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"What in the appearence of the windmills and in Quixote's self-image causes the error in perception? "

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SS3 HUMAN MACHINE INTERFACES

SS4 LOCAL POSITIONING SYSTEMS

Combination of UWB and GPS for indoor-outdoor vehicle localization

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Abstract **– GPS receivers are satellite-based devices widely used for vehicle localization that, given their limitations, are not suitable for performing within indoor or dense urban environments. On the other hand, Ultra-Wide Band (UWB), a technology used for efficient wireless communication, has recently being used for vehicle localization in indoor environments with promising results. This paper focuses on the combination of both technologies for accurate positioning of vehicles in a mixed scenario (both indoor and outdoor situations), which is typical in some industrial applications. Our approach is based on combining sensor information in a Monte Carlo Localization algorithm (also known as *Particle Filter*), which has revealed its suitability for probabilistically coping with a variety of sensory data. The performance of our approach has been satisfactorily tested on a real robot, endowed with a UWB master antenna and a GPS receiver, within an indoor-outdoor scenario where three UWB slave antennas were placed in the indoor area.**

Keywords **– Vehicle Localization, Particle Filter, GPS, UWB.**

I. INTRODUCTION

The problem of vehicle self-localization within industrial scenarios is usually tackled by exploiting the particular characteristics of the application at hand. Different approaches are usually considered according to the required accuracy, the available sensors and their cost, the type of the scenario, i.e. indoor or outdoor, etc. The latter is, apart from other considerations, the one that has major influence when deciding appropriate solutions to the problem of vehicle localization.

Indoor applications usually require a precise estimation of the vehicle pose since the workspace is smaller and contains a diversity of objects to manage and obstacles to avoid. An example in industrial applications is trucks aimed to load and carry goods within a warehouse. In general, in these scenarios triangulation systems based on lasers are commonly used, but they present problems when dynamic obstacles or the own environment configuration block the line-of-sigh of the beacons. A promising solution for that are radio signals like UWB because of its penetration capability.

On the other hand, outdoor applications usually require less precision, i.e. a vehicle moving through a road or some wide space, whose localization can be provided by global positioning systems (GPS).

In a variety of applications, vehicles have to perform within a mixed indoor-outdoor scenario, and therefore, the combination of approaches relying on both technologies (UWB and GPS) should be considered (see figure 1). A simple solution may consist of switching between different algorithms based on each technology according to whether the vehicle is in- or outside. However, in the transition areas (for example, when the vehicle is entering a warehouse), data from the both sources may coexist, though the signal quality from each source may not be good enough for precisely assessing the vehicle pose independently one from another. In these situations, the combination of both sensor data should be managed coherently and exploited to improve vehicle localization.

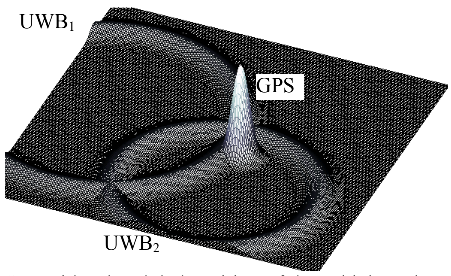

Figure 1. GPS provides the global position of the vehicle and can be modeled through a probability density function with a given standard deviation. UWB beacons (two in the figure) yield range measurements with a certain error that can be also probabilistically modeled. The most probable position of the vehicle can be obtained by means of the probabilistic combination of all sensor readings.

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In this paper we focus on mixed indoor-outdoor vehicle localization through a probabilistic combination of sensor data acquired from different sources: UWB and GPS. More precisely we propose a Monte Carlo localization algorithm, also called *Particle Filter* [19], that represents the estimations of the possible poses of the vehicle by means of a set of weighted samples (*particles*). The main advantage of this approach is its ability to combine measures from different sensors considering appropriately their probabilistic behavior. In a nutshell, this is done by assigning to each particle a weight proportional to the probability of receiving the available sensor readings from the pose they represent. The higher the particle weight is, the higher is the confident (belief) that the pose represented by the particle becomes the real pose of the vehicle.

