Monte Carlo Localization using the Global Appearance of Omnidirectional Images
Algorithm Optimization to Large Indoor Environments

Lorenzo Fernández, Luis Payá, David Valiente, Arturo Gil and Oscar Reinoso
Departamento de Ingeniería de Sistemas y Automática
Miguel Hernández University, Avda. de la Universidad s/n, Elche (Alicante), Spain

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Abstract: In this paper we deal with the problem of robot localization using the visual information provided by a single omnidirectional camera mounted on the robot, using techniques based on the global appearance of panoramic images. Our main objective consists in showing the feasibility of the appearance-based approaches in a localization task in a relatively large and real environment. First, we study the approaches that permit us to describe globally the visual information so that it represents with accuracy locations in the environment. Then, we present the probabilistic approach we have used to compute the most probable pose of the robot when it performs a trajectory within the map. At the end, we describe the kind of environments and maps we have used to test our localization algorithms and the final results. The experimental results we show have been obtained using real indoor omnidirectional images, captured in an office building under real conditions.

1 INTRODUCTION

When a mobile robot has to carry out a task autonomously in an environment, it has to face the problem of computing its location within a given map with enough precision so that it can plan the route to follow to go to the target points during the development of the task. During the last years, omnidirectional cameras have become a popular tool to carry out these localization tasks. In this work, we use the information captured by a single camera that is installed on the robot. With this system, we capture omnidirectional images from the environment and we transform these images into a panoramic format to represent locations in the environment.

When the appearance-based approach is used, each scene is represented by a single descriptor which is computed working with the scene as a whole. For example, (Menegatti et al., 2004a; Menegatti et al., 2004b) use a signature based on the Discrete Fourier Transform of panoramic images to build a visual map and to perform a probabilistic localization within this map. (Kröse et al., 2004) use Principal Components Analysis (PCA) (Kirby, 2001) of panoramic images for environment modeling and localization. On the other hand, as no relevant information is extracted, it is necessary to find a descriptor of the global appearance which optimizes the computational cost of the localization process. Also, it must work well in large environments where visual aliasing could be a usual event.

The main goal of this work consists in evaluating the feasibility of the appearance-based approaches in a localization task in a relatively large and real indoor environment and studying how the computational cost and the accuracy of the results depend on the main parameters of the descriptor. With this aim, we make use of the Monte Carlo (MC) Algorithm (Thrun et al., 2000), which has proved to be robust and efficient in localization tasks in the field of mobile robotics. We have decided to describe each omnidirectional image by a single Fourier descriptor. However, the methods described here are in fact independent of the descriptor used to represent the images.

2 MONTE-CARLO LOCALIZATION

In mobile robot localization we are interested in the estimation of the robot's pose (location and orientation, typically, the state $x_t = (\mathrm{x},\ \mathrm{y},\ \theta)$) at time t using a set of measurements $z_{1:t} = \{z_1, z_2, \ldots, z_t\}$ from the en-

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vironment and the movements $u_{1:t} = \{u_1, u_2, \ldots, u_t\}$ of the robot (Fox et al., 1999). In *Monte Carlo Localization (MCL)* (Thrun et al., 2000), the probability density function $p(x_t|z_{1:t}, u_{1:t})$ is represented by a set of M random samples $\chi_t = \{x_t^i, i = 1 \ldots M\}$ extracted from it, named particles. Each particle can be understood as a hypothesis of the true state of the robot $x_t^i = (\mathrm{x}^i,\ \mathrm{y}^i,\ \theta^i)$. The weight of each sample (particle) determines the importance of the particle. The set of samples defines a discrete probability function that approximates the continuous belief. The *Monte Carlo Localization algorithm* is described briefly in the next lines, and consists of two phases:

Prediction Phase. At time t a set of particles $\overline{\chi_t}$ is generated based on the set of particles χ_{t-1} and a control signal u_t. This step uses the motion model $p(x_t|x_{t-1}, u_t)$. In order to represent this probability function, the movement u_t is applied to each particle while adding a pre-defined quantity of noise. As a result, the new set of particles $\overline{\chi_t}$ represents the density $p(x_t|z_{1:t-1}, u_{1:t})$.

