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A Hybrid Active Global Localisation Algorithm for Mobile Robots

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Abstract— **Localisation is one of the most important tasks to be accomplished in order to realize the complete autonomy of a mobile robot. In this paper, a new strategy for global localisation is proposed. Applying this method a robot is able to safely initialise its position or relocalise itself in case of recovery of pose tracking failure. The algorithm presented adopts an hybrid approach. First a particle filter is used to generate hypotheses on the possible pose supposing that no movements are allowed to avoid collisions. Thereafter safe trajectories are planned and executed to reduce the remaining ambiguities while the hypotheses are monitored and validated by a set of parallel Extended Kalman Filters. The novelty of this approach stands on the ability to generate the pose hypotheses without any feature- based knowledge. As a consequence, a landmark-based description of the environment is no longer required for the algorithm execution.**

I. Introduction

When mobile robots operate in real world environment they require reliable localisation systems to accomplish their missions. Therefore a localisation module is always included in mobile robot control architecture.

Due to the difficulty in obtaining a reliable pose estimation, localisation has been a high active field of research in the last two decades. Indeed, mobile robots operate in environments that have not specifically engineered for them and localisation algorithms have to be able both to cope with the uncertainty of robot+environment system and to integrate data from different kinds of sensors.

There are two basic instances of the localisation problem: when starting a task determine the robot pose in absence of an initial estimate (*global localisation*) and during the motion, maintain a precise estimate of the pose by keeping track of the robot movements (*pose tracking*).

Most of the algorithms presented in literature are focused on the pose tracking, whereas less attention is dedicated to global localisation. Several research groups address localisation supposing that a rough knowledge of the initial pose is supplied to the robot[1], [2]. A widespread approach to face such instance is based on stochastic estimation theory: the pose estimation problem is translated in terms of probability density estimation. In this framework the pose tracking is solved using a uni-modal probability density, estimated by a common tool, the Extended Kalman Filter (EKF) [3].

The probabilistic approach can be adopted also to deal with global localisation, however in this case uni-modal probability density can not be used as multiple hypotheses needs to be handled [4]. As no knowledge about the initial configuration is provided, a general approach to discover the current pose consists in comparing the information extracted from sensor readings with an a priori map in order to form hypotheses. When absolute sensors (i.e., GPS, active beacons) are not available, due to the perceptual aliasing, several candidates are retrieved. In this context multi- modal probability densities have to be adopted and EKF have to be replaced with more sophisticated filters, such as grid-based or particle filters (Markov localisation [5], [6]).

Several solutions based on these classes of filters have been proposed. In [7] mobile localisation technique is presented which uses multiple Gaussian hypothesis to represent the probability distribution of the robots location in the environment. Moreover, in [8] an active global localisation for mobile robot using multiple hypotheses tracking is proposed. Markov localisation and EKF are combined in [9]. In all these works the key idea is to maintain multiple hypotheses on the robot pose during the navigation, without any interest on the trajectory executed by the robot.

This paper addresses global localisation problem when artificial beacons or GPS are not available. The proposed algorithm takes advantage of the multi-modal approach to generate the set of the most likely hypotheses when the robot is still, while during the robot motion the hypotheses are propagated and eliminated by a set of parallel Extended Kalman Filter [10], [11]. In addition, a strategy for planning safe trajectory is also implemented in order to minimise the risk of collision during the navigation.

The paper is organised as follows. Section II presents the theoretical background, section III describes the case study investigated, section IV details the proposed algorithm, and, finally, some simulation results and conclusion are reported in section V and VI respectively.

