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RobotMODIC: Modelling, Identification and Characterisation of Mobile Robots

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RobotMODIC: Modelling, Identification and Characterisation of Mobile Robots

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Abstract

The RobotMODIC project at the Universities of Essex and Sheffield investigates the underlying phenomena governing robot-environment interaction. The project aims to "identify" — in the sense of mathematical modelling and system identification — both a mobile robot's motor response to perceptual stimuli (task identification) and the perceptual properties of the robot's environment (environment identification). Models are represented as either linear or nonlinear polynomials, and are obtained using ARMAX and NARMAX system identification techniques.

1. Motivation

Industrial and technical applications of sensor-response systems (such as 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) and 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 (Nehmzow, 2002).

In science, mobile robots are arguably the most important tool to investigate the behaviour of embedded systems that interact with their environment. Because they close the loop between perception and action through their physical interaction with their environment they are the research method of choice for the investigation of intelligent behaviour in areas such as artificial intelligence and cognitive science.

We believe that there are currently two major problems in mobile robotics research: i) the lack of a theory-based design methodology for mobile robot control programs, and ii) the lack of accurate mobile robot models as a design tool.

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The lack of a formal design methodology, based on a theory of robot-environment interaction (which would allow the methodical design of mobile robot control programs) means that control programs have to be developed through an empirical trial-and-error process. This is costly and error prone. In addition, the lack of a theoretical foundation for mobile robotics means that development tools have to be based on general assumptions (e.g. idealised, simplified models of sensors) that commonly result in significant discrepancies between prediction and actually observed behaviour of the physical mobile robot.

2. RobotMODIC — Robot Modelling, Identification and Characterisation

The RobotMODIC project addresses the two problems of design and modelling by conducting a study with the following four major aspects:

1. *Modelling*: We investigate the use of non-linear system identification (polynomial NARMAX models) and quantitative performance measures to characterise robot behaviour and performance.
2. *Identification and Characterisation*: We investigate how robot attributes, sensor properties and environment characteristics influence robot behaviour, and to what extent.
3. *Theory*: We use these results to investigate how robot control programs can be designed, and to study how to obtain a theoretical framework to describe robot-environment interaction.
4. *Tools*: The eventual goal of the project is to build a novel mobile robot simulator based on accurate, transparent models of robot-environment interaction, rather than on generalised assumptions as is currently the case in state-of-the-art robot simulators.

2.1 Experimental Procedure

The experimental procedure we follow is generally as follows. Using an autonomous mobile robot — in our

