Localización activa en interiores utilizando mapas solapados

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2. **Trabajos relacionados**
3. **Marco teórico**
   - Filtro de partículas :: AMCL
   - Algoritmos de clustering
   - Ganancia de información
   - Medidas de error en la localización
4. **Especificación del problema y propuesta de la solución**
   - Especificación del problema
   - Propuesta de solución
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Problemas clásicos de navegación

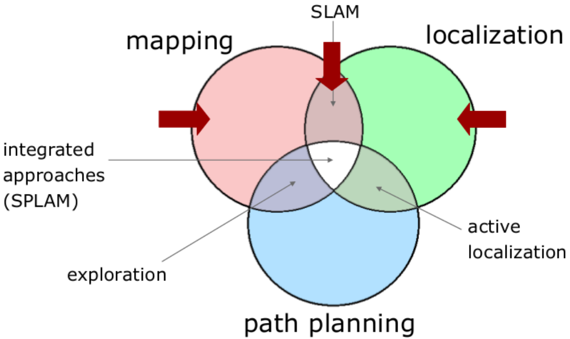

Figura 1: Problemas clásicos de navegación: mapeo, localización, planificación, slam, localización activa, exploración y splam.

Taxonomía de los problemas de localización

- Localización local versus localización global
- Entornos estáticos versus entornos dinámicos
- Localización pasiva versus localización activa
- Agente simple versus multiagente

Definiciones

Localización pasiva :: ¿Dónde estoy?

La *localización pasiva* se ocupa de mantener a un robot ubicado en un entorno a partir de un mapa (m), información sensorial (z_t) y su movimiento (u_t), sin influir en su misión o recorrido.

Localización activa :: ¿A dónde me muevo para mejorar mi ubicación?

En la *localización activa*, se eligen acciones de control *parciales* (u_t) buscando mejorar la localización del robot.

Ejemplo

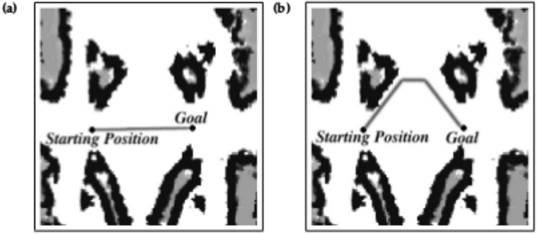

Figura 2: En (a) el robot se mueve desde la posición inicial hasta el destino por el camino más corto. En (b) busca llegar al destino por un camino rico en características para disminuir la incertidumbre.

¿Cuál es el camino más corto y con menor incertidumbre?

- No todas las trayectorias introducen el mismo nivel de incertidumbre
- Hay que decidir qué controles debo aplicar en el robot en base a la posición actual
- Se pueden adoptar varios enfoques sobre este problema:
  - Largo plazo, mediano plazo, corto plazo