II. Probabilistic framework

The localisation problem, i.e., the problem of estimation the robot's pose given noisy measurements, can be described as a *stochastic estimation problem*. In such framework localisation can be formulated in terms of estimating the probability density over the state space of the robot poses. In literature such probability density is called *Belief* and is defined as

$$Bel(x_k) = p(x_k \mid U_k, Z_k),\ x \in \Xi. \tag{1}$$

i.e., the probability to have the robot at location x_k at time k, given all the history of the proprioceptive (U_k) and

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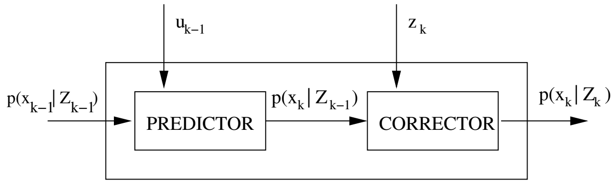

Fig. 1. Bayesian filter

exteroceptive (Z_k) measurements up the time, where Ξ is the set of the robot poses.

Most of the localisation algorithms proposed in literature are based on the well known predictor – corrector structure of Bayesian filter. The last extends the Bayes rule to temporal estimation problems: the key idea is to recursively maintain a probability distribution (*Belief*) over all poses (state space points) in the environment integrating information coming from proprioceptive sensors and exteroceptive sensors in two different steps (see Fig. 1).

Two different kinds of *Belief* can be distinguished regarding to this measurements classification: the *Prior* $Bel^-(x_k)$ and the *Posterior* $Bel^+(x_k)$. The former defined as

$$Bel^-(x_k) = p(x_k \mid U_k, Z_{k-1}) \tag{2}$$

is the *Belief* of the robot after the integration of the control data u_k, and before it receives the perceptual data z_k. The latter defined as

$$Bel^+(x_k) = p(x_k \mid U_k, Z_k) \tag{3}$$

is the *Belief* of the robot when the perceptual data z_k is also integrated. Using the *Total Probability theorem* the $Bel^-(x_k)$ can be rewritten as

$$\begin{aligned} Bel^-(x_k) \quad = \quad & \int_\Xi p(x_k \mid x_{k-1}, U_k, Z_{k-1}) \times \\ & p(x_{k-1} \mid U_{k-1}, Z_{k-1}) dx_{k-1}. \end{aligned} \tag{4}$$

The equation states that the *Prior* of being in x_k is given by the sum of the probabilities of coming from x_{k-1} to x_k conditioned on all the measurements so far. The second term of the integral represents the *Posterior* at time $(k-1)$, as the robot pose at generic step k does not depend on the action that is performed at the same step. This equation can be further simplified by means of the *Markovian assumption*, i.e. the assumption of having the past independent of the future and vice-versa, relying on the knowledge of the current state, as follows

$$\begin{aligned} Bel^-(x_k) \quad = \quad & \int_\Xi P(x_k \mid x_{k-1}, u_k) \times \\ & Bel^+(x_{k-1}) dx_{k-1}. \end{aligned} \tag{5}$$

Moreover, applying the *Bayes rule* the *Posterior* can be expressed as

$$\begin{aligned} Bel^+(x_k) \quad = \quad & p(z_k \mid x_k, U_k, Z_{k-1}) \times \\ & \frac{p(x_k \mid U_k, Z_{k-1})}{p(z_k \mid U_k, Z_{k-1})}. \end{aligned} \tag{6}$$

The equation states that the *Posterior* is the conditional probability of observing z_k, weighted by the ratio of the prior belief of being in x_k, $Bel^-(x_k)$, and the probability of observing measurement z_k conditioned on all information so far. Introducing the *Markovian assumption* again the *Posterior* can be rewritten as

$$Bel^+(x_k) = \frac{p(z_k \mid x_k)\ Bel^-(x_k)}{p(z_k \mid U_k, Z_{k-1})}. \tag{7}$$

The *localisation formula* resulting from the combination of such equations is

$$\begin{aligned} & Bel^+(x_k) = \eta P(z_k \mid x_k) \times \\ & \int_\Xi P(x_k \mid x_{k-1}, u_{k-1}) Bel^+(x_{k-1}) dx_{k-1}, \end{aligned} \tag{8}$$

where η represents $P(z_k \mid U_{k-1}, Z_{k-1})$ and can be viewed as a normalisation factor.