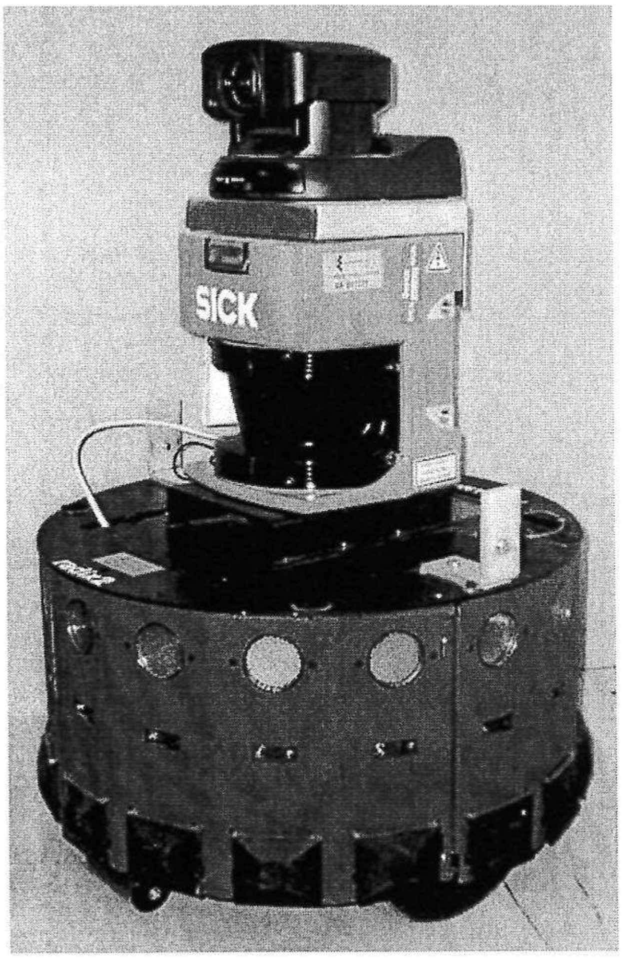

Figure 1: RADIX, THE MAGELLAN PRO MOBILE ROBOT USED IN THE EXPERIMENTS DESCRIBED IN THIS PAPER

case *Radix*, the Magellan Pro robot shown in figure 1 — we execute a sensor-motor task under laboratory conditions. During execution, we log all variables relevant to the robot's operation — all sensory perceptions and motor responses, as well as the robot's position in (x, y, ϕ) space — every 250ms. Figure 2 shows one of the experimental scenarios, and a logged trajectory.

We then model the relationship between input variables, such as for example sensory perception, and output variables, such as for instance motor response, using the ARMAX (Eykhoff, 1981, Eykhoff, 1974) or NARMAX method (Billings and Chen, 1998, Chen and Billings, 1989). This results in a transparent, analysable model of the input-output relationship under investigation, which can be used for environment or task modelling (see sections 3. and 4.).

2.2 The NARMAX Approach to Modelling

Modelling paradigms widely used in robotics to date are neural network and related algorithms. Many architectures and training procedures are available, but without exception all these methods develop models of the system that are largely opaque. The trained neural network can be used to predict future output values but it provides little information regarding the structure of the underlying system. It is very difficult to interpret the model in terms of known physical effects and consequently this approach provides limited insight into the physics of the underlying system.

There is an alternative approach which provides much more information about the underlying system and which provides results that allow the user to relate the identified model to the behaviour of the underlying system. This is known as the NARMAX (Nonlinear Auto-Regressive Moving Average model with eXogenous inputs) approach.

The NARMAX approach is a parameter estimation methodology for identifying both the important model terms and the parameters of unknown nonlinear dynamic systems. For single-input single-output systems this model takes the form

$$y(k) = F[y(k-1), y(k-2), ..., y(k-n_y), u(k-d), ..., u(k-d-n_\mu), e(k-1), \dots, e(k-n_e)] + e(k)$$

where $y(k)$, $u(k)$, $e(k)$ are the sampled output, input and unobservable noise sequences respectively, n_y, n_u, n_e, are the orders, and d is a time delay. F[ ] is a nonlinear function and is typically taken to be a polynomial or a wavelet multi-resolution expansion of the arguments. Usually only the input and output measurements $u(k)$ and $y(k)$ are available and the investigator must process these signals to estimate a model of the system.

The NARMAX methodology breaks this problem into the following steps: i) Structure detection, ii) Parameter estimation, iii) Model validation, iv) Prediction, and v) Analysis.

These steps form an estimation toolkit that allows the user to build a concise mathematical description of the system (Billings and Chen, 1998). The procedure begins by determining the structure or the important model terms, then continues to estimate the model parameters. These procedures are now well established and have been used in many modelling domains (Billings and Chen, 1998). Once the structure of the model has been determined the unknown parameters in the model can be estimated. If correct parameter estimates are to be obtained the noise sequence e(k), which is almost always unobservable, must be estimated and accommodated within the model. Model validation methods are then applied to determine if the model is adequate. Once the model is accepted it can be used to predict the system output for different inputs and to