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Planificador global

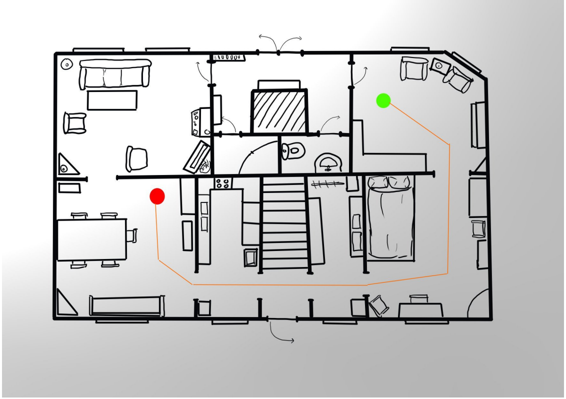

Figura 3: Planificador standard

Planificador global parametrizado :: loc. activa. largo plazo

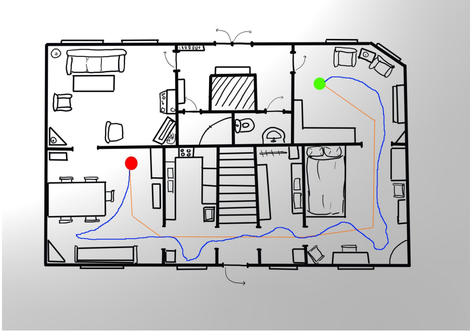

Figura 4: La ruta priorizando pasar por lugares con características relevantes

Planificador global, decisiones locales :: loc. activa. corto plazo

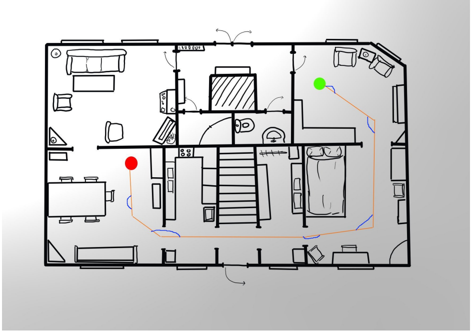

Figura 5: Acciones locales, no afectan la planficación

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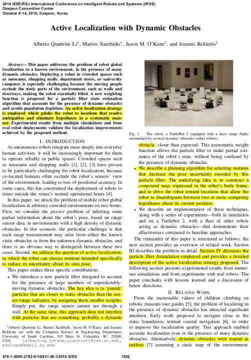
Active localization with dynamic obstacles (2016)

- Probability grid map, láser, MCL, global localization
- Forma clusters a partir del filtro de partículas
- Se obtiene un representante por cada cluster y, tomando uno de ellos fijo, superpone a los otros con sus respectivos mapas generando un mapa compuesto
- Extrae el punto con mayor ganancia de información y dirige al robot hacia esa dirección con el objetivo de eliminar a las hipótesis erróneas



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Active Localization with Dynamic Obstacles

Alberto Quattrini Li[1], Marios Xanthidis[1], Jason M. O'Kane[1], and Ioannis Rekleitis[1]

Abstract— This paper addresses the problem of robot global localization in a known environment, in the presence of many dynamic obstacles. Deploying a robot in crowded spaces such as museums, shopping malls, department stores, or university campuses is especially challenging because the moving people occlude the static parts of the environment, such as walls and doorways, making the robot essentially blind. A new weighting function is proposed for a particle filter state estimation algorithm that accounts for the presence of dynamic obstacles and avoids population depletion. An active localization strategy is employed which guides the robot to locations that resolve ambiguities and eliminate hypotheses in a systematic manner. Experimental results from multiple simulations and from real robot deployments validate the localization improvements achieved by the proposed method.

I. INTRODUCTION

As autonomous robots integrate more deeply into everyday human activities, it will be increasingly important for them to operate reliably in public spaces. Crowded spaces such as museums and shopping malls [1], [2], [3] have proven to be particularly challenging for robot localization, because co-located humans often occlude the robot's sensors' view of the environment, leading to loss of positional accuracy. In some cases, this has constrained the deployment of robots to times outside the venue's normal operational hours [4].

In this paper, we attack the problem of mobile robot global localization in arbitrary crowded environments on two fronts. First, we consider the *passive* problem of inferring some partial information about the robot's pose, based on range sensor data, in environments with a high density of dynamic obstacles. In this scenario, the particular challenge is that each range measurement may arise from either the known static obstacles or from the unknown dynamic obstacles, and there is no obvious way to distinguish between these two cases. Second, we address the question of *active* localization, in which the robot can choose motions intended specifically to reduce its uncertainty about its own pose.

This paper makes three specific contributions.

- We introduce a new particle filter designed to account for the presence of large numbers of unpredictably-moving dynamic obstacles. The key idea is to 'punish' particles that are closer to static obstacles than the sensor range indicates, by assigning them smaller weights. Simply put, the range sensor cannot see through a wall. At the same time, this approach does not interfere with particles that see something, probably a dynamic obstacle, closer than expected. This asymmetric weight function allows the particle filter to make partial estimates of the robot's state, without being confused by the presence of dynamic obstacles.
- We describe a planning algorithm for selecting motions that decrease the pose uncertainty encoded by this particle filter. The underlying idea is to construct a *compound map*, expressed in the robot's body frame, and to drive the robot toward locations that allow the robot to disambiguate between two or more competing hypotheses about its current position.
- We describe an implementation of these techniques, along with a series of experiments—both in simulation and on a Turtlebot 2, with a fleet of other robots acting as dynamic obstacles—that demonstrate their effectiveness compared to baseline approaches.