Localisation equations (4) and (8) cannot be implemented on a digital computer in their general form stated above, as the *Belief* over the space of robot poses is a density over a continuous space, hence has infinitely many dimensions. Therefore, any working localisation algorithm has to resort to additional assumptions.

For example in pose tracking a common approach is represented by the use of Kalman filter. In this context the *Belief* is modelled by a unimodal Gaussian density over the three-dimensional state space of the robot. The mode of this density yields the current position of the robot, and the variance represents the current uncertainty. As only these two parameters have to be computed to propagate uncertainty, there is no need to discretise the state space. The advantage of Kalman filter based techniques lies in their efficiency and in the high accuracy that can be obtained. However, the restriction to an unimodal Gaussian density is prone to fail if the pose of a robot has to be estimated from scratch, i.e., without knowledge about the starting position of the robot. Furthermore these techniques are typically unable to recover from localisation failures.

Several probabilistic global methods have been proposed to overcome the disadvantages of Kalman filter based techniques, relaxing Gaussian assumption and introducing the discretisation of the space state.

For instance, Monte Carlo Integration methods adopt a sampling-based approach to describe the probability distribution $Bel(x_k)$ as follows

$$Bel(x_k) \approx \{x_k^{(i)}, w_k^{(i)}\},\ i = 1, \dots, N \tag{9}$$

where $x_k^{(i)}$ is the i-th particle, $w_k^{(i)}$ represents its the weight and N is the number of particles.

Using such approach, the sampling strategy is crucial. A widespread sampling strategy is the *Sequential Importance Sampling*, where a normalised sampling distribution $\pi(x_k \mid d_k)$, which support includes the one of the posterior $Bel^+(x_k)$, is used to draw samples from. The resulting approximation is

$$Bel^+(x_k) \approx \sum_{i=1}^{N} w_k^{(i)} \delta_{x_k^{(i)}}(x_k - x_k^{(i)}), \tag{10}$$

where $w_k^{(i)}$ is the importance weight and gives an evaluation of the quality of the solution $x_k^{(i)}$. In the prediction step only an evolution of the particle is considered without any change of the weights, as shown in Algorithm 1.

Monte Carlo methods have the great advantage of allowing an approximation for a significant variety of probability distributions, such as multi-modal ones. Therefore, they turn out to be very useful to deal with the global localisation problem. However Monte Carlo methods suffer from great computational load, as a large number of samples has to be considered in order to maintain an accurate approximation of the *Belief*.

III. Problem Setting

In this work an active localisation and safe planning algorithm for mobile robots navigating in a known environment is considered.

Although, the proposed algorithm could be generalised for robots having different kinematic models and equipped with different sensory systems, here a particular set up is studied.

The test bed adopted is a mobile manipulator, composed by a mobile base carried a vertical articulated manipulator with 5 DoF. The mobile base has the kinematic model of a unicycle,

$$\begin{aligned} x_k &= f(x_{k-1}, u_k) \\ &= x_{k-1} + \begin{bmatrix} \cos\tilde{\phi}_{k-1} & 0 \\ \sin\tilde{\phi}_{k-1} & 0 \\ 0 & 1 \end{bmatrix} u_k \end{aligned} \quad (11)$$

where $x_k = (p_x, p_y, \phi_k)$ is the pose of the robot, $\tilde{\phi}_k = \phi_{k-1} + \delta\phi_k/2$ is the average robot orientation during the k-th sample time interval, and $u_k = [\delta d_k, \delta\phi_k]^T$ are the displacement and the rotation of the robot during the same sample interval.

The sensory system is composed by encoders, as proprioceptive sensors, and a sonar rangefinder as exteroceptive sensor. Encoders are used to determine the pose of the mobile base and the posture of the tip of the manipulator. The ultrasound sensor is mounted on the end-effector of the arm, and can be panned to explore the surroundings. Its model depends on the way the environment is described by the map $\mathcal{M}$. As in this work the map is represented by a list of segments, the observation model can be written as

$$z_k = h(x_h, \mathcal{M}) = \frac{\mid a_j s^x + b_j s^y + c_j \mid}{\sqrt{a_j^2 + b_j^2}}. \quad (12)$$

where (a_j, b_j, c_r) are the coefficients of the j-th segment and (s^x, s^y) is the configuration of the ultrasound rangefinder computed applying the well-known direct kinematics equations of the manipulator, not reported here due to lack of space.