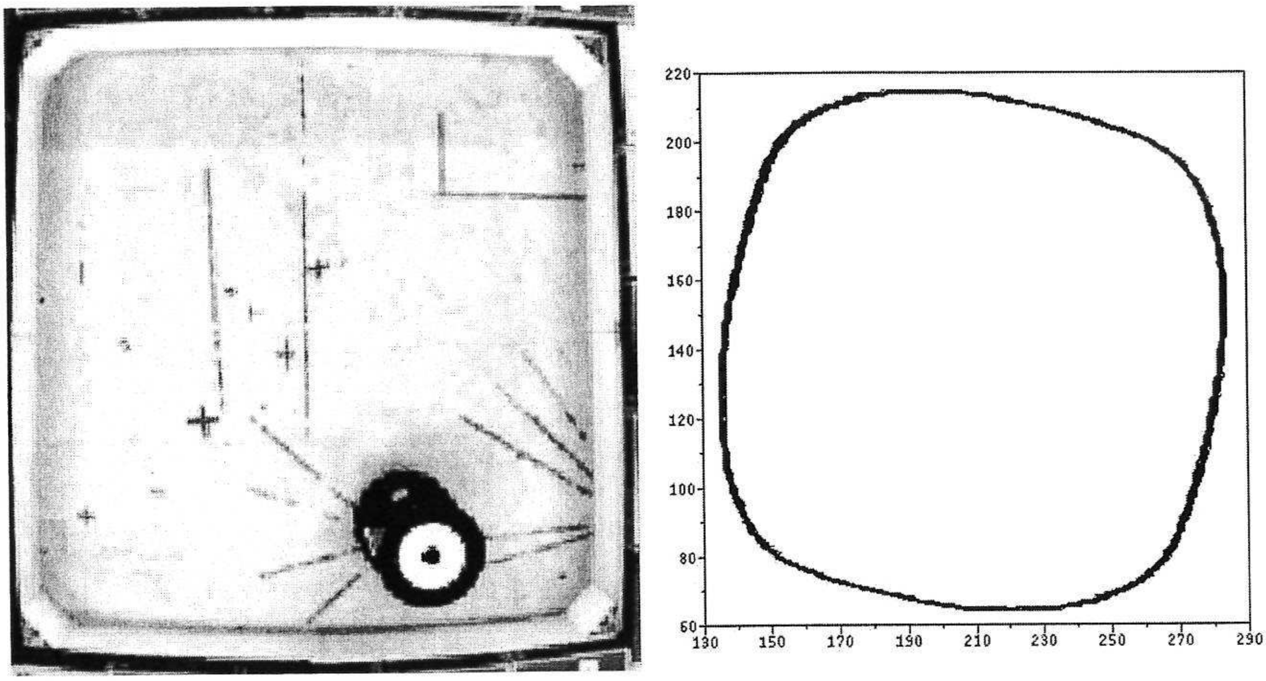

Figure 2: THE ENVIRONMENT IN WHICH EXPERIMENTS WERE CONDUCTED (LEFT), AND THE ROBOT'S TRAJECTORY (RIGHT). THE ROBOT IS VISIBLE IN THE BOTTOM RIGHT HAND CORNER OF THE LEFT IMAGE.

study the characteristics of the system under investigation.

There are considerable advantages to modelling input-output relationships using transparent polynomial functions, rather than opaque mechanisms such as artificial neural networks:

1. The input-output representations are very compact and require very little space (memory) and processing time to compute.

2. They are amenable to rigorous mathematical analysis. For example, models of robot speed can be turned into models of robot acceleration by differentiating, models of acceleration can be modified to models of speed through integration. Also, it is easier to estimate parameters such as Lyapunov exponent or correlation dimension from a closed mathematical function than from a time series.

3. Input-output relationships can be analysed graphically, plotting is straightforward, whereas in opaque models this is not possible.

4. The acquired model actually says something about the relationship between inputs and outputs. Parameters and lags indicate relevant process components.

5. The analysis of similar behaviours, obtained by different means — for example achieving a particular robot behaviour through both a controller derived from control theory and one based on machine learning techniques — is easier when the models underlying those behaviours are considered: stability, sensitivity to noise, identification of relevant and irrelevant sensor signals are easier when a transparent mathematical expression is available for analysis.

