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MARIOnET: Motion Acquisition for Robots through Iterative Online Evaluative Training

(Extended Abstract)

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1. INTRODUCTION

As robots become more commonplace, the tools to facilitate knowledge transfer from human to robot will be vital, especially for non-technical users. While some ongoing work considers the role of human reinforcement in intelligent algorithms, the burden of learning is often placed solely on the computer [2]. These approaches neglect the expressive capabilities of humans, especially regarding our ability to quickly refine motor skills. Thus, when designing autonomous robots that interact with humans, not only is it important to leverage machine learning, but it is also very useful to have the tools in place to facilitate the transfer of knowledge between man and machine. We introduce such a tool for enabling a human to transfer motion learning capabilities to a robot.

In this paper, we propose a general framework for **M**otion **A**cquisition in **R**obots through **I**terative **On**line **E**valuative **T**raining (*MARIOnET*). Specifically, *MARIOnET* represents a direct and real-time interface between a human in a motion-capture suit and a robot, with a training process that provides a convenient human interface and requires no technical knowledge. In our framework, the learning happens exclusively by the human - not the robot. However, the robot provides a natural interface for interaction, and is able to store and reuse trained behaviors autonomously in the future. Our approach exploits the ability at which humans are able to learn and refine fine-motor skills [6, 4]. Implemented on two robots (one quadruped and one biped), our results indicate that both technical and non-technical users are able to harness *MARIOnET* to quickly improve a robot's performance of a task requiring fine-motor skills.

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2. MOTIVATION

Historically robot motion has been written by experts, where behaviors are coded by hand or via extensive learning experiments using constrained parameterizations, causing a lot of wear and tear on the robots [3]. Generally, programming specialized robot motions requires a significant amount of coding, which is not possible for most people. We aim to develop an efficient method for generating cyclical open-loop sequences like stable robot gaits, without requiring expert knowledge or machine learning.

Recent breakthroughs in behavioral motor control have enhanced our understanding of the human brain and illustrate how remarkable our innate capacity for delicate motor control is [6]. Muellbacher et al. report that given a 60-minute training period, subjects can rapidly optimize performance of a complex task involving fine motor control [4]. We hope to harness this ability in this work.

The high-level motivation for *MARIOnET* is that a real-time mapping from a human to a robot will serve as a convenient interface for quickly and systematically training efficient motion sequences. While there is certainly a difference in the dynamics of robots and humans, we believe that people's ability to quickly hone fine motor skills can be exploited to rapidly train diverse robot motions. Even if the mapping from human coordinates to robot coordinates is not exact, we hypothesize that humans will be able to learn to correct for any inconsistencies. Additionally, the prospect of mapping any human limb to any robot limb allows for a flexible training process (e.g., mapping human arms to robot legs).

3. MARIONET

As the name indicates, *MARIOnET* is a form of iterative online evaluative training. The human performs a motion, and the robot mimics in realtime. The human evaluates the robot's performance, and repeats the motion accounting for any errors perceived in the robot's previous actions. This process continues until a sufficient motion sequence is obtained.

We represent each human limb as a vector of points that can be initialized to a "neutral" position. Thus, we can precisely represent any human pose by relating the current pose to a neutral position. The difference between these vectors is transformed to a coordinate system appropriate for a robot, and a resulting set of joint positions is generated by calculating a solution to inverse kinematics. The control flow of our interface can be seen in Figure 1. An initial configuration procedure correlates the bounds of each subject to the bounds of the robot, and captures a neutral human pose.

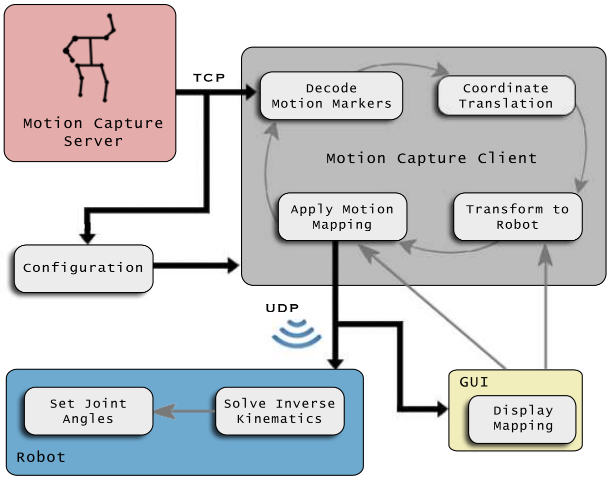

Figure 1: Control flow of the *MARIOnET* Interface

During training, it is often useful to have a "looped" motion sequence. For example, the human could take two steps and wish the robot to repeat this sequence, resulting in a continuous gait. To facilitate a natural human interface, we have implemented hand-gesture recognition to control the looping state of the robot. All loops are saved, and can subsequently be reproduced in high-level behavioral code.