The remainder of this paper is structured as follows: the next section provides an overview of related work. Section III describes the problem in detail. Section IV discusses the particle filter formulation employed and provides a detailed description of the active localization strategy proposed. The following section presents experimental results from numerous simulations and from experiments with real robots. The paper concludes with lessons learned and a discussion of future directions.

II. RELATED WORK

From the memorable videos of children climbing on robotic museum tour guides [5], the problem of localizing in the presence of dynamic obstacles has attracted significant attention. Early work proposed to navigate close to the static boundaries, termed coastal navigation [6], in order to improve the localization quality. This approach enabled accurate localization even in the presence of many dynamic obstacles. Alternatively, dynamic obstacles were treated as outliers [7] assuming a static map of the environment.

Fig. 1. The robot, a TurtleBot 2 equipped with a laser range finder surrounded by several dynamic obstacles (other robots).

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Action Selection (2012)

- Probability grid map, láser, MCL, global localization
- Genera una localization matriz a priori, basado en la utilidad de las posibles observaciones desde cada punto del mapa
- La matriz de localización se calcula offline, previo a la ejecución
- En cada paso se elige una acción en la dirección de celdas con mayor
- Para los experimentos utiliza un robot diferencial con un sensor laser range finder (30mts, 0-180°, resol. 1°) y encoder para la odometría

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Action Selection Based on Localizability for Active Global Localization of Mobile Robots

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***Abstract* – An actions selection mechanism for mobile robots is proposed to accelerate convergence of global localization without increasing computational complexity. In this mechanism, the localizability matrix of every pose is calculated off-line over the apriori probabilistic grid map, and during the phase of global localization with particle filtering, robot actions are selected actively according to maximization of localizability distinctness for all particles. Real robot and real world experiments are implemented for verifying the proposed approach. The experimental results show that the localizability matrix is able to represent the probability distribution of possible observations in the given map accurately, and the actions selection strategy improves the efficiency compared with standard global localization method.**

Index Terms* – *Localizability, Action selection, Active global localization, Probabilistic grid map, MCMC particle filter.

I. Introduction

One of the localization problems is called "Global Localization": The robot pose (position and heading) is determined in absence of the initial one [1]. It is a key topic when designing autonomous systems. In researches of global localization, the problem is naturally limited in a stochastic context to deal with uncertainty because of the initial uncertainty of the state space of mobile robot. There are many factors to influence the localization results, such as possible observations from map, proximity sensors (e.g. laser range-finder, LRF) and so on.

In early researches, the methods of global localization are almost passive ones [2, 3]. These methods do not rely on neither the robot motion planning nor the sensor controlling. Although the passive methods are capable of estimating the robot pose, it needs more convergence steps [4]. Recently, the active global localization methods are paid more and more attentions. The main idea is to select proper actions to control mobile robot partially or fully, providing the large probability to increase the efficiency.

A hierarchical approach of active global localization using Bayesian network and a Markov Chain Monte Carlo (MCMC) particle filter was proposed by Zhou and Sakane [5]. In the lower layer, authors used a standard particle filter to evaluate the posterior probability of the possible poses. When the particles converged into clusters, the higher layer generated a sensing action sequence for localization based on the Bayesian network [6]. Another method was proposed by Murtra et al. [7]. Authors proposed rational criteria to select one position of exploring particles to navigate the robot. Such an action can minimized the expected number of remaining pose hypotheses. The above two methods are all executed after particle pre-convergence. If the actual robot is near by one of these hypotheses, the methods can reduce the computational complexity. But if it is far away, i.e. the pre-convergence is failed, the expected efficiency would remain questions.