Other interesting properties of particle filters are:

- They are suitable to work with almost arbitrary sensor characteristics, motion dynamics, and noise distributions, even non-linearities, as long as some likelihood model of their uncertainty can be given.
- They can maintain simultaneously different hypotheses about the pose of the vehicle. This ability permits the localization system to track a vehicle within complex and self-similar scenarios like parking areas [5].
- Since particle filters sample the space of possible locations up to a given sampling density, their computational cost can be easily bound, and they are easy to implement [1].

In this paper we consider a set of UWB beacons for indoor localization, GPS for outdoor, and readings from both sources within the overlapped areas. The proposed particle filter approach copes well with vehicle localization where UWB and GPS readings are available, either separately or jointly, as demonstrated in real experiments.

The structure of the paper is as follows: section 2 gives an overview and a comparison of the UWB and GPS technologies for vehicle localization. Section 3 describes the mathematical formulation of Particle Filters and its use for fusing readings from different sensors. In section 4, results from real experiments conducted in a mixed environment are presented, proving the suitability of our approach. Finally, some conclusions and future work are outlined.

II. UWB AND GPS SENSORS OVERVIEW

A. UWB

The *Ultra-Wide Band* (UWB) technology [15],[22] was initially developed by the US Department of Defense in the early 1960s, demonstrating its particular suitability for radar and highly secure transmission of information. Nevertheless, the first civil applications of this technology did not appear until 1994.

Nowadays, UWB is a well-known technology for communications [4], but only a few works have exploited it for vehicle localization by deriving the distance between antennas through, for instance, the *TOA* of data packets (Time-Of-Arrival) [3].

The main characteristics and advantages of the UWB technology for vehicle localization (and also for communications) are [8]:

-*Transmission.* Unlike carrier-based systems which work on a specific frequency, UWB works by transmitting a radio signal over a wide swath of frequencies (in the band between *3.6* and *10.1 GHz*).

- *Short pulses and low power consumption.* Since the duration of pulses is of the order of nanoseconds, their spectrum is spread over a wide frequencies band, so the power spectral density of each transmitted pulse is very low (about *-41.5 dBm/MHz*). Hence, UWB can be considered as a safe system for wireless transmission and can coexist, theoretically without interference, with other radio communication technologies.

-*Materials penetration:* The characteristics of the UWB signal transmission provide this technology with a high material penetrability making it suitable for indoor communications and vehicle localization. Although, they are not affected, in theory, by multipath problems [22], [17], are not completely free from that problem.

-*Accurate positioning*: Due to the short duration of the transmitted pulses, UWB technology offers inexpensive and accurate positioning with centimeter resolution. Apart from the TOA method used in this work, other techniques can also be considered for pose estimation of antennas, such as Direction-Of-Arrival and Signal-Strength [6].

B. GPS

Global Positioning System (GPS) has become a well-known and widely accessible technology for absolute localization on the surface of Earth (geolocalization) [18], with applications in many different fields.

Basically, GPS uses two radio channels in the microwave band centered at *1575.42Mhz* and *1227.60Mhz*. Considering the radio time-of-flight lateration it achieves an accuracy in localization around 1-5 meters in outdoor areas[2] [7].

The main disadvantage of localization systems based only on GPS is that they need a good Line-of-Sight (LOS) to GPS satellites. This drawback is mainly due to the weakness of the GPS signal and their inability to penetrate through most of materials, which limits the use of GPS to outdoor and open scenarios. Moreover, GPS requires, at least, four satellites electronically visible, which is not always possible.

[2] The accuracy of GPS can be improved by means of differential GPS (DGPS) to achieve a resolution of centimeters.

C. GPS vs. UWB

Based on the general characteristics of both technologies aforementioned, they are not straightforward comparable but complementary.

Nowadays, GPS is a cheap technology that offers a sufficiently accurate localization in outdoor and open areas, almost around the world, in terms of a global frame (latitude, longitude, altitude). On the other hand, UWB provides more reliable and precise results, in terms of relative localization with respect to a local frame, at the expense of covering the working area with costly antennas. This makes UWB technology only applicable to indoor and relatively small workspaces.

Therefore, exploiting the best of both technologies may become the solution for a large variety of mixed indoor-outdoor applications, like the one considered in this work. In the following, the proposed approach for combining GPS and UWB measures is detailed.

