

Mobile Robotics: Research, Applications and Challenges

Ulrich Nehmzow

Department of Computer Science

The University of Manchester

Manchester M13 9PL

United Kingdom

<http://www.cs.man.ac.uk/robotics>

Abstract

This overview paper discusses some of the major focuses of current mobile robotics research, introduces a specific application of mobile robotics — automated inspection using autonomous novelty detection — and presents one of the future challenges of mobile robotics research: that of applying quantitative methods in mobile robotics, in order to change the discipline from an empirical one to a more precise science.

1 Introduction

Industrial and technical applications of mobile robots are continuously gaining in importance, in particular under considerations of reliability (uninterrupted and reliable execution of monotonous tasks such as surveillance), accessibility (inspection of sites that are inaccessible to humans, e.g. tight spaces, hazardous environments or remote sites) or cost (transportation systems based on autonomous mobile robots can be cheaper than standard track-bound systems). Mobile robots are already widely used for surveillance, inspection and transportation tasks — a further emerging market with enormous potential is that of mobile entertainment robots.

It is obvious that a range of fundamental competences need to be available for a mobile robot to be useful. The robot must operate safely, i.e. it must stay away from hazards such as obstacles or operating conditions dangerous to the robot itself (e.g. descending stairs), and it must pose no risk to humans in the vicinity of the robot. Section 2 discusses this question.

Mobility is almost pointless without the ability to navigate. Random movement, which does not require a navigation capability, may be useful for certain surveillance or cleaning operations, but for most scientific or industrial applications of mobile robots the ability to move in a purposeful manner is required. Section 3 discusses this in detail.

In section 4 we present recent research at Manchester University in the area of automated inspection using mobile robots. Using a self-organising novelty filter, the Manchester mobile robot *FortyTwo* is able to differentiate between common and unusual perceptions, without being given any *a priori* information regarding normality or abnormality. The robot acquires these concepts autonomously through exploration of the environment.

Finally, the paper poses a challenge to current mobile robotics research. At the moment, mobile robotics is an empirical discipline. Control programs are designed through trial-and-error, and have to be refined through experimentation with the

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robot in the target environment. Section 5 discusses a challenge to mobile robotics research to move away from an empirical discipline towards a precise science.

2 Fundamental Sensor-Motor Competences

Before any higher-level tasks can be attempted it is essential that the robot operates safely, avoiding obstacles, performing fundamental behaviours such as contour following, door traversal etc, and that it poses no risk to the environment and people in it.

The standard method to achieve this is to implement the robot with a “hard-wired” control program designed by a human operator. The major disadvantages of this approach are that because of the rigid nature of the control program the robot is not able to adapt to changes, for example in the environment (e.g. changes in surface colours or textures) or the robot itself (e.g. failure of individual sensors). Besides, the design of fixed control programs is costly and error-prone.

For these reasons, learning controllers have been developed that allow mobile robots to acquire their competences in interaction with their environment [13, 12]. Using associative memories, implemented in our case using artificial neural networks, the robot learns to associate sensory perception with motor response in an autonomous process of trial and error. The result is a control policy that is based on the robot’s perception of the world and the specific properties of the robot’s sensors. Because the robot retains the ability to learn throughout the entire period of operation, it is able to adapt to changes in the world, the task, or its own morphology.

3 Navigation

For a mobile agent, the ability to navigate is one of the most important capabilities of all. Staying operational, i.e. avoiding dangerous situations such as collisions, and staying within safe operating conditions (temperature, radiation, exposure to weather, etc.) come first, but if any tasks are to be performed that relate to specific places in the agent’s environment, navigation is a must.

Navigation can be defined as the combination of the three fundamental competences:

1. Self-localisation;
2. Path planning;
3. Map-building and map-interpretation (map use).

For all of these aspects of navigation, the fundamental choices are to either use proprioceptive information (on-board wheel encoders), or to use exteroceptive information (“landmarks”) for self-localisation, map building and path planning.

