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Loop-closing: A typicality approach

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ABSTRACT

Loop-closing has long been identified as a critical issue when building maps from local observations. Topological mapping methods abstract the problem of how loops are closed from the problem of how to determine the metrical layout of places in the map and how to deal with noisy sensors.

The typicality problem refers to the identification of new classes in a general classification context. This typicality concept is used in this paper to help a robot acquire a topological representation of the environment during its exploration phase. The problem is addressed using the INCA statistic which follows a distance-based approach.

In this paper we describe a place recognition approach based on match testing by means of the INCA test. We describe the theoretical basis of the approach and present extensive experimental results performed in both a simulated and a real robot-environment system; Behaviour Based philosophy is used to construct the whole control architecture. Obtained results show the validity of the approach.

1. Introduction

Even though great technical progress has been achieved in the area of mobile robotics, some fundamental control problems such as autonomous navigation remain unresolved. Without such ability the robot cannot avoid dangerous obstacles, reach energy sources or return home after an exploration of its environment. Although many animals have shown that they are very good at navigating, autonomous navigation is a complicated task for engineered robots. That is why research efforts have been aimed at incorporating biologically inspired strategies into robot navigation models [1,2]. The control architecture which is being developed by the authors fully embraces the behaviour-based (BB) approach Brooks [3] and the taxonomy of biomimetic navigation strategies proposed in [4]. In this context, navigation is conceived as the determination and the keeping of a trajectory towards a goal.

Autonomous exploration is one of the main challenges of robotic researchers. Exploration requires navigation capabilities in unknown environments and hence, the robots should be endowed not only with safe moving algorithms but also with the ability to recognise visited places. Frequently, the aim of indoor exploration is to obtain the map of the robot's environment, i.e., the *mapping* process.

The representation of the environment can be in terms of fine metric models or probabilistic grids [5] that requires high memory allocation and computation capabilities, or more coarse but less demanding topological models where nodes usually represent environmental locations identifiable by the robot and arcs represent the connection among nodes. Regardless of the representation used, one of the critical points of mapping an unknown environment is the robot's ability to locate itself on a partially explored map; the so-called *loop-closing* problem [6].

In this paper, a new method for topological map acquisition is presented. Each time sensor measurements identify a set of landmarks that characterise a location, the method must decide whether or not it is the first time the robot visits that location. From a statistical point of view, the problem we are concerned with is the *typicality problem*, i.e., the identification of new classes in a general classification context. Whenever a new unit must be assigned by the classifier to the appropriate class, first outliers or units that are atypical of the established classes must be identified. We addressed the problem using the so-called INCA statistic which allows one to perform a typicality test [7]. It is worth mentioning that this statistic follows a distance-based approach. In this approach, the analysis is based on the distances between each pair of units. This approach can be complementary to the more traditional approach *units* $\times$ *measurements — or features —* and offers some advantages over it. For instance, an important advantage is that once an appropriate distance metric between units is defined, the distance-based method can be applied regardless of the type of data or underlying probability distribution.

The nodes within the obtained topological map do not represent single locations but contain information about areas of the environment. The aim of the approach is to acquire the necessary knowledge to be used in a procedural map as proposed in [8] and

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extended in [9] where each node on the map is a process that outputs a compass orientation that trends the robot heading.

Experiments are performed using a simulation tool first and then in a real robot-environment system. The rest of the paper is structured as follows. Section 2 summaries the behaviour-based navigation approach. Next, the literature related to the mapping problem and the typicality problem is reviewed. Section 4 introduces the INCA test as a solution to the typicality problem. Section 5 describes the topological environment description used and Section 6 explains how the INCA test is applied during the mapping process. Section 7 describes the performed process for parameter selection. In Section 8 the robot-environment is introduced and in Sections 9 and 10 performed experiments, both simulated as well as in a real robot-environment, are explained. Finally, conclusions and further work are outlined in Section 11.

2. Behaviour-Based navigation

Behaviour-Based (BB) systems appeared in 1986, when Brooks proposed a bottom–up approach for robot control that adopted a new perspective on the development of intelligent embodied agents capable of navigating in real environments performing complex tasks. He introduced the Subsumption Architecture [3,10] and developed multiple robotic creatures capable of showing different new behaviours not seen before in real robots [11,8,12]. Behaviour-Based systems are originally inspired by biological systems. Even the simplest animals show navigation capabilities with high degree of performance. For those systems, navigation consist of determining and maintaining a trajectory to the goal [2]. The main question to be answered for navigation is not *Where am I?* but *How do I reach the goal?* and the answer does not always require knowing the initial position. Therefore, the main abilities the agent needs in order to navigate are to move around and to identify goals.