III. PROBABILISTIC LOCALIZATION AND SENSOR FUSION

A. Problem Statement

Methods for sequential Bayesian filtering provide a grounded probabilistic framework for tracking the state of a system which is observable only through indirect and noisy measurements. These techniques maintain a probability distribution that captures the knowledge about the state of the system at a given instant of time. This distribution changes over time following the evolution model of the system and it is updated with each observation by means of probabilistic sensor models. While closed form filters exist for Gaussian distributions and systems without strong nonlinearities ([10],[11]), we employ here a *Particle Filter* ([14],[1]), due to some important advantages within the scope of the present problem. Firstly, a particle filter can cope with arbitrary distributions, which enables performing global localization of the vehicle at start-up or maintaining multi-modal distributions in the presence of ambiguities. Secondly, the probabilistic observation model of UWB sensors is strongly nonlinear and leads to distributions that could be hardly approximated only by Gaussians.

We derive next the equations of our particle filter for robust UWB-GPS localization. Our purpose is to localize the robot within a planar environment provided a set of N beacons with known 3D positions $\{\mathrm{B}_k\}_{k=1}^{N}$. Let s_t, u_t, and z_t denote the system state, the robot actions, and the observations for any given time step t, respectively. Although we are interested in the robot pose (which we will denote as x_t), the system state is augmented with the set of unknown *biases* $\{b_k\}_{k=1}^{N}$ of each UWB beacon, that is:

$$s_t = \{x_t, b_1, ..., b_N\} \tag{1}$$

As discussed elsewhere [9], this provides a great improvement in terms of robustness against the effects of multi-path for this kind of radio technology. Now, by noticing that the system state s_t evolves as a Markov chain we can write down our estimation problem into the well-known sequential form:

$$\begin{aligned} p\left(s_t \middle| u_{1:t}, z_{1:t}\right) &\propto p\left(z_t \middle| s_t, u_{1:t}, z_{1:t-1}\right) p\left(s_t \middle| u_{1:t}, z_{1:t-1}\right) \\ &= \underbrace{p\left(z_t \middle| s_t\right)}_{\text{Observation model}} \int \underbrace{p\left(s_t \middle| s_{t-1}, u_t\right)}_{\text{Evolution model}} p\left(s_{t-1} \middle| u_{1:t-1}, z_{1:t-1}\right) ds_{t-1} \end{aligned} \tag{2}$$

To implement this recursive equation as a Particle Filter we start with a set of M samples in the state space $\left\{s_{t-1}^{[i]}\right\}_{i=1}^{M}$, called *particles*, which are approximately distributed according to the distribution for the previous time step $t-1$ (a uniform distribution can be assumed initially if there is not any information about the robot pose). According to *importance sampling* [1], a weight $\omega_{t-1}^{[i]}$ is also associated to each particle to compensate potential mismatches between the density of samples at a given area of the state space and the actual (unknown) density. Following the most common algorithm for particle filtering, *Sequential Importance Sampling with Resampling* (SIR) [16], the set of particles for the next time step t is generated by means of the following steps:

1. Generate the new particles by drawing samples from a certain proposal distribution, $q(s_t \mid s_{t-1}, u_t, z_t)$.
2. Update the weight $\omega_{t-1}^{[i]}$ for all the new samples based on the value of the observation likelihood of each particle.
3. Perform a resampling step in order to prevent the loss of particle diversity if a measure of quality of the particles, for instance, the effective sample size [12], falls below a given limit.

One of the most popular choices for the proposal distribution is to draw samples from the system transition model, that is, $q(s_t \mid s_{t-1}, u_t, z_t) = p(s_t \mid s_{t-1}, u_t)$. In this case, updating the importance weights simply becomes:

$$\omega_t^{[i]} \propto \omega_{t-1}^{[i]} p\left(z_t \middle| s_t^{[i]}\right) \tag{3}$$

that is, the product of the previous weight with the observation likelihood evaluated at each state hypothesis $s_t^{[i]}$. In the next subsection we discuss in detail how to compute this term, which is in charge of fusing the sensorial data from the UWB beacons and the GPS.

Regarding the system transition model, there are two separate processes involved, one for each part of the augmented state vector s_t.