In this paper, we propose an actions selection mechanism for a MCMC particle filter. Based on probabilistic grid map (PGM), localizability matrix is calculated to represent the probability distribution of possible observations. Before every phase of particle filtering, robot moves actively according to maximization of localizability distinctness for all particles. And then it continues the standard particle filtering. For not to increase the computational complexity, the localizability matrix of every pose over the apriori PGM is calculated off-line. Experiments with real robot are implemented in real worlds for verifying the proposed method. The experimental results show that the localizability matrix is able to represent the probability distribution of possible observations in the given map accurately. Through comparing with standard global localization method, the active method with the proposed actions selection mechanism improves the efficiency.

This paper is organized as follows. Section II introduces the map and the observation models. In section III, a discrete way is proposed to estimate the localizability. In section IV, method of active global localization based on localization is presented. Then in section V, the appropriateness of proposed method is verified through experiments. Finally, in section VI the conclusion is given out.

II. Map and Observation Models

A. Probabilistic Grid Map

In this paper the PGM is used to express the real world as Fig. 1.

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Localización global eficiente utilizando movimientos rotacionales (2017)

- Probability grid map, láser 360, MCL, global localization
- Utiliza solamente movimientos rotacionales
- Compara los histogramas obtenidos de las rotaciones con la lectura del láser


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Efficient Autonomous Global Localization for Service Robots Using Dual Laser Scanners and Rotational Motion

Minkuk Jung and Jae-Bok Song*

Abstract: This study presents an alternative global localization scheme that uses dual laser scanners and the pure rotational motion of a mobile robot. The proposed method extracts the initial state of the robot's surroundings to select robot pose candidates, and determines the sample distribution based on the given area map. Localization success is determined by calculating the similarity of the robot's sensor state compared to that which would be expected at the estimated pose on the given map. In both simulations and experiments, the proposed method shows sufficient efficiency and speed to be considered robust to real-world conditions and applications.

Keywords: Mobile robot localization, mobile robot navigation, sensor fusion, service robot.

1. INTRODUCTION

Localization of a mobile robot can be classified into local localization [1, 2] and global localization [3, 4]. The former estimates the robot's current pose based on the previous one, and the latter estimates the initial robot pose accurately based on a given map. In contrast, a SLAM scheme [5, 6] estimates the current robot pose based on the previous one without any additional information on the environment.

Global localization methods can differ depending on the environment and robot missions. Especially for low-cost robots such as robotic vacuum cleaners, a mission can be accomplished without any high-cost sensor-based global localization since accurate knowledge of the robot's initial pose is optional. Practical methods for low-cost sensor-based indoor localization are often based on the use of cameras. Camera-based localization methods are achieved through the association of features based on Speeded Up Robust Features (SURF), Features from Accelerated Segment Test (FAST) or arbitrarily shaped features and so on [7, 8].

On the other hand, advanced robots such as service robots require a global localization scheme that provides a highly accurate initial state because their missions usually involve transporting containers or guiding people to landmarks. Among a wide variety of methods, Markov localization [9] is the most widely used for laser scanners. To reflect the uncertainty of the information on the environment and sensors, Monte Carlo localization (MCL) with a particle filter is often used [10]. This scheme works by estimating the robot motion through a motion model, and updating the weighting values of samples through range sensors.

A conventional MCL technique shows robust performance in local localization, but has low efficiency because it requires a wandering motion during global localization. Alternatively, a hybrid localization scheme [11] estimates the robot pose using a Kalman filter to track a number of pose hypotheses based on the evidences during a wandering motion. However, these methods can be time-consuming and inconvenient because of such wandering motion required to get the environmental information. Furthermore, this wandering motion is sometimes prone to collision with dynamic obstacles.

Also, global localization in a large environment requires numerous samples, thereby causing a high computational load. To deal with this problem, a topological map was used in [12], but a large number of particles ought to be used for good performance. A tree structure method was used in [13] to reduce the computation time, but it was not very effective.