3. Example 1: Environment Modelling

3.1 Modelling Sensory Perception

As stated in section 2., one of the aims of the RobotMODIC project is to derive accurate, transparent computer models of robot-environment interaction that can be used for code development: generic simulation programs are replaced by specific models of robot-environment interaction, derived from real-world data obtained in robotics experiments.

This section explains our procedure of deriving environment models, here using a simple robot behaviour in order to make the main mechanisms clear. Figure 3 shows the modelling relationship investigated in the experiments discussed in this first example.

For the purpose of this paper, we have chosen to investigate the wall-following behaviour of a Magellan Pro mobile robot (actually, the control code used to drive the robot was *not* a wall-following, but an obstacle-avoidance program. However, the interaction of our robot with its environment resulted in a wall-following trajectory). The robot used is shown in figure 1, the trajectory we

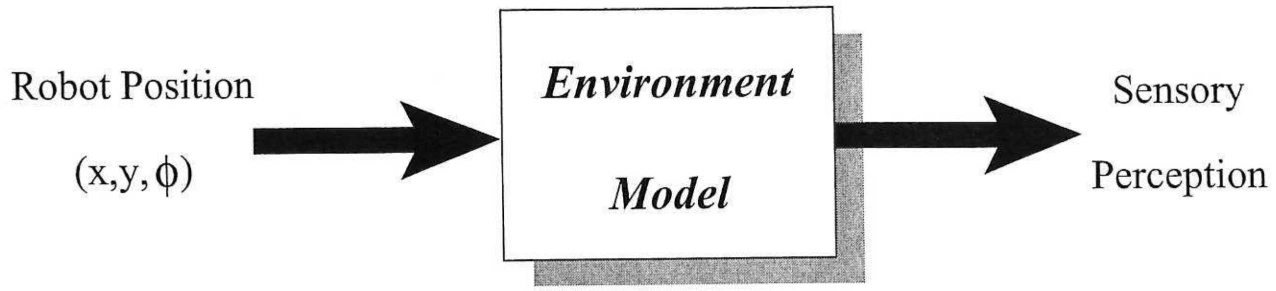

Figure 3: ENVIRONMENT MODELLING: A KNOWN FUNCTION (SUCH AS THE POLYNOMIAL GIVEN IN TABLE 1) MAPS ROBOT POSITION TO SENSORY PERCEPTION

