range (or time) difference determines an hyperbola, and the intersection point of the three hyperbolas is the estimated source location. For each receiver, the relative time of arrival is determined thanks to a correlation between the received signal and the template signal. The receiver that has the best SNR provides the reference time to get the three TDOA. Once the relative time of arrival of the reference antenna is determined, a validity window inferior to the pseudo random code length is defined for the three other receivers. This window avoids ambiguity as several periodic correlation peaks may appear. Three TDOA allow 2D positioning. To avoid error due to the fact that we are working in a 3D environment, we assume to know the height of the transmitter. So the location error only comes from direct-path signal missing or excessive propagation delay through materials. Let $[x_i, y_i, z_i]$ denote the coordinates of the i^{th} receiver, and $[x_M, y_M, z_M]$ the coordinates of the mobile transmitter. The range difference from transmitter to receivers i and j is r_{ij}. Let suppose that the reference receiver is the number 1. The 2D estimate of the transmitter is given by the following equation:

$$[x_M, y_M] = \underset{\widehat{x}_M, \widehat{y}_M}{argmin}\left(\sum_{i=2}^{4}\left(r_{i1} - \sqrt{(x_i - x_M)^2 + (y_i - y_M)^2 + (z_i - z_M)^2}\right)^2\right) \quad (1)$$

Note that in equation 1, z_M is assumed to be known.

3) The UWB Digital signal processing: Experimental results show that finding the ideal template is difficult. The UWB pulse shape suffers from important distortions through the antennas and the amplifiers, which increase the pulse duration. So it is harder to separate the multipath signals. In our suboptimal but robust signal processing, the exact received pulse shape is assumed to be unknown. As Fig. 3 shows, the method consists in taking the absolute value of the signal and correlating it by a template whose basic pattern is a square wave. Each 2ns-wide square wave is coded by the value of the corresponding chip in the bipolar pseudo random sequence.

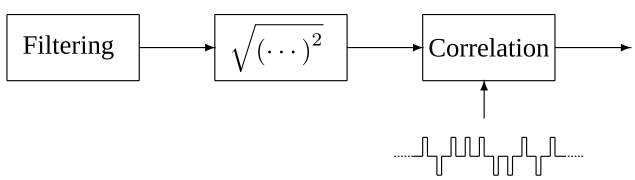
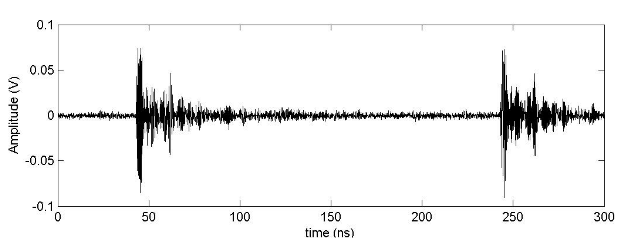


Fig. 3. Block diagram of digital signal processing at reception

The template length is chosen such as all the received energy contributes in the maximum correlation peak. A whitening filter is also implemented as the hypothesis of an additive white Gaussian noise is needed to use the maximum likelihood criterion in the next section.
A challenge of indoor UWB location is the multipath propagation in NLOS situations.



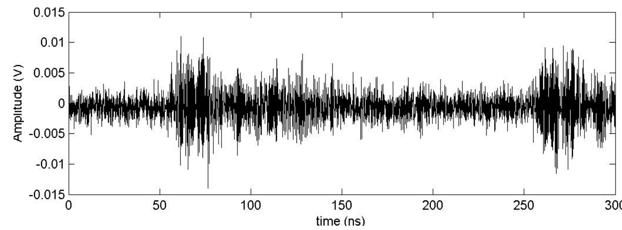


Fig. 4. Typical received signals in LOS and NLOS situations. The signal shown in the first plot was measured with a clear LOS and the other was measured in the presence of LOS blockages.