In this study, an improved global localization algorithm is proposed to address the problems mentioned above. This scheme is based on MCL, which is robust to noise disturbances [10]. The proposed scheme requires only a rotational motion for localization unlike the conventional scheme which requires both translational and rotational motions. This feature alleviates the planning of wandering motion for localization since the robot does not need

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Localización global eficiente utilizando movimientos rotacionales (2017)

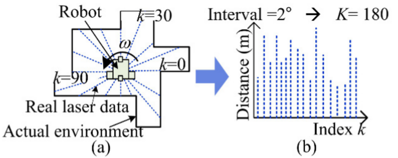

Fig. 7. (a) Range data from the robot and (b) histogram showing the range distribution.

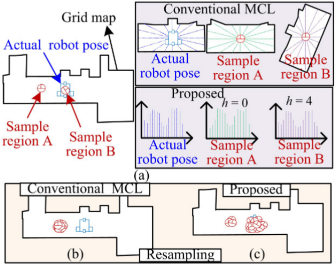

Fig. 9. Resampling proccess: (a) sample distribution and calculating weight, (b) conventional MCL, and (c) proposed method.

Percepción visual activa para localización (2009)

- Topological map, cámera, local localization
- Escanea el entorno mientras navega

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Active Visual Perception for Mobile Robot Localization

Javier Correa · Alvaro Soto

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Abstract Localization is a key issue for a mobile robot, in particular in environments where a globally accurate positioning system, such as GPS, is not available. In these environments, accurate and efficient robot localization is not a trivial task, as an increase in accuracy usually leads to an impoverishment in efficiency and viceversa. Active perception appears as an appealing way to improve the localization process by increasing the richness of the information acquired from the environment. In this paper, we present an active perception strategy for a mobile robot provided with a visual sensor mounted on a pan-tilt mechanism. The visual sensor has a limited field of view, so the goal of the active perception strategy is to use the pan-tilt unit to direct the sensor to informative parts of the environment. To achieve this goal, we use a topological map of the environment and a Bayesian non-parametric estimation of robot position based on a particle filter. We slightly modify the regular implementation of this filter by including an additional step that selects the best perceptual action using Monte Carlo estimations. We understand the best perceptual action as the one that produces the greatest reduction in uncertainty about the robot position. We also consider in our optimization function a cost term that favors efficient perceptual actions. Previous works have proposed active perception strategies for robot localization, but mainly in the context of range sensors, grid representations of the environment, and parametric techniques, such as the extended Kalman filter. Accordingly, the main contributions of this work are: i) Development of a sound strategy for active selection of perceptual actions in the context of a visual sensor and a topological map; ii) Real time operation using a modified version of the particle filter and Monte Carlo based estimations; iii) Implementation and testing of these ideas using simulations and a real case scenario. Our results indicate that,

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Monte Carlo Localization

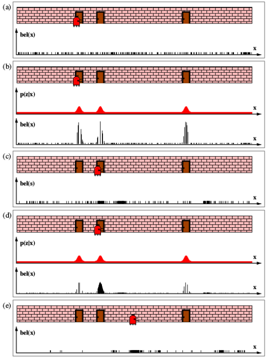
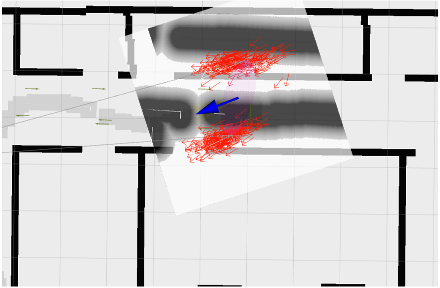


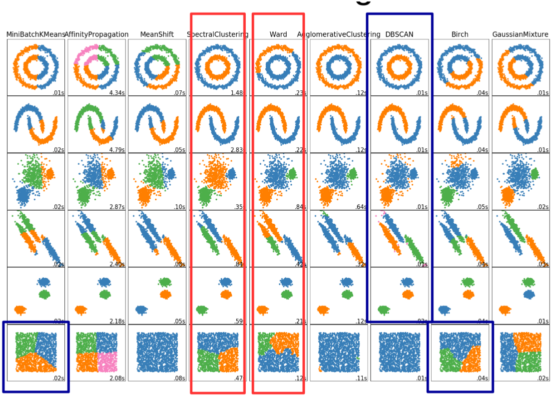
Figura 6: Integración de $p(z_t|x_t)$ y $p(x_t|u_{t-1}, x_{t-1})$ al belief

