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Towards hierarchical blackboard mapping on a whiskered robot

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ABSTRACT

The paradigm case for robotic mapping assumes large quantities of sensory information which allow the use of relatively weak priors. In contrast, the present study considers the mapping problem for a mobile robot, CrunchBot, where only sparse, local tactile information from whisker sensors is available. To compensate for such weak likelihood information, we make use of low-level signal processing and strong hierarchical object priors. Hierarchical models were popular in classical blackboard systems but are here applied in a Bayesian setting as a mapping algorithm. The hierarchical models require reports of whisker distance to contact and of surface orientation at contact, and we demonstrate that this information can be retrieved by classifiers from strain data collected by CrunchBot's physical whiskers. We then provide a demonstration in simulation of how this information can be used to build maps (but not yet full SLAM) in an zero-odometry-noise environment containing walls and table-like hierarchical objects.

1. Introduction

Touch-based mapping has two principal applications. Firstly, as a sole sensory system in environments where other types of sensors fail, such as smoky or dusty search-and-rescue sites, especially where covert (no signal emission) operation is required. Secondly, as a complement to other sensors such as vision, with which it can be fused or used as a 'last resort' during adverse conditions as in the sole sensor case.

However, the paradigm case for robotic mapping, as in Simultaneous Localisation and Mapping (SLAM) problems [1], instead considers a mobile robot with noisy odometry and vision or laser scanners. Vision and laser scanners provide large amounts of sensory information, and have effectively unlimited range in indoor environments. Such large quantities of input information allow the use of relatively weak priors, such as independent grid cell occupancy or flat priors over the belief of small feature sets [1].

This study considers the touch-based mapping problem in which only sparse, local sensory information is available. Proof that navigation from such sensors is possible is readily found in biology: rats navigate through dark underground tunnels using their whiskers [2,3], having ranges of only a few centimetres. In robotics, whisker sensors are relatively cheap in both material and computational processing terms, and their use has previously been considered in constrained tasks [4–8]. The previous robotic attempts at mapping from sparse local sensors have either used the extremely strong generic prior that the whole world is made entirely of north–south and east–west straight edges [9] or have used relatively long range but sparse ray sensors integrated over multiscans [10].

We will demonstrate touch-based mapping using a mobile robot, CrunchBot, having six whisker touch sensors only. First, it is shown that CrunchBot's whiskers are able to recover approximate position and orientation reports about contacts with surfaces. Then it is shown how these reports can be fused with strong priors to recognise hierarchical objects such as tables and chairs, as a step in building a map of the environment.

Fig. 1 gives an overview of the general framework for perception and navigation with whiskers within which this study operates. When biomimetically inspired by rodents, whisker sensors have strain sensors at their base only. When a rat investigates an object it palpates the surface in a back and forth oscillatory sweeping behaviour known as 'whisking' [11,12]. It is thought that whisking is important for gathering the most reliable signals from whisker contacts [13]. Straight whiskers can make two distinct types of contact with an object, contacting it either at their tip or their shaft. Tip contacts are generally the most useful, because they provide a standardised, constrained setting (i.e. with the contact point at a known location at precisely the end of the whisker)

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[1] Equal contributions. Fox designed and implemented the Bayesian blackboard and Crunchbot; Evans designed and implemented the classifiers; Pearson designed and implemented the whisker hardware; Prescott co-ordinated the project.

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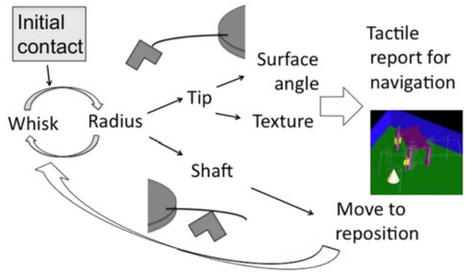

Fig. 1. A new framework for extracting contact parameters. After initial contact a whisk behaviour allows the discrimination of object location. If contact is made along the whisker shaft the agent must move to reposition the whisker for subsequent contacts. If contact is made at the whisker tip a robust discrimination of surface properties can be made. Reports of surface properties can be used by other systems, such as for navigation or to construct complex object models as in the present study.