- For the common case of robot actions u_t, represented by incremental odometry readings, the robot pose x_t is updated by adding the pose change stated by the odometry to the previous pose and corrupting it with a certain noise. This models the fact that odometry measurements can be inaccurate due to, for example, slippage or uncalibrated parameters. For more details about these models please refer to [2] or [20].

- The apparent bias of UWB ranges due to multi-path typically remains constant until new obstacles enter or leave the path of the UWB signal. Since accurate models for these effects may be extremely hard to obtain, even having a detailed representation of all the elements in the environment, we employ here the following approximate evolution model [9]. At each time step, there is a probability $P_c \in [0,1]$ for the bias b_k not to change, that is, $b_{k,t}^{[i]} = b_{k,t-1}^{[i]}$. On the other hand, we consider a change in bias with a probability of $1-P_c$. In those cases, the change in the bias is modeled as a uniform distribution, but accounting for the constraint that biases must be non-negative. Interestingly, this condition can be easily incorporated into the particle filter, while a Gaussian filter could not cope with it.

At this point we have described the basis of particle filtering using the system evolution model as proposal distribution $q(\cdot)$. We must remark that this choice leads to a highly efficient implementation, although other proposals [1] may be considered in the case of a sufficiently large number of sensors. From our real experiments and simulations we have verified that this choice for the proposal distribution is well suited to a practical number of UWB beacons, e.g. up to 10 beacons at sight at each instant of time.

B. Probabilistic Observation Models

As exposed in (3), particle weights are updated through the observation likelihood function $p\left(z_t \middle| s_t^{[i]}\right)$. The intuitive idea behind this process is assigning higher weights to those hypotheses that best explain the sensor readings, discarding in the resampling steps those particles that perform poorly.

Without loss of generality we consider that the observation z_t contains one GPS reading and a range reading for each UWB beacon at each time step *t*. Formally, we denote the observation variables by the set:

$$z_t = \left\{ z_t^{GPS}, z_t^{UWB,1}, \ldots, z_t^{UWB,N} \right\} \tag{4}$$

Since it is plausible to consider that the random errors in each of these individual measurements are independent, the observation likelihood can be factorized as:

$$p\left(z_t \mid s_t\right) = p\left(z_t^{GPS} \mid s_t\right) \prod_{k=1}^{N} p\left(z_{k,t}^{UWB} \mid s_t\right) \tag{5}$$

The GPS receivers can be appropriately modeled by a 2D Gaussian over the ground plane, that is:

$$p\left(z_t^{GPS} \mid s_t^{[i]}\right) = \mathrm{N}\left(x_t^{[i]}; z_t^{GPS}, \Sigma_t^{GPS}\right) \tag{6}$$

where the associated covariance Σ_t^{GPS} should be a function of the number of satellites observed at each instant of time. For example, for 8 satellites we set a standard deviation value of 2 meters.

Regarding the UWB sensors, we can model the range values as having an unknown bias plus a zero-mean additive Gaussian noise characterized by σ_{UWB}^2. Since the bias $b_{k,t}^{[i]}$ has been estimated jointly to the system state, the sensor model must account for the Gaussian noise only:

$$p\left(z_{k,t}^{UWB} \mid s_t^{[i]}\right) = \mathrm{N}\left(r_{k,t}^{[i]} + b_{k,t}^{[i]}; z_{k,t}^{UWB}, \sigma_{UWB}^2\right) \tag{7}$$

Here $r_{k,t}^{[i]}$ stands for the expected 3D euclidean distance between the UWB antenna onboard of the vehicle and the *k*'th UWB beacon, localized at B_k. Figure 2 illustrates the observation likelihood distributions obtained for each of the individual sensors and how they are fused.

