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APPLICATION OF UWB AND GPS TECHNOLOGIES FOR VEHICLE LOCALIZATION IN COMBINED INDOOR-OUTDOOR ENVIRONMENTS

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ABSTRACT

Ultra-Wide Band (UWB) sensors are innovative devices constructed for efficient wireless communications that have recently being used for vehicle localization in indoor environments. In contrast, GPS sensors are well-known satellite-based positioning devices widely extended for outdoor applications. We evaluate in this paper the combination of both technologies for efficient positioning of vehicles in a mixed scenario (both indoor and outdoor situations), which is typical in applications such as automatic guided vehicles transporting and storing goods among warehouses. The framework we propose for combining sensor information is Monte Carlo Localization (also known as Particle Filters), which is a versatile solution to the fusion of different sensory data and exhibits a number of advantages with respect to other localization techniques. In the paper we describe our approach and evaluate it with several simulated experiments that have yielded promising results. This work, supported by the European project CRAFT-COOP-CT-2005-017668, becomes a first step toward a robust and reliable localization system for automated industrial vehicles.

1. INTRODUCTION

Vehicle localization has been often addressed separately for indoor and outdoor environments. The main differences between both cases come from the different performances of the commonly employed sensors: typically, indoors sensors (laser range finders, radio beacons, etc) are more robust and provide more accurate positioning than outdoor sensors, like for example, GPS.
However, in those applications in which vehicle localization has to be approached in a mixed scenario, positioning methods relying on both technologies should coexist. Furthermore, the transitions between indoor-outdoor areas, where data from both type of sensors are available, should be managed coherently and exploited as a whole.
In this paper we propose the application of the *Particle Filters* as a probabilistic framework to cope with vehicle localization where UWB or GPS positioning information is available, either separately or jointly, as for example in automatic guidance of transport vehicles among industrial facilities.
Probabilistic approaches for the positioning problem are based on the estimation of a posterior probability distribution within the space of possible positions of the vehicle. They provide near-optimal results under certain independence assumptions and a given knowledge on the initial localization. One of such mechanism is the well-known Kalman filter [5], which forces the uncertainty to be Gaussian distributed. Different variations have been proposed to deal with this limitation, for example *multi-hypothesis Kalman filters* and *Markov Localization* [10].
Among the markovian methods, it is remarkable the Monte Carlo localization algorithms (MCL), also called *Particle Filters* or Condensation Algorithms [7], which work by representing the posterior estimation of the possible positions by a set of weighted samples, or *particles*. This approach exhibits the following advantages [10]:

-They have the ability to work with almost arbitrary sensor characteristics, motion dynamics, and noise distributions, even non-linearities.
-They can represent several position hypotheses simultaneously.
-Computational resources are well focused, since these methods sample proportionally to the posterior distribution.
-Particle filters are easy to implement.
-They provide a suitable framework for the fusion of sensory information provided by different devices.

They have also some disadvantages:

-Since the prediction is supported by particles, that is, by samples, a vehicle with a well-know position can loose its track because none of the generated samples is near enough to the true position.
-Paradoxically, too accurate sensors cause the impoverishment of the sample space.

In spite of these limitations, there are practical approaches, as shown further on, to overcome these problems. The structure of this paper is as follows: section 2 gives an overview of the UWB and GPS sensors as positioning technologies; section 3 describes the mathematical formulation of Particle Filters and its use for sensor combination; section 4 presents some simulated results of the combination of UWB and GPS readings to estimate the pose of vehicles within mixed scenarios. Finally, some conclusions and future work are outlined.

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2. UWB AND GPS SENSORS OVERVIEW

Ultra-Wide Band (UWB) is a quite new technology with major advantages for wireless communications [11]. It is based on the transmission of short pulses in the band between 3.6 and 10.1GHz. Apart from communication, it can also be exploited for positioning, since the distance between two antennas can be accurately derived through TOF (time-of-flight).

From the localization point of view, the main advantages of this system are:

-UWB signals are not affected by multipath fading.

-The signals can penetrate through objects.

-It exhibits precision ranging at centimetre level.

-As the signals are of very-low power, there can be small transmitters and receivers.