Filtro de partículas



Algorithm Particle_filter($\mathcal{X}_{t-1}, u_t, z_t$):
$\bar{\mathcal{X}}_t = \mathcal{X}_t = \emptyset$
for $m = 1$ to M do
sample $x_t^{[m]} \sim p(x_t \mid u_t, x_{t-1}^{[m]})$
$w_t^{[m]} = p(z_t \mid x_t^{[m]})$
$\bar{\mathcal{X}}_t = \bar{\mathcal{X}}_t + \langle x_t^{[m]}, w_t^{[m]} \rangle$
endfor
for $m = 1$ to M do
draw i with probability $\propto w_t^{[i]}$
add $x_t^{[i]}$ to $\mathcal{X}_t$
endfor
return $\mathcal{X}_t$

- DBSCAN
- K-means
- Spectral Clustering



Desorden del sistema (entropy)

$$\mathrm{H} = -\int Bel(l)\,\log(Bel(l))\,dl, \tag{3}$$

measures the uncertainty in the robot position: If $\mathrm{H} = 0$, $Bel(l)$ is centered on a single position, whereas H is maximal, if the robot is completely uncertain and $Bel(l)$ is uniformly distributed. The general principle for action selection can be summarized as follows: *Actions are selected by minimizing the expected future entropy.*

$$a^* = \operatorname*{argmin}_a (E_a[H] + \alpha v(a)) \tag{9}$$

Here $\alpha \geq 0$ determines the relative importance of certainty versus costs. The choice of α depends on the application. In our experiments, α was set to 1.

This completes the description of active navigation with the purpose of localization. Note that active sensing is realized simply by pointing the sensor into the direction which minimizes the expected entropy of the action $a = move(0, 0)$. To summarize, actions represent arbitrary target points relative to the robot's current position. Actions are selected by minimizing a weighted sum of (1) expected uncertainty (entropy) and (2) costs of moving there. Costs are considered because they may vary drastically between different target points.

Métricas [Bugard, Fox, Thrun])

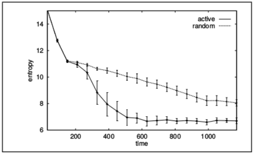


Fig. 11. Entropy of belief states

The results are depicted in Figures 11 and 12. Fig. 11 plots the entropy of $Bel(l)$ as a function of the number of sensor measurements, averaged over 12 runs, along with their variances (bars). As can be seen here, the entropy (uncertainty) decreases much faster when sensors are selected actively. Of course, minimizing entropy alone is not an indicator of successful localization; even a low-entropy estimate could be wrong.

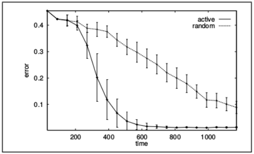


Fig. 12. Estimation error

Fig. 12 plots the error in localization (measured by the L_1 norm, weighted by $Bel(l)$) for both approaches as a function of the number of sensor measurements. Here, too, the active approach is more efficient than the passive one. These results demonstrate the benefit of active localization.

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Preguntas de investigación

¿Se puede mejorar la ubicación del robot con la técnica de localización activa con mapas solapados aplicada a un robot que ya está localizado?

¿Qué otros algoritmos de clustering se pueden adecuar al problema en lugar de DBSCAN, teniendo en cuenta que la técnica se aplica a un robot localizado?

Setup

- Grid map conocido
- Posición inicial conocida
- Posición final conocida (waypoints)
- Entorno estático
- Un solo robot, diferencial
- Sensor láser range finder

Propuesta

Extender la técnica presentada en el artículo *Active localization with dynamic obstacles* en el contexto de un robot localizado, aplicado localización activa localmente.

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Active Localization with Dynamic Obstacles

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Fig. 1. The robot, a TurtleBot 2 equipped with a laser range finder surrounded by several dynamic obstacles (other robots).