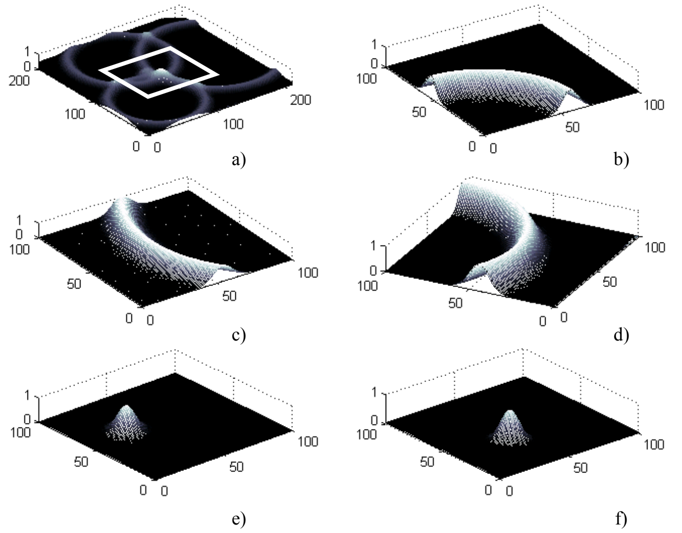


Figure 2. UWB and GPS likelihood probabilities and their combination. a) Distribution for 3 UWB beacons and the GPS. The marked rectangle determines the area of conjunction of all measures. b)-d) A detailed and separated view of each UWB distribution within the conjunction area. e) The GPS distribution. f) The resulting combination of all distributions, that yields the probability distribution of the vehicle localization.

We must highlight that the GPS and the UWB sensors do not measure directly orientation of the robot. Although, in practice, odometry readings incorporated through the robot motion model in the filter are enough to provide an accurate estimation of the robot heading. In the case we need a more precise estimation of the robot absolute heading, the robot should be equipped with two or more UWB devices. The process for fusing their measurements would be the same as discussed above.

Finally, we must account for not all the measurements in (4) to be available simultaneously (as in the real experiments described later on). In these cases the likelihood for the absent readings can be set to any arbitrary constant value. Looking at the general Bayesian filter equations (2), it is clear that any constant value, i.e. constant between different particles, does not modify the estimated probability distribution, which is normalized at each step.

IV. EXPERIMENTS

In order to test the proposed method for vehicle localization we have carried out real experiments within a mixed indoor-outdoor scenario, combining UWB and GPS readings.

In our test scenario, the parking area and the main entrance of the Computer Science building of the University of Malaga (see figure 3), three UWB beacons were placed to cover the indoor part and most of the outdoors (although the UWB signals are weaker in the outdoor part). UWB-GPS combination takes place in that outdoor part.

Within this scenario, a mobile robot equipped with an UWB antenna (PulsOn210 [21]), a GPS receiver, and a laser scanner is commanded to track a circular path previously recorded. During navigation, data from UWB and GPS are available each 111ms and 1s, respectively, and the combination of both, when available, is used for estimating the robot pose. The real position of the robot (ground truth) is calculated by matching the laser measurements with a map of the environment previously created [13].

Figure 3. Our mobile robot navigating in a mixed scenario at the parking of the Computer Science building of the University of Malaga

In this setup, we have compared three different situations: i) the robot only relies on the odometric system to follow the path, ii) the robot position is estimated through our filter particle approach by also considering UWB range measurements, and iii) the GPS information is also combined in the filter to improve robot localization when it is available.

Figure 4 shows the results of our experiments. Figure 4a-b depict the path to be followed and one-loop trajectory tracked by the robot considering only UWB and UWB+GPS, respectively. Figure 4c depicts the localization error for each case during the whole experiment (around two loops). In this chart, the shadowed areas represent the parts of the experiment where GPS and UWB data is combined for improving the vehicle localization, while in the rest, only UWB measurements are available.

Notice that in the zone covering from area A to B (indoor part) only UWB data is available yielding an acceptable localization error (20 cm. at maximum). The portion between B and C corresponds to the outdoor area (in fact, a large transition area), where GPS is available and weak measurements coming from the UWB beacons are sporadically present. Note that the localization error when considering UWB only is higher as the robot goes far from the beacons, being significantly reduced when UWB measurements are combined with GPS (see figure 5).