As the ultrasound sensor can be moved in the workspace of the arm, several measurements can be retrieved at each sample interval, and composed to form a pattern as shown in Fig. 2.

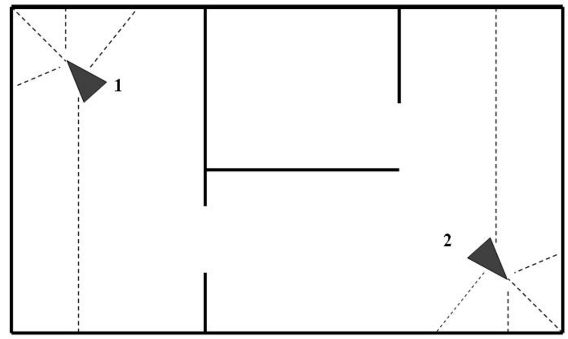

Fig. 2. Same pattern of ultrasound measurements (dashed line) in an office like environment retrieved by two different robot poses (triangle) . Here the stroboscopic view of the arm is not report.

Notice that, even using a predefined set of sonar positions, the same pattern can be produced by different robot pose, due to the perceptual aliasing.

IV. Active localisation Algorithm

The algorithm for global localisation proposed in this work can be broken down into two step:

- Hypothesis generation
- Safe planning and tracking

During the first step the robot does not know its pose in its working area and is still in order to avoid collisions. However, the robotic arm is able to safely explore the environment moving the ultrasound sensor on the end effector. The pattern retrieved by sonar measurements is used to generate hypotheses about the possible pose of the robot in the environment by means of a particle filter.

Due to perceptual aliasing several hypotheses are retrieved and the residual ambiguity has to be reduced adopting a different strategy. For this reason, in the second step safe path are planned and executed by the robot. During the navigation the hypotheses are tracked using Kalman filters in order to monitor their reliability. When an hypothesis looses its reliability is discarded until the real position of the robot, otherwise a restart of the algorithm is required.

In the sequel the steps will be detailed.

A. Hypotheses generation

The algorithm, proposed to face the pose recovery problem for a mobile manipulator, is based on a particle filter. A possible implementation for the k-th iteration, in which the *Bayesian Importance Sampling* approach has been adopted, is shown in the pseudo-code Algorithm 1.

Several differences between the classical implementation and the presented one can be singled out. These differences mainly concern the assumption of stillness that has been done for the mobile base. From this point of view the algorithm can be considered as an optimisation algorithm, where some interesting aspects of a multi-modal filter still remain.

At the first time a uniform probability distribution, covering the entire environment, is considered, as global localisation problem comes without any knowledge about the initial

Algorithm 1: Particle Filter

Data: $Bel(x_{k-1})$, z_k

Result: $Bel(x_k)$

```
/* Importance Sampling                                  */
```
for *i=1* **to** *Ns* **do**

  Particle evolution $Bel^{-}(x_{k-1}) \sim \{x_k^{(i)}, w_{k-1}^{(i)}\}$

  Weights update $Bel^{+}(x_{k-1}) \sim \{x_k^{(i)}, w_k^{*(i)}\}$

  Normalisation $\tilde{w}_k^{(i)} = \frac{w_k^{*(i)}}{\sum_{j=1}^{Ns} w_k^{*(i)}}$

end

Evaluate $N_{eff} = \frac{1}{\sum_{i=1}^{Ns} (w_k^{(i)})^2}$

```
/* Resampling                                           */
```
if $N_{eff} \geq N_{thres}$ **then**

  $Bel(x_k) = \{\tilde{x}_k^{(i)}, \tilde{w}_k^{(i)}\}$

else

  $Bel(x_k) = Resampling(\{\tilde{x}_k^{(i)}\ ,\ \tilde{w}_k^{(i)}\})$

end

pose of the robot. At this stage, the number of particles has to be carefully fixed in advance, in order to guarantee the coverage of the state space.

