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Perceptual ambiguity maps for robot localizability with range perception

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ABSTRACT

A mobile robot equipped with 2D or 3D range sensors can move without changing its range readings if the perceived environment is poor in features. This is an ambiguous situation because a single perception can be associated with several robot poses. In consequence, robot localization capability is reduced. The problem we address is the quantification of this *perceptual ambiguity* as a property inherent to the system composed of the sensor and the static environment. Perceptual ambiguity is different from uncertainty of robot localization, although it is a cause of it. We propose an ambiguity model independent of the robot navigation system. It includes a probabilistic model of the indistinguishability of range readings, a generic range sensor model that supports laser and sonar sensors, and a generic range scanner model that supports any 2D or 3D range perception platform. Ambiguity is expressed in colour floor maps, which may be available before navigation starts, and where “bad localization” zones are easily detected. Experiments with virtual and real environments perceived from 2D laser and sonar scanners are presented, including the validation of the model with a real scans dataset. Results show how ambiguous zones are precisely determined, how to determine the optimum scanner orientation and aperture, and how to reduce the number of readings per scan for improving the robot’s computational load and navigation speed.

1. Introduction

Robot navigation in indoor environments is strongly based on exteroception (Nehmzow, 2003; Thrun, Burgard, & Fox, 2005), typically vision and range perception. Robot self-localization must allow the estimation of robot position with enough precision to navigate and carry out assigned tasks. When using range perception there is an intrinsic source of degradation of this process: the environment geometry. In areas of the environment with few perceivable features, it may occur that the robot moves, but readings of its range sensors do not change. An ambiguity situation arises because a single perception can be associated with several robot poses (positions and orientations). In ambiguous zones, robot localization capability is reduced. Well-known examples are corridors in which large estimation error can be accumulated in walls direction. This ambiguity, that we name *perceptual ambiguity*, can be studied as a property intrinsic to the sensor-environment system. Perceptual ambiguity represents the potential localization difficulty or risk of robot loss, due to references poorness and limitations of the particular range sensor used.

As related to the finite instrument resolution, perceptual ambiguity is one of the sources of the measurement uncertainty (Joint Committee for Guides in Metrology, 2008a, 2008b), which is a component of the localization uncertainty. Therefore, perceptual ambiguity should imply localization uncertainty, but not necessarily the opposite.

If this property is quantified then ambiguous zones of a given environment could be eventually represented as an ambiguity map. Perceptual ambiguity maps could identify areas with different degree of difficulty for robot localization. Fig. 1 shows an intuitively drawn ambiguity map of a large hall, where zones (blue, orange, red, and white) of different perceptual richness are identified. The small green circle is the robot, and the dashed circumference around it represents its maximum capturable range. Blue means localizable positions, close to corners, doors, furniture, etc. Positions in red zones are highly ambiguous, too far from any obstacle. Orange positions are an intermediate case between blue and red, which perceive only one wall or two parallel walls that will produce the corridor effect. White positions indicate zones where the frontiers between colour zones should be but it is difficult to

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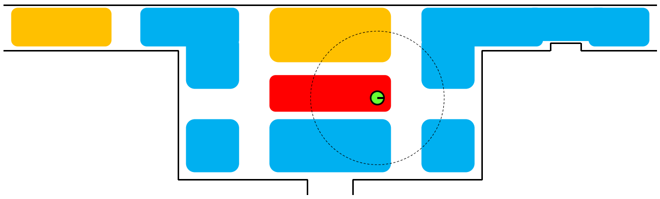

Fig. 1. Intuitive map of perceptual ambiguity in a huge hall. Blue means potential localization, enough perceivable obstacles within the sensors scope. Orange means ambiguous perception, features poorness. Red means high ambiguity, no perceivable obstacles. White means difficult to predict. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

predict their location. The quantification of perceptual ambiguity could allow obtaining complete and exact (non-intuitive) ambiguity maps.

Note that people or moving objects have not been mentioned. In this first work on perceptual ambiguity, we limit our study to the static part of the environment.

The specific problem we focus on is how to formalize and quantify the perceptual ambiguity produced by the static environment to be perceived from a given range scanner device, in order to generate ambiguity maps that can be effectively computed.

The solution we propose is an ambiguity model based on the concept of indistinguishability of ranges, which is defined as the probability of being captured in the same discretized value. A generic scanner model is included, which can be applied to habitual laser and sonar devices, including 3D and heterogeneous perception platforms. This solution is a completely original contribution in robot localizability estimation, not derived from any previous work.

The rest of the paper is organized as follows: Section 2 presents previous work. Section 3 describes the contribution. Section 4 shows performed experiments and their results. Finally, our conclusions are stated in Section 5.