Fig. 4 shows the acquisitions of two typical received signals in case of a LOS and NLOS situations. Two UWB pulses and their multipath replicas are distinguishable. The transmitted pulses are separated by a chip duration of 200 ns. It appears that in the absence of a clear line of sight (NLOS situation) the direct-path signal is not always the strongest one. So the accuracy of the location depends on the direct-path detection error. A GML (Generalized Maximum Likelihood) algorithm was proposed in [11] based on the CLEAN algorithm [14]. The hypothesis is that the received signal is a linear combination of replicas of the single path signal with different delays and amplitudes. The noise is assumed to be an additive white Gaussian noise. The basic steps are:

1) Compute the cross-correlation $R_{ST}(t)$ of the absolute value of the received waveform $S(t)$ with the template $T(t)$.
2) Find the strongest correlation peak in $R_{ST}(t)$. Keep the amplitude and time delay $\{a_{max}, \tau_{max}\}$.
3) Find the first correlation peak satisfying:

$$\frac{a_k}{a_{max}} \geq \theta_\rho \qquad \tau_k \in [\tau_{max} - \theta_\delta, \tau_{max}[$$

where :

- θ_ρ is the threshold on the correlation peak amplitude. The range of values of θ_ρ are from 0 to 1 as the correlation peaks are normalized.
- θ_δ is the maximum delay relative to τ_{max}. All τ_k must be searched within $[\tau_{max} - \theta_\delta : \tau_{max}[$.

Those two last parameters need to be dimensioned. They determine two probabilities the False Alarm probability (P_{FA}) which is due to the detection of some noise, and the Missed-Path probability (P_M) which is the detection of a multipah signal for the direct-path.
Those two last probabilities must be minimized to get the optimum parameters. Here the determination of those parameters has been done given the following criteria:

- Find θ_δ so that the probability that the direct-path signal delay is not contained in $[\tau_{max} - \theta_\delta : \tau_{max}[$ is equal to α. Typically $\alpha = 0.001$.
- Choose θ_ρ minimizing the sum $P_{FA} + P_M$.

It is helpful to notice that P_{FA} only depends on the SNR and signal processing at the receiver. On the other hand, P_M is entirely determined by the channel statistics. In our experiment, the channel statistics realized by Cramer, Win and Scholtz [15] were used and the SNR is evaluated for each received signal in order to determine the optimal adaptive threshold θ_ρ.

III. Particle filter and sensor fusion

A. The particle filter

Nowadays, the map of all the public or companies 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 tries to represent the density function of the mobile-position by a set of random samples with associated weights (i.e. a particle) [7]. Each particle explores the environment according to the motion model and map-information, the weight is 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.

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

1) 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:

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

where $\left[x_k, y_k, V_{x_k}, V_{y_k}\right]^T$ 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. $\left[\nu_{x_k}, \nu_{y_k}\right]^T$ is a gaussian random process, which is realistic for a pedestrian move, 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.

When the new position of a particle is known, it is possible to include the map information, in order to remove the particles with 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. When this checking is finished, it is possible to assign a weight $Pr\left[x_k|x_{k-1}\right]$ as follows:

$$Pr\left[x_k|x_{k-1}\right] = \begin{cases} 0 & \text{if a particle crossed a wall} \\ 1 & \text{if a particle did not cross a wall} \end{cases}$$

Then some particles disappear when they cross a wall.

2) Correction: When a measurement (n-uplet 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 a signal strength or UWB impulse responses n-uplet, and that particles are characterized by their position, the n-uplet must be translated into a position. The mapping between the position and the signal strength is performed thanks to the empirical database. In fact, the algorithm presented in section II to find the position of the mobile given the RSS coverage in the building is used. Then it is possible to estimate $Pr\left[z_k|x_k\right]$.

3) Particles update and resampling: The weight update equation is given in [4], [5]:

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

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 (non zero weight). To avoid having just one remaining particle, a re-sampling step is triggered.

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. Various re-sampling algorithm were proposed. We did not choose the simple SIS (Sequential Importance Sampling) particle filter [4], but the re-sampling approach presented in [6], 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.

B. *Sensor fusion*

The particle filter introduced in section III-A is the tool that enables to merge different information as it relies on the probability densities of the sensors. Combining the information can be done in the expression of the posterior law expressed in III-A.2:

$$Pr\left[z_k|x_k\right] = Pr\left[z_k^{wifi}, z_k^{uwb}|x_k\right]$$

As a simplification, the hypothesis that the Wifi and UWB measurements are uncorrelated has been chosen. This is not true as the the received Wifi or UWB measurements condition one another. With this hypothesis, it becomes possible to write the posterior law as follows:

$$Pr\left[z_k|x_k\right] = Pr\left[z_k^{wifi}|x_k\right] \cdot Pr\left[z_k^{uwb}|x_k\right]$$

where z_k^{wifi} is the measurement coming from the Wifi sensor (here the position delivered by the database) and z_k^{uwb} the measurement from the UWB sensor. Here it is considered that z_k^{wifi} and z_k^{uwb} will be the positions obtained from the Wifi sensor and the UWB TDOA based positioning system respectively.