In practice, proprioceptive methods fail very quickly because of incorrigible drift errors that cannot be detected by the robot. True robot position and perceived position drift apart considerably after journeys as short as 5 metres.

For this reason, methods based on external sensory perception — “landmark-based” methods, where “landmark” denotes any identifiable sensory perception — have been used more widely and successfully in mobile robotics [13]. These systems have successfully been used for localisation [20, 19]. In particular Markov decision processes have been used for self-localisation [1, 4, 5, 6]. [3] presents such a localisation system implemented on Manchester’s mobile robot *FortyTwo*.

The use of self-organising mechanisms can be extended to, for instance, route learning and free navigation. In [14] a route learning and navigation mechanism is discussed that allows a mobile robot to be trained to follow arbitrary routes and to navigate freely in unknown environments, without prior map installation and without modifications to the environment (such as the installation of beacons).

4 Application Example: Automated Inspection Robots

There are many applications of mobile robots, and their importance in industrial processes continues to grow. Mobile robots can be used for transportation tasks, surveillance, or cleaning. Increasingly, they play an economic role also in the entertainment industry (artificial pets being the best known example).

One application of mobile robots of considerable economic importance is that of automated inspection. Manual inspection is a very costly process that is tedious to a human operator, thereby increasing the risk that faults etc. are overlooked. It is obvious that inspection would benefit from automation.

A major aspect of automated inspection is to detect abnormalities automatically. Such novelty detection is hard to achieve with classical machine learning methods, because those methods typically require a balanced number of data points in all signal classes to be classified. Yet by definition abnormalities are rare, so that a classical machine learning algorithm cannot be applied.

A new approach to detect abnormality is to define *normality* by some method, and then to compare all data points with that measure of normality. Large deviations from “normal” signals can then be flagged as “novel”. Kohonen’s novelty filter [7, 8] is an autoencoder neural network trained using back-propagation of error, so that the network extracts the principal components of the input. After training, any input presented to the network produces one of the learned outputs, and the bitwise difference between input and output highlights novel components of the input. Other approaches include the manual *a priori* definition of features to be detected to separate novel perceptions from common ones [18].

It is possible to automate the acquisition of a model of normality. In [10, 11] we present the implementation of an automatic system for novelty detection, implemented on a mobile robot and evaluated in unmodified “real world” environments. Using the self-organising novelty filter presented there, *FortyTwo* is able to construct a representation of “normal” perceptions in its environment, and to detect novel perceptions without prior knowledge installation.

5 A Challenge: Scientific Mobile Robotics

In the established sciences such as physics or chemistry, to name but two examples, it is accepted practice that experimental results are independently verified. To facilitate this, precise (i.e. quantitative) descriptions of results are used.

Because research on quantitative descriptions of mobile robot behaviour is still in its infancy, mobile robotics to date is still an empirical discipline that uses existence proofs extensively. Robot systems to perform certain tasks are implemented, but, for want of precise performance measures and behavioural descriptions, are not independently verified.

The first step towards a science of mobile robotics, therefore, would be the development of *quantitative*, rather than *qualitative* descriptions of mobile robot behaviour. Some attempts have been made to introduce quantitative evaluations to robotics. Schöner et al. [16] use dynamical systems theory to investigate robot-environment interaction, and Smithers [17] discusses the use of quantitative performance measures as a tool of scientific mobile robotics research.

In [13, 9, 2] we present quantitative evaluations of robot localisation systems (based on contingency table analysis). Current work at Manchester concentrates on the general, quantitative analysis of robot-environment interaction, irrespective of the specific task carried out or the control strategy used. This is done using measures from chaos theory, [15] presents the approach and results.

In short, besides the technological challenges of mobile robotics — fundamental sensor-motor competences, robot navigation and application-oriented capabilities such as novelty detection — the scientific challenge is to move mobile robotics from a discipline of empirical practice towards a precise science.

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