At k-th sample interval a particles evolution and a weights update have to be computed. In this context, in which the mobile base is motionless, there is no proper particles evolution. Therefore, the localisation problem is based only on the data coming from the ultrasound rangefinder which the arm has been equipped with. This consideration points out an interesting aspect: the temporal step k-th can be considered as the k-th iteration of an optimisation algorithm as well.

In order to update the weights of the particles, a suitable computation strategy has to be adopted. Here, the quadratic error between the ultrasound rangefinder measures, coming from the mobile base, and the expected ones, coming from the i-th particle, is computed using eq. 12

$$v_{j,k}^{(i)} = (z_{j,k} - z_{j,k}^{(i)})^2, \tag{13}$$

where $z_{j,k}$ represents the k-th sensor reading related to the j-th configuration of the robotic arm and $z_{j,k}^{(i)}$ is the expected observation.

Consequently, the weight is updated has:

$$w_k^{(i)} = \frac{\beta}{\sum_{j=1}^{N_{pos}} v_{j,k}^{(i)}}, \tag{14}$$

where β is a scaling dimensional factor, whom nominal value is negligible because of 15.

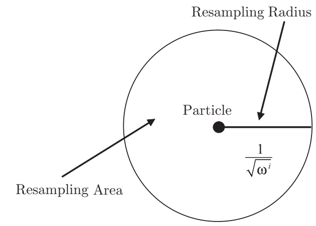

Fig. 3. Choice of resampling area for mutation

Finally, in order to obtain the following approximation for the *Belief* a normalisation has to be performed to satisfy the constraint:

$$\sum_{i=1}^{N} w_k^{(i)} = 1. \tag{15}$$

Notice that previous weights are not taken into account for the computation of the actual weights. These choices are explained with the fact that the robot is still. As a consequence, the same pattern is available at each iteration. Therefore the algorithm iteratively improves the solution in order to find out the most likely hypotheses.

The resampling step has been introduced to overcome the *depletion problem*, i.e., the problem of having most of particles with a negligible weight after few steps. To this aim, all the particles except the very best ones, are discarded and new ones are generated by resampling.

In literature, several strategies have been proposed to deal with this problem. Here, the availability of observations is limited by the motionless state of the mobile base and an evolutionary approach is suggested, in order to find out the most likely hypotheses.

Particles are regarded as elements of a population, whose chromosoma is represented by the space state vector. The evolutionary resampling is performed by means of a *mutation* strategy and an additional random action, called *randomisation*.

The former draws new particles within a fixed circular area, whose boundary are described in Fig. 3, to reinforce the presence of particles where the probability to find the mobile base is higher.

The latter spreads a fixed percentage of particles within the whole environment, to mitigate the centralising effect of the mutations and guarantee a minimal coverage of the environment.

The recovery algorithm stops when a stable solution is reached. The stable solution is detected monitoring a fixed percentage of the most likely hypotheses. These last will be used in the trajectory planning and tracking step.

B. Trajectory planning and tracking

After the generation of the hypotheses, the robot moves in the environment along safe path in order to reduce the residual ambiguity.

At each planning step a via point is generated in the proximity of the nearest obstacle: in this way a path generated for a candidate is safe for all, as shown in Fig.4.

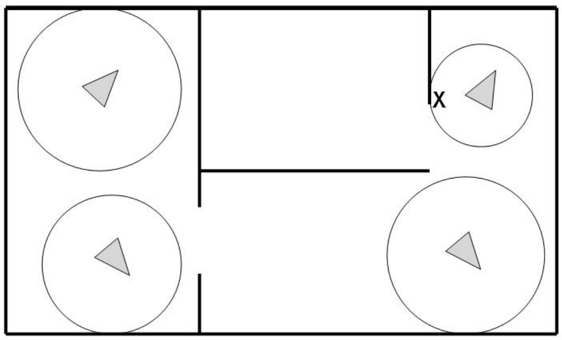

Fig. 4. Via point selected (x) using the nearest obstacle technique.