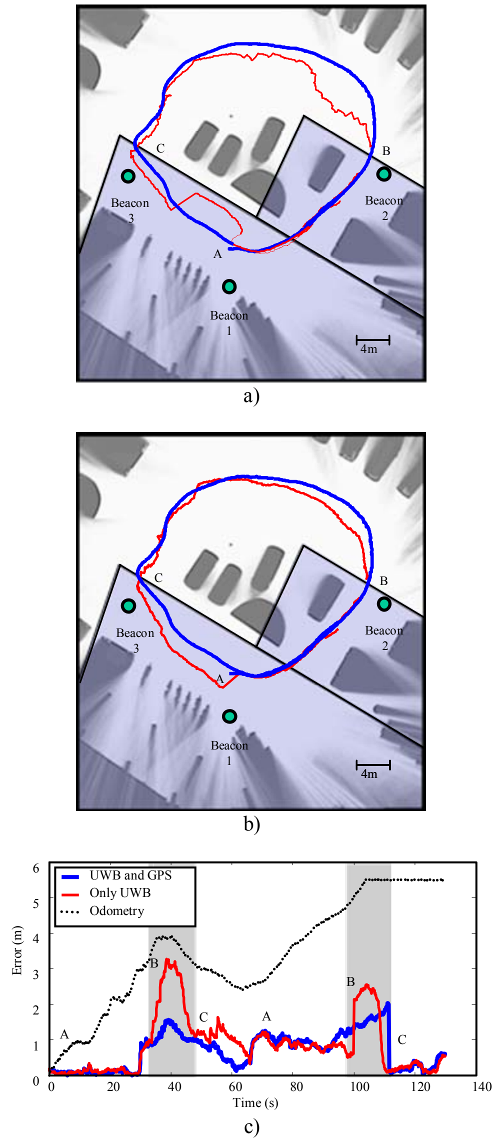
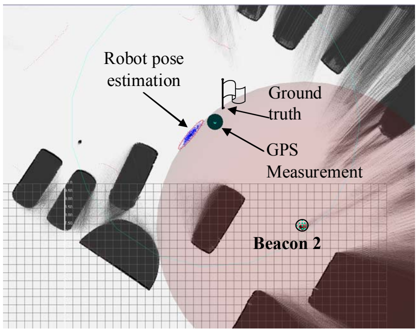
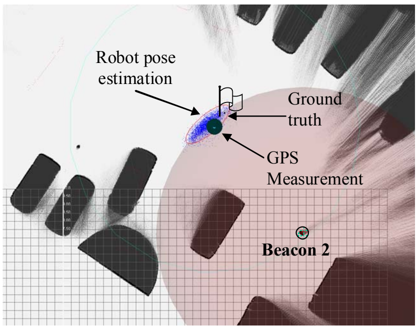


Figure 4. Estimated paths and localization errors. Plots (a) and (b) show the considered scenario where indoor areas are shown in dark and the fixed beacons are marked as circles. (a) Real (*thick line*) and tracked path employing odometry and UWB range measurements (*dotted line*). (b) Real (*thick line*) and tracked trajectory using odometry, UWB range measurements and GPS position estimations (*dotted line*). (c) Errors in the estimation of the robot position along two loops employing different sensory information: only odometry (black dotted line), odometry and UWB (thin line), and odometry, UWB and GPS (thick line). The shadowed areas represent parts of the navigation where GPS and UWB readings were combined.

Also note that, despite the navigation between C and A going indoor, the error in the position estimation is unexpectedly high. This is because at that point the vehicle usually loses the connection with the farther UWB beacons for a certain time, being available only the range measurement of one beacon and the odometry. As soon as the other beacons are accessible at some time, the system re-localizes the vehicle. It is important to remark, that albeit three beacons are, at least, necessary for estimating the vehicle pose by triangulation, our probabilistic approach maintains a reduced error during some periods of time when information from only two or even one of them are available.



(a)



(b)

Figure 5. Vehicle localization in a transition area where GPS and UWB signal from a beacon are available. a) Vehicle localization using only the UWB range and odometry. b) Pose estimation when also combining GPS measurement.

V. CONCLUSIONS AND FUTURE WORK

In this paper, we have implemented and evaluated a probabilistic framework for vehicle localization that combines different sensory sources. Our approach, based on particle filter, considers UWB, GPS and the combination of both technologies to reliably estimate the pose of a vehicle that moves both in indoor and outdoor scenarios. This permits a vehicle to robustly perform in a variety of situations, for example in some industrial environments.

Results from real experiments have been presented proving the suitability of the proposed approach with a mobile robot.