Update Phase. In this second phase, for each particle in the set $\overline{\chi_t}$, the observation z_t obtained by the robot is used to compute a weight ω_t^i. This weight represents the observation model $p(z_t|x_t)$ and is computed as $\omega_t^i = p(z_t|x_t^i)$. The weights are normalized so that $\sum \omega_t^i = 1$. As a result, a set of particles accompanied by a weight $\overline{\chi}_t = \{x_t^i, \omega_t^i\}$ are obtained.

The resulting set χ_t is calculated by resampling with replacement from the set $\overline{\chi}_t$, where the probability of resampling each particle is proportional to its importance weight ω_t^i, in accordance with the literature on the SIR algorithm (Sampling Importance Resampling) (Smith and Gelfand, 1992; Rubin, 1988). Finally, the distribution $p(x_t|z_{1:t}, u_{1:t})$ is represented by the set χ_t.

By means of computing a weight w^i for each particle the Monte Carlo algorithm introduces the current observation z_t of the robot. In this case we consider that our map is composed of a set of N bidimensional landmarks $L = \{l_1, l_2, \ldots, l_N\}$ and the position of these marks on the environment is known. Each landmark l_j is represented by an omnidirectional image I_j associated and a Fourier Signature descriptor d_j that describes the global appearance of the omnidirectional image (Fernandez et al., 2011), thus $l_j = \{(l_{j,\mathrm{x}}, l_{j,\mathrm{y}}), d_j, I_j\}$. d_j is constructed from the bidimensional Fourier signature with all the elements arranged in a vector. Using this Fourier descriptor we compare the descriptor d_t with the rest of descriptors $d_j,\ j = 1 \ldots N$ and find the B landmarks in the map that are closest in appearance with the current image I_t. In this sense, we allow the correspondence of the current observation to several landmarks in the map.

In this work, we propose to compute the weight of each particle $\omega_t^i = p(z_t|x_t^i)$ through a sum of gaussian functions centered on each landmark position and considering the difference in the descriptors of the landmarks (images).

$$\omega_t^i = \sum_{j=1}^{B} \exp\{-v_j \Sigma_l^{-1} v_j^T\} \exp\{-h_j \Sigma_d^{-1} h_j^T\} \qquad (1)$$

where, $v_j = (l_{j,\mathrm{x}}, l_{j,\mathrm{y}}) - (\mathrm{x}^i, \mathrm{y}^i)$ is the difference between the position of the landmark l_j and the position $(\mathrm{x}^i, \mathrm{y}^i)$ of the particle i. The matrix Σ_l is a diagonal matrix $\Sigma_l = diag(\sigma_l^2, \sigma_l^2)$. The variance σ_l^2 is chosen experimentally in order to minimize the error in the localization. $h_j = |d_j - d_t|$ defines the difference between the module of the Fourier descriptor associated to the current image observed and the module of the descriptor associated to the landmark l_j. The matrix $\Sigma_d = diag(\sigma_d^2)$ is a $k \times k$ matrix, being k the length of the Fourier descriptor.

3 EXPERIMENTAL RESULTS

In order to acquire the necessary data for the experiments we have used a Pioneer P3-AT mobile robot, equipped with an omnidirectional camera, and a fixed platform equipped with an omnidirectional camera and a laptop. The map was built by carefully obtaining omnidirectional images at different positions on a regular grid in an office-like environment using the fixed platform. Next, the robot performed some trajectories within this environment, capturing a new omnidirectional image and odometry data whenever it traversed a distance equal to $0.1m$. The robot captured a total of 515 images and traveled around $55m$. The map is composed of a set of 381 images placed on a grid with a resolution of $0.4m$. The map has a size of $11m$ in the x axis and $25m$ in the y axis.