2. Related work

In robot navigation literature, a pioneer work on the effects of environment richness on navigation is Roy, Burgard, Fox, and Thrun (1999), where the coastal navigation technique was introduced. They modelled navigation uncertainty as the entropy of the probability distribution of the robot's pose estimation during navigation. Several works used this technique, most of them in the motion planning area (Feder, Leonard, & Smith, 1999; González & Stentz, 2007; Makarenko, Williams, Bourgault, & Durrant-Whyte, 2002; Prentice & Roy, 2007; Stachniss, 2006). Some applications of this technique can be found in the context of wireless sensor network localization (Schaffert, 2006), and vision with artificial landmarks (Wen, Yuan, Zou, Chai, & Zheng, 2009). This navigation uncertainty includes the effects from the particular localization algorithm and from other navigation subsystems, such as the motion model. The main difference between works that follow coastal navigation technique and our approach consist in that coastal navigation models navigation uncertainty and therefore is dependent of the localization algorithm. Our approach, by contrast, does not model navigation uncertainty. It exclusively models a source of localization difficulty due to the sensor-environment interaction, which is independent of the localization algorithm.

In Kollar and Roy (2008), a trajectory optimization for mapping is presented. They use a reward function to select the trajectories, which minimizes the estimated map error. Their function, although independent of the localization algorithm, depends on the mapping algorithm. The main difference of our approach is that we measure the intrinsic ambiguity, instead of the mapping error.

The idea of studying navigation limits was approached in Censi (2007), which presented a theoretical limit to the precision of localization methods employing laser range-finder data. His model is based on Cramér–Rao Bound, based on the inverse of the Fisher information, which requires the analytic function of the environment's walls to be differentiable. This condition is not met in the borders of obstacles (e.g. corners), but laser range-finders have linear perception cone, perceiving these borders from positions of the environment whose total area is zero. Sonar sensors have a considerable perception cone (25° to 30°), therefore the non-computable area is significant and resulting localizability maps are not useful. Consequently, a main difference with respect our model, not based on Cramér–Rao Bound, is that this work cannot be applied to sonar, while our model includes both sensor types. Some works base their models on the Cramér–Rao Bound presented in Censi (2007). They are presented as follows.

In Liu, Chen, Wang, and Wang (2014), the objective is to develop a time-efficient method that enables mobile robots to actively and cooperatively localize themselves in a large environment with uncertain information. Their approach is to estimate the localizability for mobile robots previously to an action selection mechanism which encourages mobile robots to select complementary actions. Liu, Chen, and Wang (2015) propose a multilayer matching based incremental mapping algorithm designed to keep map accuracy and consistency in large scale and spacious environments. In this algorithm, the data association is built by the multilayer matching method, and the uncertainty is described with the Fisher information matrix. In addition, a localizability-based particle filter localization algorithm is utilized to maintain localization accuracy in dynamic environments. Wang, Chen, and Wang (2014) present a localizability-based particle filtering localization algorithm in high-occluded and dynamic environments. In Wang, Yang, and Chen (2015), an application of localizability estimation is presented. They address a localization and alignment method, to accurately control the navigation and localization of a transfer cask, a huge (80ton) transportation container carried by a hovercraft equipped with a laser range-finder. In Wang, Chen, Wang, and Wang (2015), a localizability-based action selection mechanism for mobile robots is proposed to accelerate the convergence of global localization, taking the uncertainty of a prior-map into account. Hu, Chen, Wang, and Wang (2016) present a path planning method for a mobile manipulator based on localizability. They use the information matrix of Censi (2007) to indicate the uncertainty of the localization, and cubic Bezier spline to represent the path. Qian, Ma, Fang, Dai, and Zhou (2016) propose a real-time observation localizability estimation method for robot localization in unstructured environments with low-cost sensors. They estimate the robot localizability by means of a dynamic localizability matrix computed online by combining a factor of influence of dynamic obstacles detected from actual robot's perception, with a static localizability matrix obtained from a priori environment's map. These localizability matrices, derived from the work of Y. Wang et al. (2015), are discrete models of the Fisher information matrix.

As mentioned above, previous works are grounded on the seminal work of Censi (2007). In general, they estimate the localizability as the determinant of the inverse covariance matrix for localization. A difference respect to our work is that their models, as based on the Cramér–Rao Bound, by the same reason explained for Censi (2007), cannot be applied to sonar. Other aspects that differenciate from our work are the following. Their model is limited to laser range-finders. Their sensor model includes gaussian noise, but this noise is not procedent from the sensor calibration, as our model includes. It comes from the uncertainty of the probatilistic grid map used for represent the environment. Their sensor model does not represent the discretization of the instrument. Our model represents this discretization with a probabilistic approach that