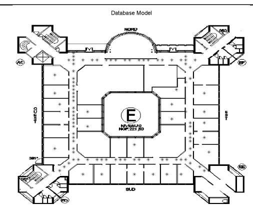
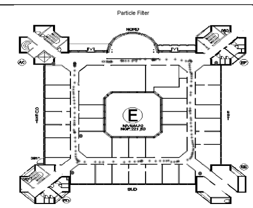
It has been assumed that both $Pr\left[z_k^{wifi}|x_k\right]$ and $Pr\left[z_k^{uwb}|x_k\right]$ are gaussian probabilities centered on the position delivered by the corresponding sensors. As the availability of the UWB positioning system is limited, it is necessary to select the frames which can deliver a coherent position. The most natural thing to use is an estimate of the SNR of the UWB channels to decide if the received channels must be taken into account to find the position of the mobile. In this system, the SNR that was used is the one estimated when a new frame is received. The higher the SNR on each channel is, the better the estimation of the position must be, and the greater the confidence in the measurement will be. The variance of this UWB gaussian law depends on the estimations of the SNR of each channel.

IV. Experimentations

A. *The Wifi based positioning demonstrator*

To experiment all those techniques and estimate their capabilities and accuracy to localize a device, a demonstrator has been built. The database is built with one measure in each room, and a measurement every two meters in the corridor. A single floor problem is considered. The criterion to define the error is the mean error over a trip in the building. 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).

TABLE I. Comparison of the different filters

	Database	Particle filter
Trajectory		
Mean error (m)	3.50	1.99

A large improvement may be noticed when a particle filter is 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. A temporal averaging filter (5 samples sliding average) is also used to smooth the variations of the instantaneous RSS. On the contrary, the particle filter succeed in giving a coherent trajectory. It removes most of the wall crossings due to the RSS variations. 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. However, over the whole trajectory, the number of wall crossings decreases. The figure below gives more information about the performances of this filter. It provides the cumulative distribution function of the root mean square errors over the trajectory.

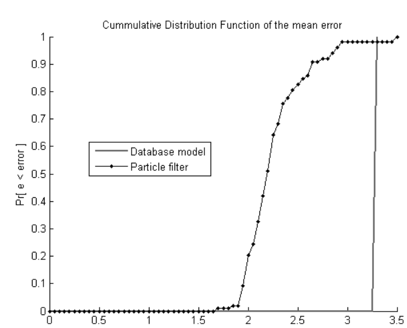


Fig. 5. Cumulative Distribution Function of the different filters

The performances achieved by the Wifi technology to localize a mobile can be sufficient to determine the room where it stands, but not accurately its position in that room. The performance that can reach an UWB system in positioning should help the Wifi tracker to determine the position of the mobile in a room, as long as this service is available. Some few results about this innovative system will be discussed next.

B. The UWB location experiment

Actual data was collected to test our direct-path search method to localize an UWB transmitter. An application was created to collect the data, process it and display the position on a map (real time). The data was recorded in a typical office environment. The four static receiving antennas formed a square of about 6×6 m and were approximately 2.3 m high. As fig. 6 shows, one of the antennas was placed in a room whose dimensions are 7×7 m. The three other antennas were in the corridor surrounding this room. So our UWB location system was conceived typically to test NLOS situations. Wherever the mobile was in the area, at least one of the four receiving antennas was not in line of sight with the transmitter. Note that no trigger signal was needed. We expected better location accuracy for mobile locations in the central room and the corridor because the surrounding zones suffered higher attenuations. Indeed the transmitted signal could have to go through two walls to reach one of the receiving antennas. As fig. 6 shows, 10 transmitter locations were tested in a zone whose dimensions are approximately 20×20 m. TABLE II gives the 75^{th} best location estimation from the 100 set of acquisitions taken for each location.