4. RESULTS

To evaluate the effectiveness of *MARIOnET*, we tested the methodology using two different robots, a quadruped (the Sony AIBO) and a humanoid (the Aldebaran Nao). We primarily evaluated the ease of the training interface and assessed the ability of a human to quickly improve at a task involving fine-motor control. A typical training session using our humanoid can be seen in Figure 2.

We had 3 technical and 5 non-technical subjects perform shape-tracing and complete an episodic task involving moving a toy car from a source location to a sink location using the Nao (called Car-Park).l All of the users were able to considerably improve performance over 60 episodes of Car-Park, reducing their average completion time from 28.5 seconds for the first 10 episodes to 6.8 seconds for the final 10. The solution for Car-Park that every user eventually found was to use both arms - one to nudge the car and the other to stop it at the correct location. This coordinated sequence is the type of motion that might have taken a standard ML algorithm a long time to find, and would certainly require significant exploration of the state space.

Also, we tested generation of cyclical open-loop gaits using the AIBO. A majority of the subjects exhibited dramatic improvement in walk speed over the course of their training session. The fastest walk achieved a velocity of 18.8 cm/s, and the subject had only trained for 17 minutes before achieving this speed. To put this number in context, some of the fastest AIBO walks found through optimization algorithms are in excess of 34 cm/s[5], while the standard walk Sony included with the AIBO is 3.2cm/s. However, most parameter optimization techniques start with a decent hand-coded walk – *MARIOnET* starts from scratch. It should be noted that the output of the *MARIOnET* learning could be used as the starting point for these optimizations. A video of *MARIOnET* in action can be found at
`www.cs.utexas.edu/~AustinVilla/?p=research/marionet`.

Figure 2: A sample training session using our humanoid, the Aldebaran Nao

5. CONCLUSIONS

As more robots appear with complex body dynamics, it is vital that interaction is possible for all types of users, both technical and non-technical. However, it is very difficult to systematically construct motion controllers that exploit the specific properties of a robot, even for a roboticist. *MARIOnET* allows the layman to precisely develop specialized robot motions, and represents a promising route for shaping the behavior of tomorrow's robots.

While the similarities of human movement and robot locomotion have been investigated [1], our idea of exploiting human motor skills for rapid training of robot motions takes a completely new approach. We train the robot not by modeling its dynamics or optimizing parameters of an ML algorithm, but by taking advantage of the most finely-tuned and sophisticated control mechanism known to man: himself.

We have applied *MARIOnET* to two classes of robots, but one of its strengths is that it can be used to control any robot with an end effector that is able to compute a solution to inverse kinematics. In this first specification of *MARIOnET*, we have laid the groundwork for much future work. As mentioned earlier, *MARIOnET* abstracts the task of learning away from the robot and places this burden on the human. Although our results indicate that this approach is viable, a more robust set of problems could be approached and optimized if the robot and human learned in harmony. Using the effective combination of human reinforcement and machine learning, we plan to address this important question in future work.

6. ACKNOWLEDGMENTS

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7. REFERENCES

[1] C. Azevedo, B. Espiau, B. Amblard, and C. Assaiante. Bipedal locomotion: toward unified concepts in robotics and neuroscience. *Biological Cybernetics*, 96(2):209–228, 2007.

[2] S. Chernova and M. Veloso. Interactive policy learning through confidence-based autonomy. *Journal of Artificial Intelligence Research*, 34:1–25, 2009.

[3] N. Kohl and P. Stone. Machine learning for fast quadrupedal locomotion. In *The Nineteenth National Conference on Artificial Intelligence*, pages 611–616, July 2004.

[4] W. Muellbacher, U. Ziemann, B. Boroojerdi, L. Cohen, and M. Hallett. Role of the human motor cortex in rapid motor learning. *Experimental Brain Research*, 136(4):431–438, 2001.

[5] M. Saggar, T. D'Silva, N. Kohl, and P. Stone. Autonomous learning of stable quadruped locomotion. *Lecture Notes in Computer Science*, 4434:98, 2007.

[6] R. Schmidt and T. Lee. *Motor Control And Learning: A Behavioral Emphasis*. Human Kinetics, 2005.