In the future we plan to combine more sensory sources, such as inertial navigational systems and visual landmarks, within a more complex scenario.

REFERENCES

[1] Doucet, A., de Freitas, N., and Gordon, N. Sequential Monte Carlo methods in practice. Springer-Verlag, 2001.

[2] Eliazar, A.I. and Parr, R. Learning probabilistic motion models for mobile robots. ACM International Conference Proceeding Series, 2004.

[3] Eltaher A. and Kaiser Th. Positioning of Robots using Ultra-wideband Signals. IRA workshop on Advanced control and Diagnosis, Karlsruhe, Germany, November 2004

[4] FCC, “New Public Safety Applications and Broadband Internet Access among uses Envisioned by FCC Authorization of Ultra-Wideband Technology”,FCC 02-48, Feb. 14,2002.

[5] Fox, D., Burgard, W., Dellaert, F., and Thrun, S. Monte Carlo localization: Efficient position estimation for mobile robots. Proc. of the National Conference on Artificial Intelligence (AAAI), vol. 113, 1999.

[6] Gezici S., Tian Z., Giannakis G.B., Kobayashi H., Molisch A.F., Vincent H., and Sahinoglu Z., “Localization via UWB” IEEE Signal Processing Magazine, vol. 71, 2005..

[7] Hofmann-Wellenhof B., Lichtenegger H., and Collins J. GPS Theory and Practice, Third, revised Edition, Springer-Verlag Wien, Austria, 1992, 1993 and 1994.

[8] Jonietz E., Ultra Wideband Wireless, Magazine of Innovation Technology, September 2004.

[9] Jourdan, D.B., Deyst, J.J., Jr., Win, M.Z., and Roy, N., “Monte Carlo localization in dense multipath environments using UWB ranging”, IEEE International Conference on Ultra-Wideband, 5-8 Sept. 2005, pp. 314-319.

[10] Julier, S.J. and Uhlmann, J.K. A new extension of the Kalman filter to nonlinear systems. Int. Symp. Aerospace/Defense Sensing, Simul. and Controls, Vol. 3, 1997.

[11] Kalman, R.E. A new approach to linear filtering and prediction problems. Journal of Basic Engineering, Vol. 82, nº 1, 1960, pp. 35-45.

[12] Liu, J.S. Metropolized independent sampling with comparisons to rejection sampling and importance sampling. Statistics and Computing, vol. 6, n. 2, 1996, pp. 113-119.

[13] Martínez J.L., González J., Morales J., Mandow A., and García-Cerezo A. Genetic and ICP Laser Point Matching for 2D Mobile Robot Motion Estimation. Journal of Field Robotics. John Wiley & Sons Ltd. Vol.: 23(1), 2006.

[14] Ristic, B., Arulampalam, S., and Gordon, N. Beyond the Kalman Filter: Particle Filters for Tracking Applications. Artech House Ed. 2004.

[15] Roy S., Foerster J.R., Somayazulu V.S., and Leeper D.G., Ultrawideband radio design: The promise of high-speed, short-range.

[16] Rubin, D.B. Using the SIR algorithm to simulate posterior distributions, Bayesian Statistics, vol. 3, 1988, pp. 395-402.

[17] Sarmiento, R. de Armas, V. Lopez, J.F. Montiel-Nelson, J.A., and Nunez, A., “Rapid acquisition for ultra-wideband localizers”, Ultra Wideband Systems and Technologies, 2002, 2002 IEEE Conference on, 21-23 May 2002 Pages:245 – 249.

[18] Spilker J.J. GPS signal structure and performance characteristics. Journal of the Institute of Navigation, vol. 25, no. 2, pp. 121–146, Summer 1978.

[19] Thrun S., Fox D., Burgard W., and Dellaert F., Robust Monte Carlo Localization for Mobile Robots. Artificial Intelligence 128(2001), pp 99-141.

[20] Thrun, S., Burgard, W., and Fox, D. Probabilistic Robotics. The MIT Press, 2005.

[21] Time Domain. http://www.timedomain.com

[22] Yang L. and Giannakis G.B. Ultra-wideband communications: An idea whose time has come. IEEE Signal Processing Mag., vol. 21, no. 6, pp. 26–54, Nov. 2004.