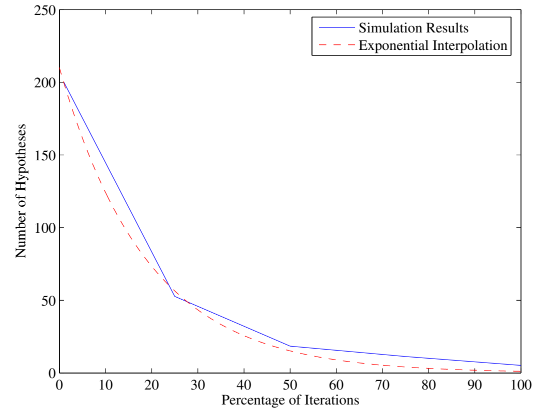

Fig. 5. Trend of convergence for an initial set of 1000 particles averaged over 50 runs.

The robot is driven towards the via point by means of the control law proposed in [12] and not reported here for lack of space.

During the navigation each candidate is monitored by a Extended Kalman Filters. The EKF uses the kinematic model of the robot to form a prediction estimate of a candidate pose $x_k^{(i)}$:

$$\begin{aligned} x_{k|k-1}^{(i)} &= f(x_{k-1|k-1}^{(i)}, u_k) \\ P_{k|k-1} &= J_x^f \, P_{k-1|k-1} \, (J_x^f)^T + J_u^f \, C \, (J_u^f)^T + Q. \end{aligned} \tag{16}$$

Here, J_x^f and J_u^f are the Jacobian matrices of $f(\cdot)$ with respect to $x_{k-1}^{(i)}$ and u_k, $P_{k-1|k-1}$ is the covariance matrix at time instant $k-1$, C is the covariance matrix of the Gaussian white noise which corrupts the input measure and Q is the covariance matrix of the Gaussian white-noise which directly affects the state in the kinematic model.

The correction estimate is obtained comparing the measurements available at k-th sample time:

$$\begin{aligned} x_{k|k}^{(i)} &= x_{k|k-1}^{(i)} + K_k[z_k - h(x_{k|k-1}^{(i)})] \\ P_{k|k} &= P_{k|k-1} - K_k \, S_k \, K_k^T. \end{aligned} \tag{17}$$

where K_k is the Kalman gain matrix

$$K_k = P_{k|k-1} (J_x^h)^T \, S_k^{-1} \tag{18}$$

and S_k is covariance matrix associated to the innovation

$$v_k^{(i)} = z_k - h(x_{k|k-1}^{(i)}). \tag{19}$$

In order to determine the correspondence between the real pattern retrieved by the ultrasound rangefinder and the ones generated by the hypotheses a data association test is set up, using Mahalanobis metric and χ square test

$$v_k^{(i)} S_k^{-1} (v_k^{(i)})^T \leq \chi^2 \tag{20}$$

where χ is a threshold that validate the candidates.

Due to the perceptual aliasing a complete disambiguation is not always possible. Indeed, as explained above the symmetry of the environment should not produce the expected disambiguation: for example in an environment having the shape of a Greek cross it is difficult to retrieve less than four hypotheses at the end of the trajectory planning and tracking.

V. Simulation Results

The algorithm has been tested in simulated environments in order to validate its effectiveness. Such simulations have been performed exploiting a framework, developed by the authors, able to provide several kinematic models as well as an emulation for several kinds of sensors, such as laser rangefinders. The robot configuration used for such simulations is shown in table I:

TABLE I
SETUP CONFIGURATION

Parameter	Description	Value
N	Number of Particles	$200 \div 1000$
N_{pos}	Pattern Beams	16
H	Selected Hyp. [%]	20
χ	Validation Gate [%]	40

Two indexes of quality have been taken into account to evaluate the performance of the algorithm :

- Percentage of successful trials
- Convergence trend.