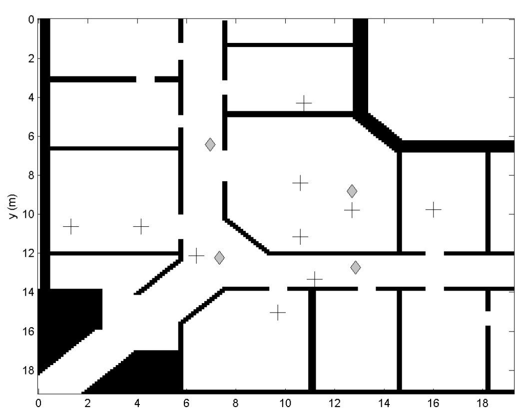


Fig. 6. Basement floor plan of the building where the experiments were conducted. Diamond marks stand for the locations of the receiving antennas and the cross marks indicate every transmitting antennas location.

TABLE II. location error versus location and method (cm).

Location number	1	2	3	4	5	6	7	8	9	10
Error with adaptive threshold	51	32	27	22	13	50	53	52	69	115
Error with invariant threshold	60	57	32	31	39	55	89	41	86	191
Error with maximum peak detection	428	350	214	313	98	681	355	366	341	493

Two methods of direct-path signal detection were tested. The adaptive threshold described in section II-B.3 was compared to an invariant threshold. This invariant threshold was intuitively chosen to work as well as possible. Moreover, the results from taking the maximum correlation peak are given. In this case, errors typically larger than one meter occurred. This shows the importance of the direct-path signal investigation. For most transmitter locations the adaptive threshold led to the best results. An analysis shows that it estimates much better the TDOA and prevents most large false alarm errors thanks to the SNR estimation. A tracking experiment was also conducted. The transmitter was carried by a user through the experimentation area. Fig. 7 shows the results of the tracking experiment.

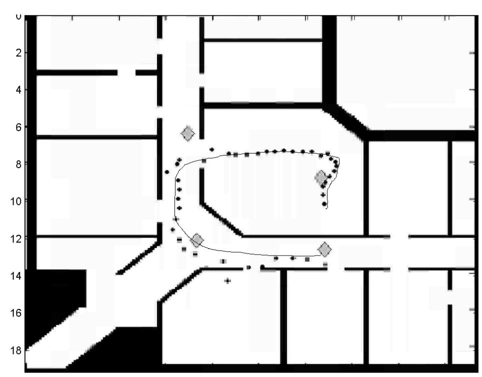


Fig. 7. Estimated user itinerary (Tracking experiment). Circular marks stand for the estimated mobile itinerary. Continue line stands for the real itinerary.

This section has shown the performances of the UWB technology in positioning systems. A good accuracy can be obtained in the coverage area (about 0.5m). But with the same number of equipment in the network as with the Wifi technology (4 APs in Wifi and 4 receivers in UWB) the coverage area of UWB is far smaller. So the idea is to combine those two technologies, in order to improve the accuracy of the Wifi technology in the area where the UWB positioning is available, and then to enable the tracking all over the building even if the UWB positioning is not present. The following section will describe such a system taking into account those two positioning technologies.

C. A multi-scale system

As it was presented earlier, the key idea is to combine the two previous systems that commit some positioning errors due to a measurement noise. Fusing the information should lead to a better accuracy in the area where both technologies are available. On the other hand, as it was previously presented, the coverage area of each technology is not the same. On one hand, there is a wide area coverage ($1600m^2$) enabled by the Wifi technology, on the other hand the UWB covering a small area ($400m^2$). It can be noticed that the accuracy scale is not the same either. With the UWB system, it becomes possible to know the position of the mobile in a room, whereas the Wifi system could only provide the information of the room where the mobile was. To achieve the best performances, it is necessary to design a simple but robust algorithm allowing to take into account those information. As the Wifi positioning is always available, it is natural to use it all the time. But as the UWB system is not always available, it is necessary to define a criteria that will define the frames (and then positions) that must be taken into account to be fused with the Wifi information. Here the most natural and simple way to handle these information is to select the measurements depending on a SNR level. If one of the SNR is too low then it means the confidence in the delivered position must be low. On the contrary, if all the SNR are very high, it means extracting the direct path will be easy and a good positioning will be done. In this experiment, it has been considered that the influence would be introduced by the variations of the variance of the gaussian law associated to this process. This following law is given by:

$$\sigma_{uwb} = \begin{cases} \infty & \text{if } \min\left[SNR_i\right] < SNR_{low} \\ \sigma_{wifi} & \text{if } SNR_{low} \leq \min\left[SNR_i\right] < SNR_{high} \\ \frac{\sigma_{wifi}}{\alpha} & \text{if } \min\left[SNR_i\right] \geq SNR_{high} \text{ and } \alpha > 1 \end{cases}$$