I. INTRODUCTION

As autonomous robots integrate more deeply into everyday human activities, it will be increasingly important for them to operate reliably in public spaces. Crowded spaces such as museums and shopping malls [1], [2], [3] have proven to be particularly challenging for robot localization, because co-located humans often occlude the robot's sensors' view of the environment, leading to loss of positional accuracy. In some cases, this has constrained the deployment of robots to times outside the venue's normal operational hours [4].

In this paper, we attack the problem of mobile robot global localization in arbitrary crowded environments on two fronts. First, we consider the *passive* problem of inferring some partial information about the robot's pose, based on range sensor data, in environments with a high density of dynamic obstacles. In this scenario, the particular challenge is that each range measurement may arise from either the known static obstacles or from the unknown dynamic obstacles, and there is no obvious way to distinguish between these two cases. Second, we address the question of *active* localization, in which the robot can choose motions intended specifically to reduce its uncertainty about its own pose.

This paper makes three specific contributions.

- We introduce a new particle filter designed to account for the presence of large numbers of unpredictably-moving dynamic obstacles. The key idea is to 'punish' particles that are closer to static obstacles than the sensor range indicates, by assigning them smaller weights. Simply put, the range sensor cannot see through a wall. At the same time, this approach does not interfere with particles that see something, probably a dynamic obstacle, closer than expected. This asymmetric weight function allows the particle filter to make partial estimates of the robot's state, without being confused by the presence of dynamic obstacles.
- We describe a planning algorithm for selecting motions that decrease the pose uncertainty encoded by this particle filter. The underlying idea is to construct a *compound map*, expressed in the robot's body frame, and to drive the robot toward locations that allow the robot to disambiguate between two or more competing hypotheses about its current position.
- We describe an implementation of these techniques, along with a series of experiments—both in simulation and on a Turtlebot 2, with a fleet of other robots acting as dynamic obstacles—that demonstrate their effectiveness compared to baseline approaches.

The remainder of this paper is structured as follows: the next section provides an overview of related work. Section III describes the problem in detail. Section IV discusses the particle filter formulation employed and provides a detailed description of the active localization strategy proposed. The following section presents experimental results from numerous simulations and from experiments with real robots. The paper concludes with lessons learned and a discussion of future directions.

II. Related Work

From the memorable videos of children climbing on robotic museum tour guides [5], the problem of localizing in the presence of dynamic obstacles has attracted significant attention. Early work proposed to navigate close to the static boundaries, termed coastal navigation [6], in order to improve the localization quality. This approach enabled accurate localization even in the presence of many dynamic obstacles. Alternatively, dynamic obstacles were treated as outliers [7] assuming a static map of the environment.

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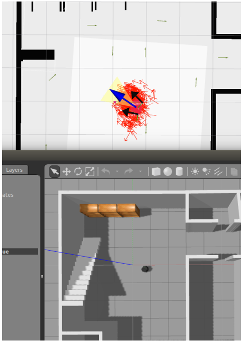
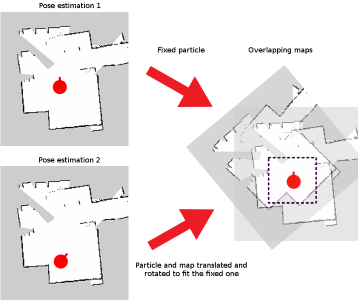
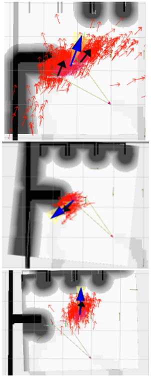
Etapas

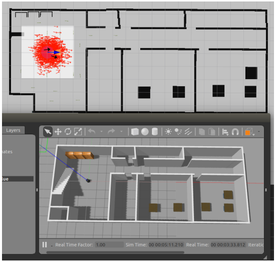


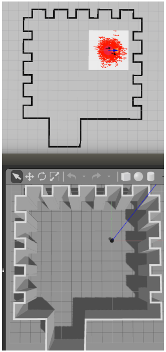

Pose estimation 1
Pose estimation 2
Fixed particle
Overlapping maps
Particle and map translated and rotated to fit the fixed one