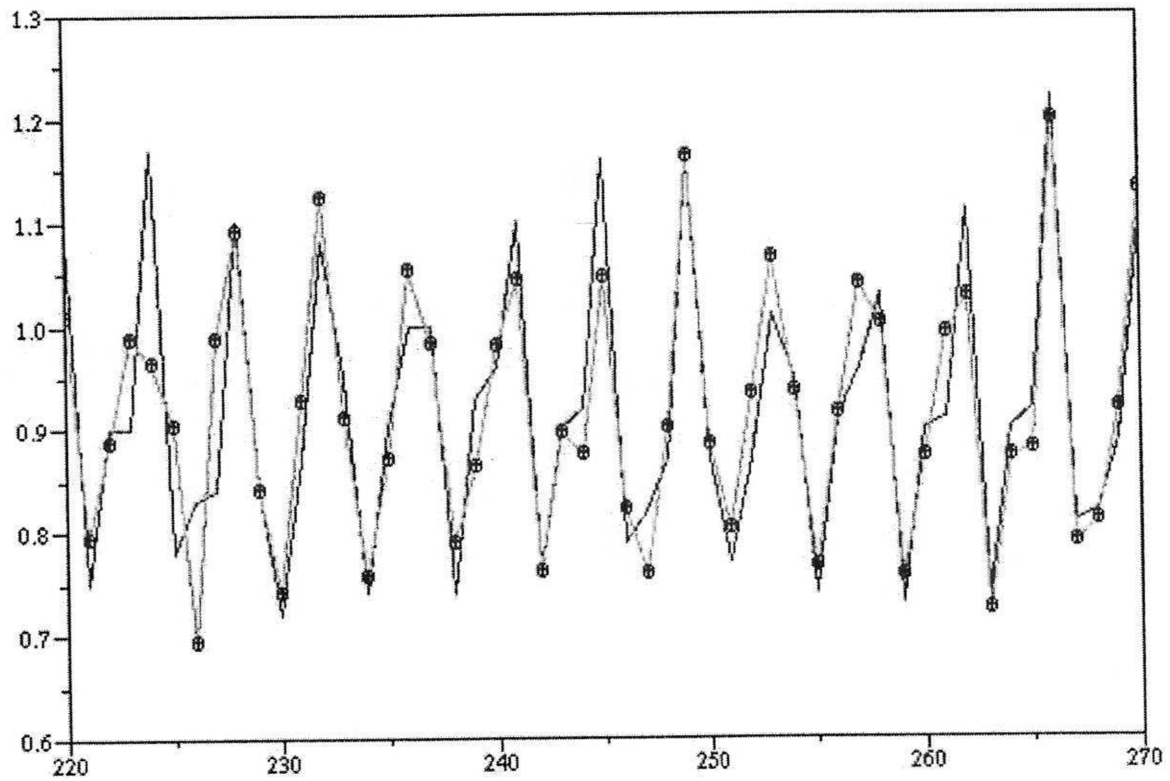

Figure 4: MODELLING THE ROBOT'S LASER PERCEPTION $L67$ AS A FUNCTION OF POSITION (SEE ALSO TABLE 1). TRUE SENSOR PERCEPTION IS SHOWN AS A SOLID LINE WITH CIRCLES, THE MODEL-PREDICTED OUTPUT AS A SOLID LINE.

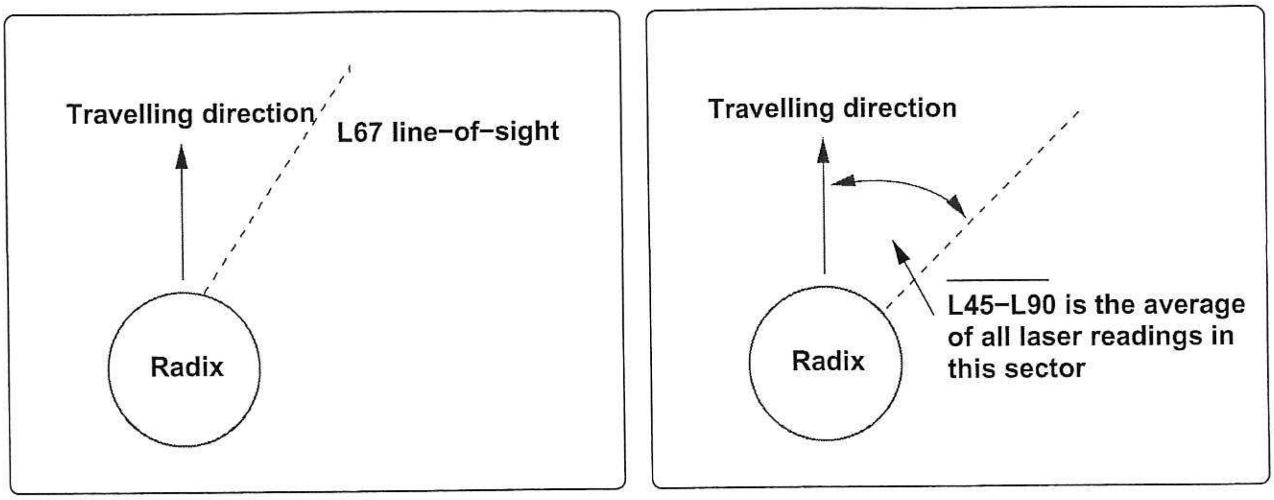

Figure 5: L67 (MODELLED IN TABLE 1) IS THE ROBOT'S SINGLE-RAY LASER PERCEPTION TOWARDS THE RIGHT HAND SIDE OF THE ROBOT. $L = \overline{L45 - L90}$ IS THE AVERAGE OF ALL LASER RAYS ON THE RIGHT HAND SIDE OF THE ROBOT.

logged every 250ms with an overhead camera is shown in figure 2. For analysis, this data was subsequently subsampled at a rate of 1:15, so that the time elapsed between data points is 3.75s. The average speed of the robot in this experiment was 8cm/s, so that the distance travelled between logged robot positions is about 30cm.