To test the performance of our appearance-based Monte-Carlo Localization method we have carried out a series of simulation experiments of robot tracking using the sets of images described in the previous paragraph. We have used an associations number B equal to 4. We have computed the average error in the robot position along the trajectory, depending on the number of Fourier components for different number of particles. The average error has been obtained taking as a reference the real path (ground truth) (Figure 1 (a)). We must take into account the average error of the robot odometry data comparing with the ground truth is $0.736m$. As shown in Figure 1 (a) as we increase the number of Fourier components, the localization error along the trajectory tends

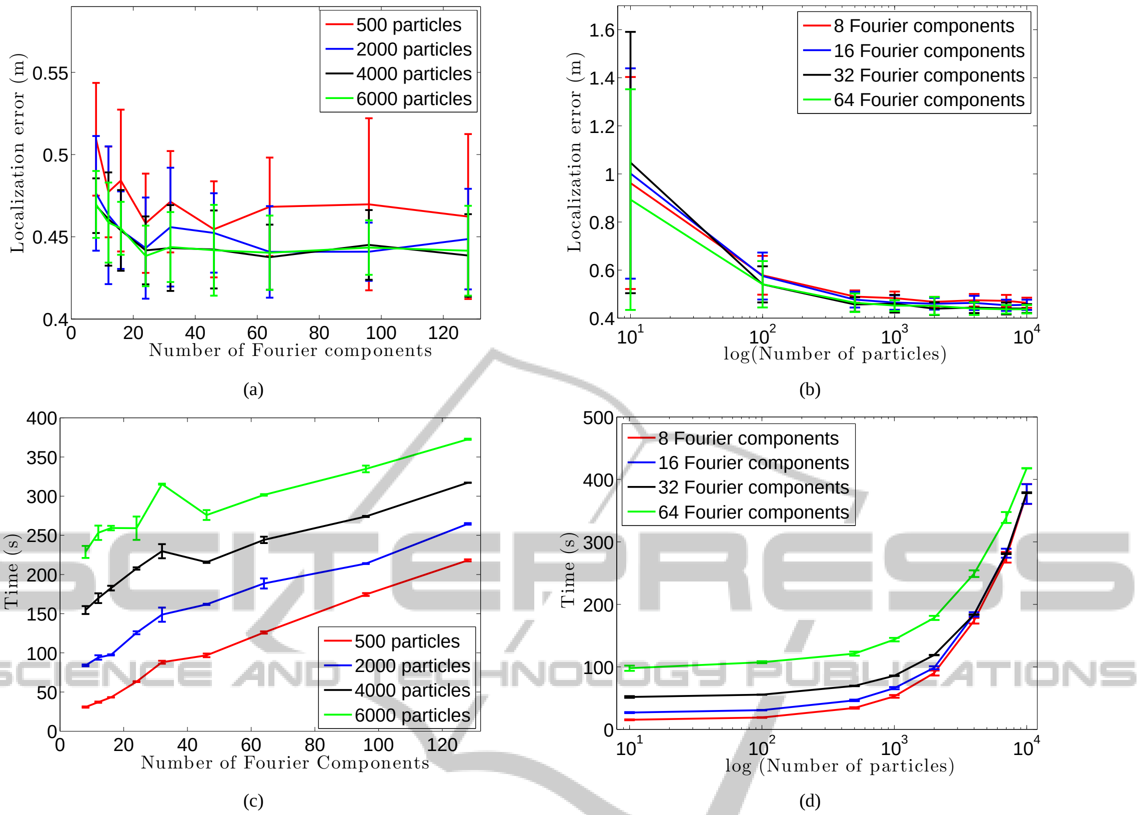


Figure 1: (a) Trajectory average error in position versus the number of Fourier components for different number of particles and (b) trajectory average error in position versus the number of particles for different number of Fourier components, with respect to the real path, (c) computation time needed to complete the estimation of the trajectory of the robot versus the number of Fourier components for different number of particles and (d) versus the number of particles for different number of Fourier components.

to decrease, but a threshold number of components appears and when we increase this number, the error does not decrease significantly (this threshold is around 24 Fourier Components for a relatively high number of particles). We can also see that the graph tendency is quite similar for the four different number of particles tested.

