Robot Learning in Practice

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Robotics researchers have made great efforts to model real environments in designing controllers. Thanks to the rapid increases in the computational speed of affordable computers and to the developments in sophisticated machine-learning algorithms, the acquisition of an environmental model and designing controllers from measured data with less prior information has become a practical approach. Work toward developing such robot-learning approaches can be expected to significantly contribute to the entire field of robotics research.

On the other hand, state-of-the-art robot platforms, such as humanoid robots, have many sensors and actuators. It would be difficult to naively apply the existing machine-learning methods to these robots, in particular, because of the curse of dimensionality. The application of learning algorithms to large-scale problems in a real environment can be considered the key problem in robot learning.

The articles in this special issue present studies on the robot-learning problem along with the practical applications and results. It consists of one survey article and five regular articles. We briefly introduce the contents of each article below.

Our first invited article, "Learning Control in Robotics" by Schaal and Atkeson, is an introductory survey on the use of learning methods in robotics. It first clarifies a rough taxonomy of learning methods, distinguishing between model-based and model-free learning, imitation learning, reinforcement learning, and supervised learning methods. All categories are then discussed in more detail by providing references to the state-of-the-art methods in each case. Special attention is also given to the issue of problem decomposition and to existing libraries for efficient trajectory optimization. The article provides a valuable survey on the continuously growing field of robot learning for students and experts.

Bridging the gap between symbolic representations of actions and their continuous sensorimotor signals is one of the central issues in organizing complex behavior. The work by Krüger et al. addresses this problem in the context of imitation learning, where continuous movements of a demonstrator are observed. The article proposes an integrated framework for extracting action primitives from such continuous observations and representing them with an extension of hidden Markov models. No presegmentation or hand labeling of observed actions is needed. The action primitives learned allow the system to recognize and synthesize actions. Interestingly, the extraction of primitives also exploits information on the objects involved in manipulation.

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The topic of dynamical primitives expressing humanoid motion has emerged as a wider topic of interest across the robot learning and humanoid robotics communities. Such dynamical primitives provide a promising avenue to explore imitation learning, where a robot constructs its policy based on the demonstrations of humans by expressing time-independent predictions of motion actions. In imitation learning, dynamical predictions serve to explain observed motion and form motion trajectories with respect to the robot's known gestural actions. More broadly, such primitives can be used as a priori models for applications such as motion planning and human pose estimation. Calinon et al. describe their approach to learning and representing dynamical primitives through the application and combination of Gaussian mixture models over joint input–output spaces with hidden Markov models. This approach to dynamical primitives is demonstrated through three sets of experiments for dancing with an iCub humanoid, table tennis striking with a Barrett WAM robotic arm, and feeding tool use with a Fujitsu HOAP-3 humanoid. Experimental comparisons with supervised regression methods highlight the viability of unsupervised learning and prediction with dynamical primitives.

Even though imitation-learning methods can provide a practical approach for large-scale robot-learning problems, the skills transferred from the experts usually do not supply the optimal strategy for the learner, since the dynamics and kinematics between the experts and learners are different in many cases. Kober and Peters show that the proposed reinforcement-learning method can efficiently improve the transferred skills. The experimental results of two tasks are presented: the ball-in-a-cup task to examine the learning performance of single-stroke movements and the ball-paddling task to examine the performance of rhythmic movements. In both tasks, a real Barret WAM was used. This article also attempts to present the details in such a way that allows the readers to easily implement the proposed method.

Moving beyond laboratory environments and into real-world field applications is another critical challenge for robot learning in practice. To further progress in the development models and algorithms, machine learning can overlook or make limiting assumptions about factors faced by real-world applications of robotics, such as scaling to large data sets, real-time constraints, and the integration of diverse technologies into an effective system. Robot learning, grounded and tested in field domains, serves to ensure the real-world validity of theoretical assumptions and laboratory conclusions. One such problem is the large-scale terrain-modeling problem addressed by Vasudevan et al. in the context of autonomous robotic mining. As part of a larger nonparametric terrain estimation trend, Vasudevan et al. seek to move beyond polygonal tessellations to estimate surfaces by using statistical methods to account for ambiguous and incomplete sensing common to field robotics applications. Their article surveys a larger integration project, demonstrating that Gaussian process regression can model complex terrain by fusing multiple sensing modalities with consideration of local smoothness, large-scale data, and heteroscedasticity.

The unmanned ground vehicle (UGV) has been a challenging robot-learning problem for many years. Recently, it has been demonstrated that robot-learning approaches can be quite useful in constructing automatic vehicle-control systems, especially through the Defense Advanced Research Projects Agency (DARPA) Grand Challenge and Urban Challenge. However, these competitions were held in relatively structured environments. Bagnell et al. present the results emerging from their entry in the DARPA UPI program. In this challenge, the environment is truly complex and unstructured, which means that the terrain was difficult to model. Therefore, the robot-learning approach can be useful, and the article shows how the proposed robot-learning methods were practical in that program.

We hope the readers will enjoy the articles in this special issue and learn more about the state-of-the-art practical robot-learning methods.

FROM THE EDITOR'S DESK

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vitally important—the magazine has to continue to be the thing that you can read in a train or in a plane. We hope to launch digital delivery later this year.

In this issue, our special feature is on machine learning in practice. Learning has always been important for robotics, and the articles highlight how far the field has come and how it can be used in practice.

One of the odd things about being involved in a quarterly publication is the long lead time. You will be reading this in June, after the IEEE International Conference on Robotics and Automation, and I am writing this in March the day after I received my copy of the March issue, which I had helped prepare in December. I am always happy to receive your comments about the magazine: what you like and what you don't like.

Enjoy this issue and get busy writing articles for the future issues.

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PRESIDENT'S MESSAGE

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The Conference Activities Board, chaired by Vice President Prof. Nikolaos Papanikolopoulos, the Financial Activities Board, chaired by Vice President Prof. William Hamel, the Industrial Activities Board, chaired by Vice President Prof. William Hamel, the Industrial Activities Board, chaired by Vice President Dr. Alex Zelinsky, the Member Activities Board, chaired by Vice President Prof. Stefano Stramigioli, the Publication Activities Board, chaired by Vice President Prof. Peter Luh, the TAB, chaired by Vice President Prof. John Hollerbach, and the Long-Range Planning Committee, chaired by President-Elect Prof. David Orin, were scheduled to have their first face-to-face meetings in Anchorage, together with other committee meetings such as Steering Committee for Technical Programs, chaired by Prof. George Lee, and the Electronic Products and Service Board Committee, chaired by Prof. Stefano Stramigioli.

Our Society budget for 2011 is finalized in Alaska. This year's budget and Society activities are based on the discussions in the spring AdCom in Kobe last year. Our new actions discussed in Alaska will be implemented next year. In the next column, we will introduce some of the discussions in Alaska about our strategic plan.

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