The model equation in table 1 computes the distance measured by the laser sensor at 67 degrees from the left of the robot (L67) as a function of its position (x, y). It shows that the robot's laser perceptiong L67(t) can be modelled as a function of the robot's (x, y) position at times t and $t-1$ easily and accurately. Pearson's correlation coefficient between modelled and true data is 0.75 (significant, $p<0.01$).

It is interesting to note that the robot's orientation ϕ is not needed in order to model the perception of the laser sensor. The reason for this is the restricted motion of the robot (following the perimeter of the environment), which by specifying (x, y) essentially also specifies orientation ϕ, so that ϕ is not needed explicitly in the model.

3.2 Obtaining the Model

In order to obtain the non-linear model equation in table 1, a NARMAX model identification methodology was followed. First, the model structure is determined by choosing regression order and degree of the inputs and output. 'Degree' is defined as the sum of all exponents in a term, where a 'term' is a mathematical expression as shown in each line of tables 1 and 2.

To determine a suitable model structure, we us the orthogonal parameter estimation algorithm described in (Korenberg et al., 1988). This indicates (prior to the calculation of the model) which model terms are significant for the calculation of the output.

We then obtain the model, using the first half of the available data ("training data"), and validate it using the remaining half ("validation data").

4. Example 2: Task Characterisation and Identification

In task identification the objective is to obtain a model of the control program of the robot. This results in the "compression" of program code into a single polynomial equation. An immediate advantage in doing this is the ease of communication of a robot task in cases where the actual code implementation of the task is of little interest (as opposed to the robot's behaviour resulting from the execution of the task).

Like the control program, the task model maps sensory perception to robot motor response (see figure 6). In order to obtain the model of a control program, the robot's sensory perception and its response to that perception is logged while it is executing the control program. Using the sensory perception as input and motor response as output the same modelling technique used in environment modelling (see section 3.) is used here in order to find a suitable model of the control program.

The model presented in table 2 and figure 7 produces the robot's rotational velocity (the model's output) from a single input L which is the mean value of the laser sensor readings in the range 45-90 degrees (figure 1). As can be seen from table 2, the behaviour of the robot in this case is easily modelled and requires only very few input components, with short regression order. Figure 2 shows that the model is accurate, the Pearson correlation coefficient between modelled and true rotational velocity of the robot is $r = 0.987$ (significant, $p<0.01$). For further, more detailed discussion of this experiment see

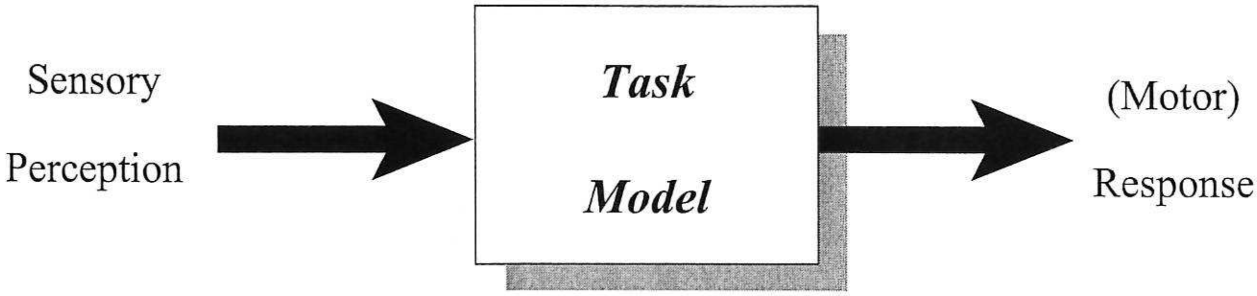

Figure 6: Task identification: a known function (such as the polynomial given in table 2) maps sensory perception to robot motor response