On the other hand, GPS [2] is a satellite geolocalization technique that has been widely exploited in the last years. Basically, it uses the signals received from satellites to develop a tri-lateration process. For positioning, the system uses two radio channels in the microwave band, centered at 1575.42MHz and 1227.60MHz. The accuracy of GPS can be improved by the usage of differential GPS (DGPS) to achieve a resolution of tens of centimetres. The transmitted signals cannot penetrate most materials, which limits the performance of the system and makes GPS appropriated only for outdoor applications, but not for localization among buildings, dense urban environments, forests, etc.

Another difference is the type of information provided by these sensors: UWB radio devices provide range measurements, while the GPS system gives the position and orientation (*x,y,phi*) of the vehicle. For our simulations, Gaussian models have been adopted for both sensors, being the uncertainty of the UWB characterized by the standard deviation of its measurements and the one of GPS by a *3x3* covariance matrix of the (*x,y,phi*) coordinates [7].

Next, our approach for combining both types of sensor data through particle filters is presented.

3. PARTICLE FILTERS FOR SENSOR COMBINATION IN VEHICLE POSITIONING

In section 3.1 we firstly summarize the basis of the Particle Filters: Bayes filtering. Section 3.2 delves into our particular implementation of a Particle Filter Localization algorithm which copes with the combination of different sensory devices.

3.1. Bayes filtering

The description of Bayes filtering can be found in many bibliographic references [10][9], but no unified nomenclature has been proposed yet. Through this paper we will follow the denominations used in [10].

Bayes filters estimate a posterior probability density, called the *belief,* denoted $Bel(x_t)$ (belief of being at position x at a time t), over a space of possible positions conditioned on the observation data. These filters are based on the *Markov assumption*, for which the past and future data are independent. Thus, the belief function will be recursively calculated as:

$$Bel(x_t) = \eta p(o_t \mid x_t) \int p(x_t \mid x_{t-1}, a_{t-1}) Bel(x_{t-1}) dx_{t-1} \quad (3.1)$$

where $\eta = p(o_t \mid a_{t-1}, \ldots, o_0)^{-1}$ is a normalization constant, o_t is the sensor observation taken at time t, and a_t the action executed at time t. Jointly with an initial probability distribution, this equation allows us to estimate future believes about the vehicle position.

For the calculation of (3.1) two probability densities must be known: $p(o_t \mid x_t)$ and $p(x_t \mid x_{t-1}, a_{t-1})$. The former is the *observation model* or *sensor model*, and provides the particular characteristics of each sensor; the later is the *motion model* and reflects the motion behaviour of the vehicle.

3.2. Particle filters

Particle Filters become an efficient way of solving the Bayes Filter (3.1) by representing the belief function $Bel(x)$ by a set of weighted samples, or *particles*, distributed according to:

$$Bel(x) \approx \left\{ x^{(i)}, w^{(i)} \right\}_{i=1,\ldots,m} \quad (3.2)$$

Particles $\left(x^{(i)} \right)$ represent the plausible positions of the vehicle following its motion model. *Weights* $w^{(i)}$, also called *importance factors*, represent the "goodness" of each particle for approaching the real belief function. This set of pairs *particle-weight* permits us to easily integrate information from different sensors. The position represented by the weighted mean of the particles will be assumed as the vehicle location.

In our work we follow the *Sequential Importance Sampling (SIS) Algorithm* [9] for implementing the particle filter. It is divided in four stages:

Step 1: Prediction. Draw the set of m particles according to the last motion action.

Step 2: Update. Assuming the sensors are mutually independent, the weights for particles are updated as:

$$w^{(i)}{}_t = w^{(i)}{}_{t-1} \cdot p(o_t^1 \mid x_t^{(i)}) \cdot p(o_t^2 \mid x_t^{(i)}) \cdot \ldots \cdot p(o_t^N \mid x_t^{(i)}) \quad (3.3)$$

where N is the number of different observations. Particularizing to our case, the available observations will be range measurements provided by UWB sensors, positions supplied by GPS, or both, and thus their respective sensor models are considered.