The first index gives a measure of the efficacy of the propose active localisation algorithm. In order to provide an accurate analysis, the algorithm has been run 50 times for each fixed number of particles, and mean values have been considered. Therefore, in Tab. II is shown the percentage of successful trials considering a variable number of particles, ranging from 200 to 1000.

TABLE II
PERCENTAGE OF SUCCESSFULLY TRIALS

Number of Particles	200	300	500	700	1000
Successfully Trial [%]	65	80	90	95	100

On the other hand, the second index provides a statistical law for the prediction of the algorithm convergence time. For this purpose, the algorithm has been run several times with a fixed number of particles. Afterward, a normalised temporal axis has been computed in order to compare the trials. Finally, a common convergence law has been retrieved

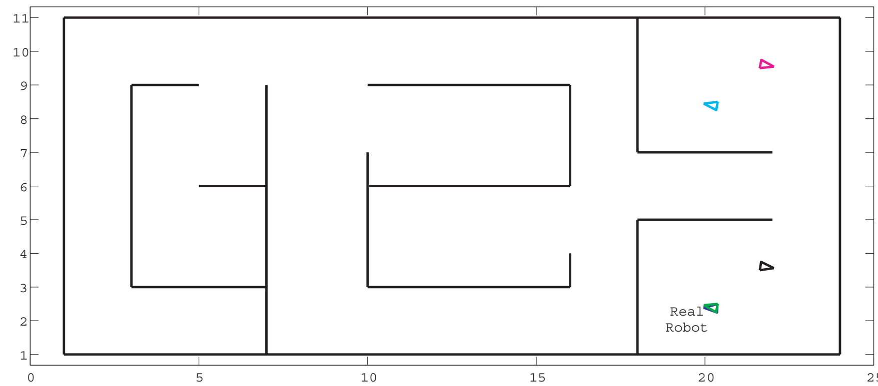

Fig. 6. Example of presence of multiple likely hypotheses.

respect to the number of remaining hypotheses. According to this, Fig. 5 shows the trend of convergence when considering an initial set of 1000 particles averaged over 50 runs. An additional exponential interpolation has been done to better understand the convergence velocity trend. The figure proves the efficacy of the proposed planning strategy to disambiguate as only 25% of hypotheses are considered after 30% of the overall planning iterations. Note that once the algorithm stops, there is no guarantee that the solution retrieved is represented by a unique pose. This behaviour can arise because of two different conditions:

- Hypotheses overlapping
- Environmental structural ambiguities.

Fig. 6 shows an example when both of these conditions arise. In particular, four hypotheses remain when the algorithm stops, according to the structural ambiguities of the environment. In this case, the algorithm is unable to discern the real robot pose relying only on the simple proposed planning approach, therefore a random path generation can be added in order to overcome such limitation.

VI. CONCLUSION

In this paper, a hybrid approach to solve the active localisation problem, without a global positioning devices, has been proposed. The algorithm relies on two steps: hypothesis generation and safe planning and tracking technique. The former exploits a particle filter to find out the most likely hypotheses with the assumption of stillness of the robot. The latter plans safe trajectories to reduce the remaining ambiguities using an extended Kalman filter for each hypothesis when the robot is moving. The novelty of this algorithm is related to the ability to localise the robot without any feature-based knowledge of the environment, consequently a more general use of this approach is possible.

An extensive analysis has been performed in order to validate the proposed algorithm. In particular, two indexes of quality have been adopted to study the convergence velocity to the real robot pose (first index) as well as to verify its efficacy (second index). According to the simulation results, the algorithm is able to localise the robot with a reasonable level of reliability. Moreover, the simple planning strategy has proved to be useful to quickly remove unlikely hypotheses that had been generated because of the environmental similarities. Some interesting challenges still remain for future work, among them an implementation of the proposed algorithm on a real robot.

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