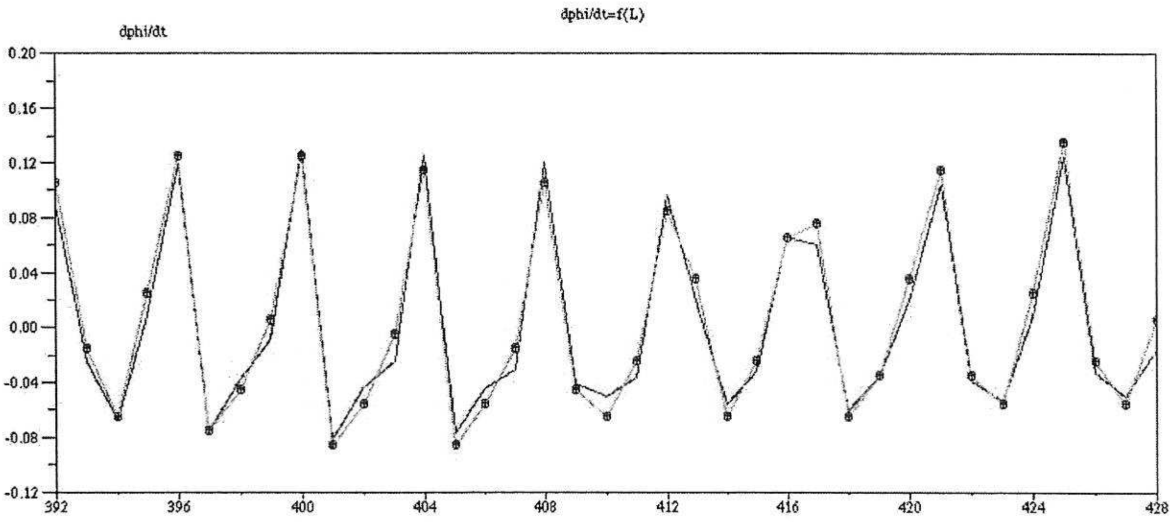

Figure 7: Modelling the robot's motor response (rotational velocity $\dot{\phi}$) as a function of laser sensor perception L (see also table 2). True rotational velocity is shown as a solid line with circles, the model-predicted output as a simple solid line.

```
L67(t)=
+1.8801351
+0.0087641 * x(t)
-0.0116923 * x(t-1)
-0.0060061 * x(t-2)
+0.0116420 * y(t)
+0.0143721 * y(t-1)
-0.0064808 * y(t-2)
+0.0004983 * x(t)^2
+0.0021232 * x(t-1)^2
+0.0006722 * x(t-2)^2
-0.0002464 * y(t)^2
+0.0018295 * y(t-1)^2
+0.0015442 * y(t-2)^2
-0.0028887 * x(t)   * x(t-1)
+0.0023524 * x(t)   * x(t-2)
+0.0002199 * x(t)   * y(t)
-0.0025234 * x(t)   * y(t-1)
+0.0022859 * x(t)   * y(t-2)
-0.0029213 * x(t-1) * x(t-2)
+0.0006455 * x(t-1) * y(t)
+0.0014447 * x(t-1) * y(t-1)
-0.0027139 * x(t-1) * y(t-2)
-0.0004945 * x(t-2) * y(t)
+0.0003262 * x(t-2) * y(t-1)
+0.0009349 * x(t-2) * y(t-2)
-0.0010366 * y(t)   * y(t-1)
+0.0013326 * y(t)   * y(t-2)
-0.0037855 * y(t-1) * y(t-2)
```

Table 1: Parameters of the polynomial modelling the robot's single-ray laser perception L67 as a function of the robot's position (x,y). The time series of this model is shown in figure 4. See also figure 5.

also (Iglesias et al., 2004).