Step 3: Normalization. The new weights are normalized to represent a probability distribution as:

$$\hat{w}_t^{(i)} = \frac{w_t^{(i)}}{\sum_{i=1}^{m} w_t^{(i)}} \quad (3.4)$$

Step 4: Resampling. This stage aims to avoid particle impoverishment. In our approach, resampling is implemented as a systematic method, which is executed

when the number of high-weighted particles is under a given threshold [9].
The evolution of the filter maintains a set of particles that accurately represent the vehicle pose.

4. EXPERIMENTS

This section presents some preliminary results of the EU project CRAFT-COOP-CT-2005-017668 intended to combine positioning information from different sensory sources to be implemented within industrial scenarios. Thus, test scenarios are mixed indoor-outdoor synthetic environments where the ground truth position can be known.
Firstly we present separately some results of the accuracy of UWB and GPS sensors for localization and then, we study their combination in a mix scenario.
For both cases, a kinematical model of the vehicle is needed. The assumed model considers Gaussian noise in the motion commanded to the vehicle (X_{action}) [7]:

$$X_{action}(t) = \begin{bmatrix} x_{action}(t) \\ y_{action}(t) \\ \phi_{action}(t) \end{bmatrix} = \begin{bmatrix} x_{action}(t-1) - \sin(\phi(t-1)) \cdot \Delta_s \\ y_{action}(t-1) + \cos(\phi(t-1)) \cdot \Delta_s \\ \phi_{action}(t-1) + \Delta\phi \end{bmatrix} + V(t) \quad (3.5)$$

where Δ_s is the travelled distance in a time step, $\Delta\phi$ is the change of orientation in radians, and *V(t)* is an additive Gaussian noise. In our experiments we consider as the ground truth position of the vehicle the same expression without the added noise.

4.1. UWB-GPS independent results

For testing localization using particle filter with only UWB readings, we consider a scenario where a vehicle is commanded to follow a circular path. Our setup includes a variable number of UWB radio stations, at known locations, around the circular path (see fig. 1a). The UWB range measurements are modelled with σ_{UWB} = 3 cm. suggested in [11]. This experiment is aimed to assess the influence of the number of particles and sensor observations in the accuracy in position and orientation of our approach. In order to evaluate the effect of the dispersion of the particle set in the performance of the system, we measure the error at one point as the weighted mean of the distances between each particle and the ground truth. Fig. 1b depicts the influence of the number of particles involved in the filter with 3 UWB beacons. Note that an error in pose estimation under 2cm. can be obtained with this configuration. Also note that, surprisingly, the accuracy does not improve using a large number of particles. On the other hand, fig. 1c shows that, for this scenario, at least 3 beacons are required to achieve localization errors under 2 cm. (using 200 particles). Focusing on orientation, we notice that the modification of the number of particles or beacons does not improve the performance of the system, as the UWB sensor do not provide orientation information, the particle filter is not able to reduce the error in orientation. This limitation is particularly important in the case where only one beacon is present, where the uncertainty area around the sensor is large (as there is no intersection with other beacons, no triangulation is possible) and the performance is very dependant on the relative position of the beacon and the target.

(a)

(b)

(c)

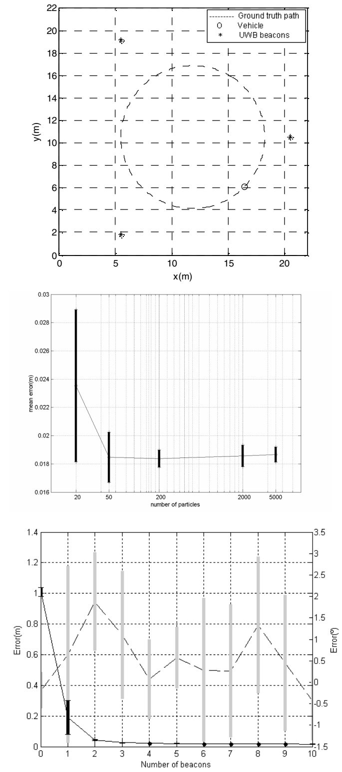

Fig. 1 UWB sensor performance for Particle Filter positioning. Plot (a) represents the simulation environment with 3 beacons. Figures (b) and (c) plot the position and orientation error and standard deviation of the estimated position with 3 beacons (varying the numbers of particles) and with 200 particles (varying the number of beacons), respectively. The position error is marked with a continuous line for the mean and black bars for the confidence intervals, while the values for the orientation errors are marked with dashed lines and grey bars respectively.