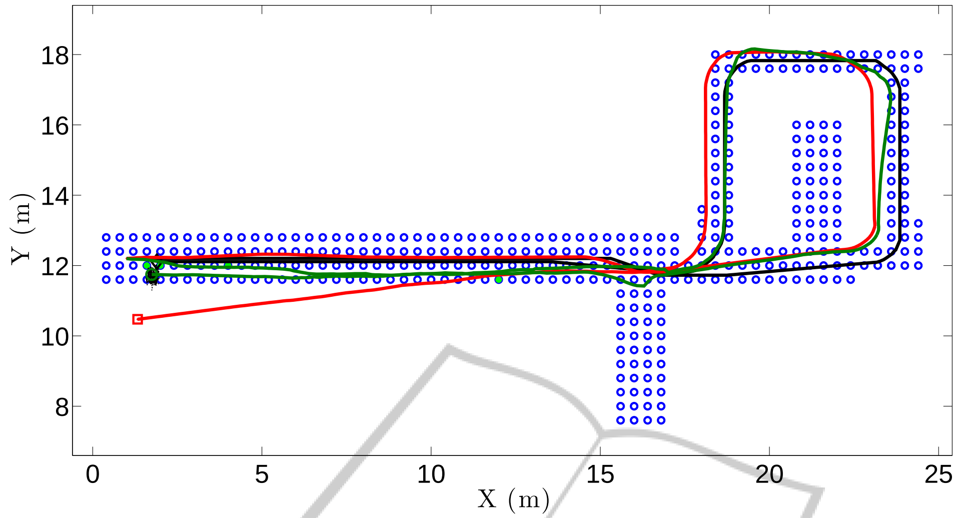
To compare the performance of our method with respect to the number of particles we have carried out a set of experiments of robot tracking in which we have tested the trajectory average error in the position of the robot depending of this number of particles. Figure 1 (b) shows how the increase of the number of particles makes the error with respect the real path to decrease until a certain value from which the error remains small (about 2000 particles). We arrive to the same conclusion as in the previous experiment.

Figure 1 (c) shows the average time needed to carry out the complete Monte-Carlo localization experiment with respect to the number of Fourier components and for different number of particles. On the other hand, Figure 1 (d) show the dependence of the computation time with respect to the number of particles.

Figure 2 presents an example of a relatively accurate case of robot tracking using 4000 particles and 32 Fourier components. In this figure, the position of the map images is indicated with a blue circle, the position of the associated landmarks is indicated with a green solid circle (four associations are used, as stated before), the real path is represented by a black line, the robot odometry path is presented by a red line, the path obtained with our method is shown as a green line and finally, the particles are represented as black dots. As we can observe, our algorithm is able to cope with robot turnings and the trajectory estimated is accurate enough for many robot applications in indoor environments.

4 CONCLUSIONS

In this paper we have tested the performance of a Monte-Carlo localization technique using the global



(a)

Figure 2: An experiment of Monte-Carlo localization using 4000 particles and 32 Fourier components.

appearance of panoramic images. We compare our results with the real trajectory in an large indoor environment. We have built the appearance-based descriptor using the Fourier signature of panoramic images. We have evaluated the performance of the method in the case of a local localization. Our system is able to track the position of the robot while moving if we tune correctly the parameters involved in the process. We have proved that the precision of our method varies with the number of particles used and the number of Fourier components. Furthermore, as we increase the number of particles in the system, the average error of localization decreases rapidly until a certain point from which the error remains small with no appreciable improvement. Finally, as we increase the number of Fourier components, the localization error decreases, but from a number of components the error does not decrease significantly. These experiments show the feasibility of using appearance-based techniques in robot localization, maintaining a reasonable computational cost, so, the navigation can be carried out in real time.

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