The behaviour-based approach to robot navigation relies on the idea that the control problem is better assessed by a bottom–up design and an incremental addition of light-weight processes, called behaviours, where each one is responsible for reading its own inputs and sensors and deciding the adequate motor actions. As there is no centralized world model and data from multiple sensors do not need to be merged to match the current system state in the stored model, the motor responses of the different behavioural modules must be somehow coordinated in order to obtain a valid intelligent behaviour. *Way-finding* methods rely on *local navigation strategies*. How these local strategies are coordinated is a matter of study known as *motor fusion* in BB robotics, as opposed to the well-known *data fusion* process needed to model data information. The aim is to match subsets of available data with motor decisions; outputs of all the active decisions are merged to obtain the final actions. In this case there is no semantic interpretation of the data but behaviour emergence.

3. Related work

While mapping an environment the robot must determine whether or not it is the first time it visits a certain location. The loop-closing problem cannot be solved neither relying only on extereoceptive information (due to sensor aliasing) nor relying only on propioceptive information (cumulative error). Both, environmental properties and odometric information must be used to disambiguate locations and correct robot position. Fraundorfer et al. [13] present a highly scalable vision based localisation and mapping method using image collections, while Se et al. [14] use vision mainly to detect the so-called *Loop-closing* — the place has already been visited by the robot — in robot localisation; Tardós et al. [15] introduce a perceptual grouping process that permits the robust identification and localisation of environmental features from the sparse and noisy sonar data. On the other hand, the probabilistic Bayesian inference, along with a symbolic topological map is used by Chen and Wang [16] to relocalise a mobile robot. More recently, Olson [17] presents a new loop-closing approach based on data association, where places are recognised by performing a number of pose-to-pose matches; a review of loop-closing approaches related to MONOSLAM can be seen in [18]. Nowadays, probabilistic methods are widely applied to find solutions to several robotic problems. *Probabilistic robotics* is a new and growing area concerned with perception and control in the face of uncertainty [19]. Kalman filters, Bayesian Networks and particle filters are used to maintain probability distributions over the state space while solving mapping, localisation and planning.

The mapping problem can be stated from a classification perspective. In most classification problems, there is training data available for all classes of instances that can occur at prediction time. In this case, the learning algorithm can use the training data to determine decision boundaries that discriminate among the classes. However, there are some problems that are amenable to machine learning, but exhibit only a single class of instances at training time. At prediction time, new instances with unknown class labels can either belong to this target class or to a new class that was not available during training. In this scenario, two different predictions are possible: *target*, an instance that belongs to the class learned during training, and *unknown*, where the instance does not seem to belong to the previously learned class. Within the Machine Learning community, these kinds of problems are known as *One-Class* problems and as *typicality* problems within the statistics research.

To give some examples, in [20] the probability distributions of the class variable known values are used to determine if a new case belongs to one of these known class values or if it should be considered as a different class member. One-Class categorisers have a wide range of applications; in [21] One-Classification is used for document categorisation, in order to decide whether a reference is relevant or not in a database searching query; the same authors combine this approach with the SVM paradigm for Document classification purposes [22]; in [23] the same idea is applied to texture recognition in images. A thorough review of One-Class classification can be found in [24].

Regarding the mobile robotics area, one-class classification approaches can be applied to robot mapping, i.e., to learn in an automatic manner the structure of its environment. In this way, Brooks and Iagnemma [25] present an use of this approach to deal with terrain recognition, and Wang and Lopes [26] use this One-Class classification technique to identify user actions in Human–Robot-Interaction; direct uses of this approach have not been found in the literature with this particular name.

There are different approaches found in the literature to deal with the typicality problem [27–30,7]. Some of them are only suitable for normal multivariate data, others are appropriate for any kind of data but are limited to $k = 2$, being k the number of classes. The latter one offers the most general framework to be applied. However, and in spite of the high diversity of the used methods, to the top of the authors knowledge, neither Typicality nor One-Class approaches appear in the literature to this end.

The approach proposed in this paper combines the INCA statistic [7] with the topological properties of the environmental locations considered; we present it as a new approach to tackle with the robot mapping problem as a typicality case.

4. Typicality test by means of the INCA statistic

In this section we introduce the INCA statistic, and we propose the INCA test as a solution to the typicality problem.