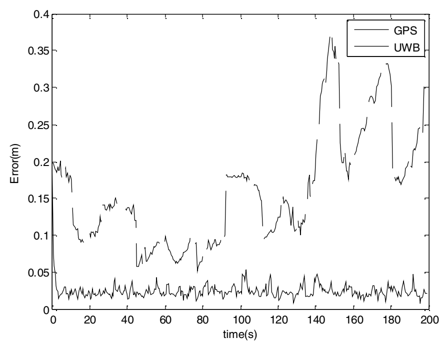

Fig. 2 Positioning error using separately 3 UWB beacons and GPS for a vehicle following a circular trajectory.

For testing GPS positioning, we have employed the Omnistar model [8] within the same setup (circular path and 200 particles). Yielded results confirm the lower accuracy of GPS compared to UWB, as shown in fig. 2, where its average localization error is *16* cm.

4.2. UWB-GPS combined results

We have setup the simulated indoor+outdoor environment depicted in Fig. 3 using 200 particles and 4 UWB beacons inside each warehouse. In this scenario, as the vehicle goes out the first warehouse, it loses UWB signals but starts to receive GPS readings. At this transition area, although the vehicle eventually only receives readings from 2 or less UWB beacons, the localization error reduced due to the measures provided by the GPS (see fig. 4).

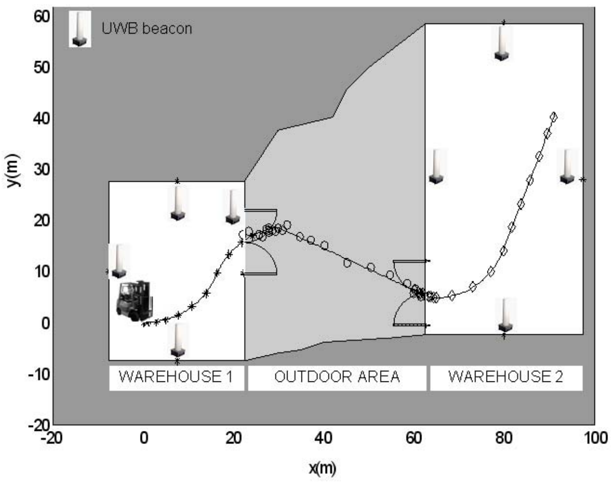

Fig. 3 Vehicle localization within a combined indoor-outdoor environment. Marks on the path indicate the estimated positions of the vehicle. Note than when both sources of information are jointly available (at transition areas), the inaccuracy of the GPS is corrected, permitting the vehicle to pass through the gates.

5. CONCLUSIONS AND FUTURE WORK

In this paper we have evaluated a probabilistic framework for the positioning of a vehicle in a combined indoor+outdoor scenario. We have studied the performance of UWB sensor technology for indoor positioning and GPS for outdoor areas. Simulated experiments have demonstrated the suitability of our particle filter approach to merge readings from these two types of sensors for vehicle localization in mixed environments.

In the future we plan to carry out experiments in real scenarios, using the exact probabilistic model of a particular UWB kit.

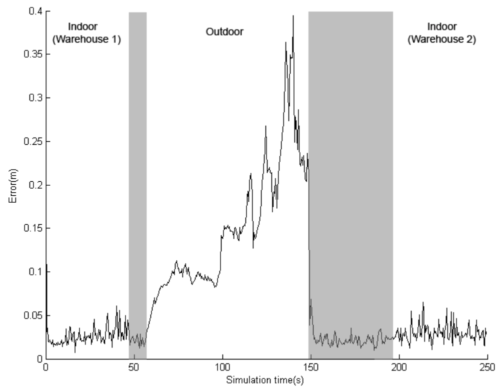

Fig. 4 Localization error of the vehicle with respect to the ground truth path for the mixed scenario. Note the accuracy in the pose estimation along indoor as well as in mixed areas where both UWB and GPS observations are combined.

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