Fig. 2. CrunchBot, a whiskered mobile robot platform.

from which surface properties such as orientation and texture can be identified [6,8]. In contrast, shaft contacts are less informative. For example, an unknown distance to an object along the shaft can confuse attempts to classify surface orientation and texture [14]. Shaft contacts are rare in practice in both rodents and mobile robots, occurring only when small objects enter the field of multi-whisker arrays between the whisker tip points. In the scheme used here, a feature based radial distance estimator [15] is first used to make a decision of whether the contact is at the tip or the shaft. If it is a shaft contact, then the robot should use the radial distance information to move to another location that is likely to yield a more useful tip contact. Following a tip contact, we can read surface orientation and texture information (and possibly speed of object when there are moving objects in the world) and pass them as an observation to a navigation or mapping system.

This study provides an implementation of the distance and angle stages of this framework on CrunchBot (Fig. 2). Individual components of such a system have previously been investigated in isolation, including whiskered texture recognition [8,16,17,14,18], surface shape recognition [6,19,20,15], and object recognition [21]. These components have previously been tested under ideal laboratory conditions or in individual mobile settings [22]; here we present steps integrating them into a single platform for hierarchical object recognition, along with results and observations on their performance 'in the wild' in a common arena environment.

To compensate for the sparseness of the sensory information available from these distance-orientation reports, we fuse them with strong hierarchical priors about objects in the world. Hierarchical object recognition models were popular in classical AI in the guise of 'blackboard systems' [23–25] but have recently been recast in terms of dynamically constructed Bayesian networks [26–29]. Here we provide an application of Bayesian blackboards to robotic mapping. We do not consider the full SLAM problem here, but instead work in a simulation of CrunchBot having zero odometry noise to avoid the localisation problem and focus on mapping only. Related object-based mapping models have recently appeared [30–33] using laser sensors to recognise and learn complex but non-hierarchical spatial models. However as data available through whiskers to CrunchBot is much sparser than that from laser scanners, the required level of sensor detail is unavailable, therefore we compensate with the new mapping technique of fusing contact reports into *hierarchical* models. For example, on recognising a single table leg, we may infer the probable presence the rest of the table, including other leg objects, and edges and corners making up these legs, without ever sensing them directly. To construct hierarchical objects, we use hypothesis priming and pruning heuristics as in classical blackboard systems. However, following [26], we treat such heuristics as approximations to inference in a dynamically constructed, Monte Carlo Markov Chain (MCMC) sampling Bayesian network, whose observations are the distance-orientation reports from the whiskers.

2. Methods

2.1. Whiskers

CrunchBot's six whiskers measure 160 mm in length, 1.45 mm diameter at the base tapering linearly to 0.3 mm at the tip. They are built from nanocure25 using an Evisiontec rapid prototyping machine. A magnet is bonded to the base of the whisker and held in place by a plug of polyurethane approximately 0.75 mm above a Melexis 90333 tri-axis Hall effect sensor IC [34]. This sensor generates two outputs representing the direction of the magnetic field (in two axes) with respect to its calibrated resting angle. These two 16-bit values are sampled by a local dsPIC33f802 microcontroller which, in turn, is collected using an FPGA configured as a bridge to a USB 2.0 interface. Up to 28 whiskers can be connected to this FPGA bridge at one time. Using the vendor provided software driver and API (Cesys GmbH), a user can request the data from all whiskers at minimum intervals of 500 μs (a maximum sample rate of 2 kHz).

2.2. Robot platform

CrunchBot is based on the iRobot Create base (www.irobot.com) platform, with the whiskers mounted in the cargo bay, being positioned on an adjustable metal bar and rapid prototyped ball joint mountings. These mountings allow adjustment of the whiskers. For data collection experiments in the present study, only four whiskers are used, configured in the horizontal plane to detect objects in an arena (the other two whiskers scrape along the floor and are used in other experiments, such as for texture discrimination in our previous study, [35]). We have also extended the cargo bay mounting to accommodate a netbook PC, which is used for local control of the robot. The netbook runs Ubuntu 10.10 on a single-core Intel Atom processor. A circular buffer in shared memory is used to make data from the Cesys driver available to other processes. The netbook hosts a Player server (player-stage.sourceforge.net) which provides high-level, networked API interfacing to the Create's serial port commands. Processes such as texture and shape recognition and basic motor control run on the netbook, reading the raw data from the fast circular shared memory buffer, and writing their results every 0.1 s to a Python Pyro server (pyro.sourceforge.net) on the remote desktop which runs hierarchical object recognition and mapping.