# Representation Schemes and Learning Algorithms for Predictive Robot Models: A System Identification Approach

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## 1 Introduction

Assume that a robot continuously creates and maintains predictive models of the dynamics of its body and immediate surroundings. Can it then make use of internal simulations to increase its adaptive capabilities, and what would be suitable choices of model representation schemes and optimization algorithms for this purpose?

Anticipatory behavior can be described in general terms as behavior that does not only depend on the past and the present, but also on predictions, expectations, and beliefs about the future. As noted in [1], anticipatory systems can be broadly divided into implicit and explicit ones. Implicit anticipatory systems are systems in which anticipation is a result of the design or evolution of a control system. The present work however, is concerned with explicit anticipatory systems, where predictions about the future are explicitly represented in some form. In such systems, there are two aspects to anticipation: (1) the model representation itself; and (2) how the predictions are used.

Several theories for how predictions are built, represented, and utilized in higher animals and humans have been proposed, two of which are closely related to this work. Hesslow's *simulation hypothesis* (SH) [2] suggests that thinking consists of internal simulations of agent-environment interaction. Grush's *emulation theory of representation* (ETR) [3] is based on the idea that the brain, while engaging with the body and the environment, constructs neural circuits that act as a model of the body and the environment. It is suggested that running these models offline can produce imagery and estimates of outcomes of potential actions.

This work focuses on robots that can learn predictive models while behaving in their environment, and then use these models for the purpose of generating goal-directed behavior. It rests on the assumption that system control benefits, in terms of stability and robustness, from using predictions of future action-dependent information [4]. Important first steps have been made towards learning and using predictive models for robust robot behaviors, e.g. [5–7]. This work is mainly inspired by the work by Bongard *et al.* [5], where explicit models were optimized by a coevolutionary algorithm, and then used to generate locomotive behavior before and after the robot had been damaged. However, several questions remain concerning how robots could learn and use predictive models, and from a computational modeling perspective the questions of how predictions should be represented, generated, and used to influence, e.g., motor control, decision making, and learning is still much out in the open.

Using a *system identification* (SI) [8, 9] approach to modeling, this work intends to use automated, general-purpose[1] methods for the generation of an explicit anticipatory system. More specifically, it aims at: (1) identifying suitable model representation schemes and optimization algorithms for structural and parametric learning of predictive robot models; and (2) exploiting these models for the purpose of increased robustness in goal-directed behaviors.

## 2 Predictive Internal Models: A System Identification Approach

The SI approach to modeling is, loosely speaking, the process of adapting a mathematical model to describe the behavior of a system, represented by experimental data. This can be compared to physical modeling, which uses basic physical laws or other known relationships to derive a system model.

With the embodied turn in artificial intelligence [10–12] came the realization that an agent's body, brain, and environment are really coupled dynamical systems and thus it is in the interaction of these that behavior occurs and should hence be studied. This view has important consequences that motivates an SI approach to the generation of predictive internal models for autonomous robots. It first more or less rules out a physical modeling approach since the underlying system dynamics are not completely known. Second, it implicates that experimental data, from which a model could be built, should be generated while the robot behaves in its environment.

Linear time invariant (LTI) systems share characteristics that have made it possible to develop standard model structures and optimization techniques, see for example [8]. Nonlinear processes however, typically do not share many properties. Therefore a great challenge in nonlinear SI is universalness, that is the capabilities: (1) of the model structure to describe a wide class of structurally different systems; and (2) of the optimization algorithm to cope with structural as well as parametrical optimization. For this reason, universal approximators such as recurrent neural networks (RNNs) [13], and biologically inspired global optimization techniques like evolutionary algorithms (EAs) [14] have become popular in nonlinear system identification.

Whether linear or nonlinear, system identification techniques can roughly be classified in two categories: offline techniques and online techniques, respectively. In offline system identification, a complete data set is collected and made

[1] Suitable for a variety of robot platforms.

available for the SI process to exploit. As noted in [15], such techniques are well suited when data is freely available but not controllable, such as stock market data. On the other hand, online techniques use the data as it becomes available, and is often referred to as *recursive system identification.* While online SI can be the only option due to intrinsic system limitations on the collection of data, it can also be a useful approach when modeling for adaptive control or fault tolerance. For example, it opens up the possibility for *active learning* (AL) [16], an approach where new experiments are selected for the purpose of generating useful data. In our case the model is, broadly speaking, supposed to answer the question of what are the best predictions of some time-steps ahead. For this purpose, it is useful to have a model that can be adjusted online, while the robot behaves in its environment.

## 3 Model Representations and Learning Algorithms

This work assumes that a goal is made available to the robot from a user or designer. The modeling process can then be divided into two parts. The model building is an information-gathering task; its goal is to reduce model uncertainty. The model is used, however, in a goal-directed task, where the purpose is to generate a desired robot behavior (e.g. to approach or avoid some object or to generate a gait before and after damage). This is a case of modeling for control, where the accuracy of the model is important only insofar as it produces the desired behavior. Since we are interested in an automated modeling-control process, a restriction on any learning algorithm is that it must be able to deal with model training and model use, but also with model retraining.

We hypothesize that using an AL approach in the model building phase will outperform passive techniques, something that is also supported by the findings in [5]. Furthermore, results from evolutionary robotics experiments [17, 18] suggest that the best performing predictors may not actually be, as one might expect, those that minimize sensor prediction errors. However, it is also known that evolutionary optimization methods have a tendency to exploit model weaknesses to achieve good fitness. For this reason, we hypothesize that comparing evolutionary methods with more traditional methods for prediction, such as the *Kalman filter* (KF) algorithm, or its extended version for nonlinear systems, will give important insights as to whether prediction error is a good quality measure of a predictive internal model.

Our experimental setup involves using wheeled as well as legged robots (in simulation), and comparing the performance of a set of representation scheme-learning algorithm pairs. The overall performance measure of each pair is how well the robot succeeds in reaching its goals when properties of it itself or its environment changes. However, we also consider the efficiency of the model inference phase as well as the explicit predictive capabilities of the generated models, in terms of their prediction errors over a range of prediction horizons.

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