5. Conclusion

5.1 Summary

In this paper we argue that there are two pressing problems in mobile robotics research — i) the lack of a theory-based robot design methodology and ii) the lack of *accurate* robot models. The RobotMODIC project is aimed at these issues, and seeks to model both robot reaction to sensory stimuli (task) and sensory perception as a function of position (environment) through polynomial models, using a NARMAX process.

In this paper, we present a simple experimental setup — wall-following behaviour of a Magellan Pro mobile robot — and the application of our modelling paradigm to this scenario. We demonstrate that it is possible to model both the robot's response to sensory stimuli (section 4.) and the robot's sensory perception

```
dphi(t)/dt=
+0.5436893
-0.6750176 L(t)
+0.0984578 L(t-1)
```

Table 2: Parameters of the polynomial modelling the robot's rotational velocity $\dot{\phi}$ as a function of laser perception $L = \overline{L45 - L90}$. The time series of this model is shown in figure 7. See also figure 5.

at certain locations of the environment (section 3.).

5.2 Discussion

5.2.1 Motivation

Computer-modelling of robot-environment interaction is a very useful tool in robotics research, for three main reasons:

1. Software development cycles are shortened,
2. 'what if?' scenarios can be investigated,
3. direct, 'absolutely fair' comparisons between two approaches to the same robot task are possible, because both approaches would be executed using identical 'robots' in identical environments.

One major reason why robot-environment modelling has not yet fulfilled these promises is the lack of faithfulness of existing models. Usually, models are constructed using generic models of sensor and environment properties (e.g. modelling sonar sensors as cones). A second limitation hampering robotics research is the fact that we still lack quantitative descriptions of robot-environment interaction (Nehmzow and Walker, 2003).

The RobotMODIC project addresses these issues, by constructing transparent models of robot-environment interaction that use real data[1] to model the behaviour of one specific robot in a specific environment. Unlike generic models that inevitably fail to pick up idiosyncrasies of a particular robot or environment, this approach will detect those local aberrations.

5.2.2 Weaknesses of the RobotMODIC approach

The work discussed in this paper models the interaction of a specific robot with a specific environment. This can be viewed as a restriction, in that it limits the generality of the approach — modelling using real data produces not a generic model, but a specific one. Our reply to this point is that *generic* modelling of the operation of a

[1] Data obtained by operating a physical robot in the desired environment.

physical robot in the physical world cannot be accurate enough to be useful, because local idiosyncrasies have a fundamental influence on the operation of the robot. Any useful computer model of robot-environment must be of a specific experimental scenario. A detailed discussion of this can be found in (Lee, 2000).

A second point is that the quality of the acquired models is dependent upon the data used to construct the model. The first model discussed in this paper in section 3. is an example: the aim was to obtain a model of sensory perception as a function of robot location (see figure 3). However, because all training data was obtained in a limited region of the available space — the space along the edges of the experimental arena — the acquired model will only make credible predictions in that region. In analogy to photography we refer to this aspect as that of obtaining a 'sensorgraph', i.e. a comprehensive representation of sensory perceptions in as many different positions and orientations as possible. Figure 8 shows such a sensorgraph for the square arena of figure 2.

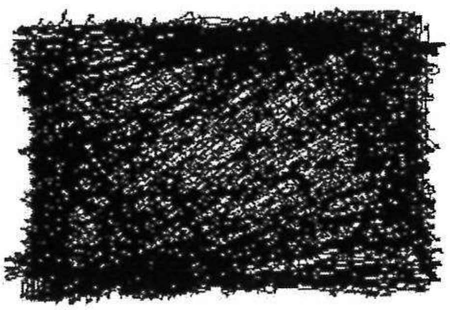

Figure 8: TRAJECTORY FOLLOWED BY THE ROBOT TO OBTAIN A 'SENSORGRAPH' OF THE ARENA SHOWN IN FIGURE 2

Methods for data logging that are best suited for obtaining faithful models of robot-environment interaction are currently under investigation at Essex.

Acknowledgements

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