Some measurements have been carried out to estimate the performances of this sensor fusion, compared to the one achieved with each single technology.
A reference path has been considered. The results of this experimentation are shown in the following figures:

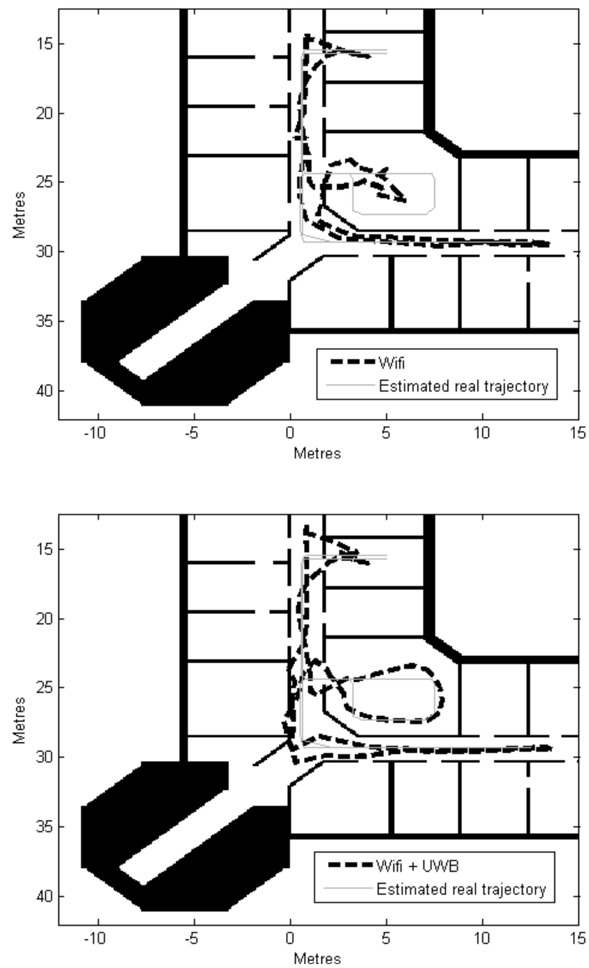


Fig. 8. Comparison of the estimated path when only using the Wifi (upper picture), and then when using the Wifi and the UWB systems (lower picture). The dot line represent the estimated real path whereas the two other path represent the one estimated by the particle filter.

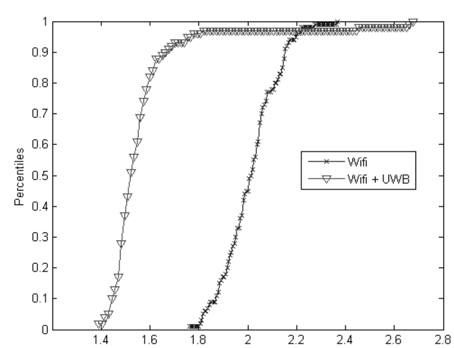


Fig. 9. Cumulative distribution function of the mean error over 100 estimations of the path presented above.

Those last results show that a better estimation of the mobile can be reached when both technologies are available. In fact, with only Wifi, it is possible to detect where the mobile is with an accuracy of about 1.8m (particle filter). But when Wifi and UWB systems are available it is possible to detect the position of the mobile with a 50cm accuracy in the room and fusing those two systems leads to a 1.4m accuracy location. Those performances can be noticed on the cumulative distribution of the mean error over the estimated path.

So combining UWB and Wifi positioning may be a good way to localize a mobile thanks to the Wifi network. This first infrastructure would provide a wide coverage area for positioning, but with a 1.80m accuracy, whereas locally, it would be possible to accurately foresee the position of the mobile when an UWB infrastructure would be available and combined with the previous network.

V. Conclusion

In this paper, we have presented a positioning and tracking system for indoor environments. The use of a particle filter which takes into account the human motion, the map information and the signal strength received, leads to a positioning accuracy of 1.8m. When combined with another technology, such as UWB, it is possible to locally and accurately detect the position of the mobile. The experiments carried out show an improvement of 40cm on the global mean error. This study also focused on the performances of UWB systems that can accurately find the position of the mobile (about 50cm), even in NLOS environments. But those performances can be reached just on little coverage area. Moreover, the particle filter is a useful tool to introduce the sensor fusion as demonstrated earlier.

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