Experimentos

- 2 escen
- 4 estrategias
  - pasivo
  - dbscan
  - kmeans
  - spectral c.
- 10 corridas x esc x ag.
- tarea simil. cubrimiento
- medimos
  - gterror
  - dispersión
  - tiempo
- Otros: 5000 part, ROS + Gazebo, diferencial, láser range finder





Resultados

Estrategia	GT Error (cm)	Entropía (m)	Tiempo
Pasivo	17	155.5	3m25s
DBSCAN	17.7	134.8	3m38s
Spectral C.	11.5	93.8	10m
Kmeans	10.5	104.2	4m33s

Cuadro 1: Escenario Oficinas InCo

Estrategia	GT Error (cm)	Entropía (m)	Tiempo
Pasivo	34.1	194.3	5m30s
DBSCAN	32.3	204.3	5m50s
Spectral C.	24.7	113	10m35s
Kmeans	26.4	138.3	7m

Cuadro 2: Escenario Simétrico Abierto

- La aplicación de la técnica propuesta durante la navegación mejora sensiblemente la localización del robot. Kmean y Spectral C. mejoran la localización un 30 % aprox. Esto se debe a que el disparo regular del algoritmo mantiene baja la entropía y ayuda a controlar el error. DBSCAN no presenta cambios relevantes frente a la localización pasiva. Se entiende que esto ocurre porque DBSCAN no genera más de un cluster por lo que no se dispara el algoritmo de localización activa.
- En cuanto al tiempo, el uso de la técnica enlentece la navegación entre un 30 % y un 200 %, debido a que el robot ejecuta el algoritmo con bastante frecuencia.
- De estos resultados se concluye que la aplicación de la técnica se adecua a tareas que requieran mayor precisión en la ubicación y que permitan ser realizadas en un lapso mayor de tiempo y con un consumo mayor de energía.

Referencias

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¿Preguntas?

Stack de navegación :: núcleo

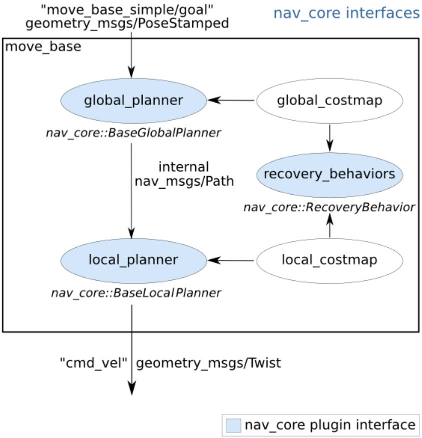

Figura 7: Componentes del stack de navegación de R.O.S

Stack de navegación :: interfaces

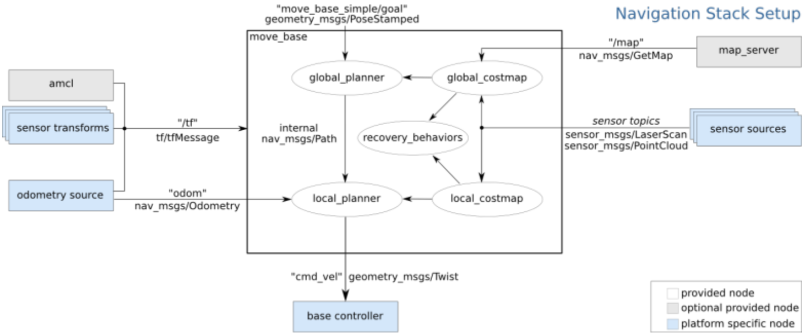

Figura 8: Stack de navegación completo.

Este trabajo se va a enfocar en el nodo *local planner*. El nodo de

API

Input del módulo (subscripciones)

- $setMap(Map\ m)$
- $setGlobalPath(GlobalPath\ gp)$
- $setActualPosition(Pose\ p)$ //del nodo de localización amcl

Output del módulo (publicaciones)

- $getCmdVel() :: geometry\_msgs :: Twist$
- $getLocalPath() :: vector < geometry\_msgs :: PoseStamped >$