A human-based genetic algorithm applied to the problem of learning in-hand manipulation tasks

Javier González-Quijano, Mohamed Abderrahim, Choukri Bensalah, Abdulla Al-kaff
University Carlos III of Madrid (jgonza1,mohamed,cbensala,akaff@ing.uc3m.es)

***Abstract*—The in-hand manipulation problem with anthropomorphic robotic hands constitutes a challenging area of research. While imitation learning and programming by demonstration have demonstrated to help in this problem, other supervised learning techniques providing more interactivity between an expert teacher and the robot have several advantages. The human-based genetic algorithm is able to enhance such interactivity. In this work, some experiments applied to the learning of simple in-hand manipulation primitives using this relatively new paradigm will demonstrate its scope.**

I. INTRODUCTION

Robot in-hand manipulation is currently an important research topic in robotics. While robot grasping has been subject of study for many years and several good methods do actually exist, in-hand manipulation is still an open problem. This skill allows humans to perform very complex dexterous manipulation tasks where, many times, the use of tools is needed. Unlike robot grasping, in-hand manipulation includes translational and rotational movements of the object being manipulated with respect to the robotic hand palm coordinate frame. Very few studies have demonstrated to address this problem successfully, despite the existence of some interesting attempts [1] [2]. In any case, due to the difficulty of the problem, completely autonomous learning of in-hand manipulation is still far from being achieved. Nevertheless, supervised learning based techniques are demonstrating to overcome problems where autonomous learning is still not possible. In this sense, the most popular supervised learning techniques, in robotics field, are probably imitation learning and programming by demonstration. In these frameworks, an expert teacher usually provides an initial solution to the learning problem. Then, most of the existing techniques perform a local optimization of this solution. The knowledge that is interchanged between the teacher and the robot usually flows only once and just in one direction: from the teacher to the robot. There is no bidirectional interaction between both entities, thus making the teaching-learning process very rigid. In the case of learning manipulation skills, a dataglove with tactile sensors or a complete haptic device are usually employed to gather the robotic hand joint kinematic variables and force/torque information [3]. Nevertheless, this technology is expensive, imprecise, uncomfortable and need complex calibration processes. Therefore, more natural methods avoiding this technology are desired.

Unlike most supervised robot motor skill learning approaches, such as the already mentioned imitation learning or programming by demonstration, this work aims at demonstrating that providing a flexible and bidirectional interactivity between a human expert supervisor and the robot could be more effective. Following this idea, a human-based computation scheme with the aim of providing such interactivity has been adopted. This scheme is a relatively new paradigm in which a computational process performs its function by outsourcing certain steps to humans. The human-based genetic algorithm [4], a subclass of the human-based computation paradigm, has been adopted in this work. In this algorithm, not only the evaluation actions (fitness and selection) are outsourced to the human expert teacher, but also the innovation actions, the crossover and mutation operations, which are usually grouped as recombination operators.

II. HUMAN-BASED COMPUTATION APPLIED TO IMPEDANCE CONTROL LEARNING

The human-based genetic algorithm scheme that has been implemented (Figure 1), is indeed a human machine interface that handles the interaction between a human expert teacher and a robotic hand. A graphical user interface allows to make this interaction easy and intuitive. The human supervisor can visualize the execution of the robot in the GUI from different perspective views. Then, the human expert teacher can affect the learning process by guiding the modification of the controller reference commands that lead to such executions. The human machine interface has a database that keeps a population of the candidate solutions. These solutions consist of impedance controller reference commands.

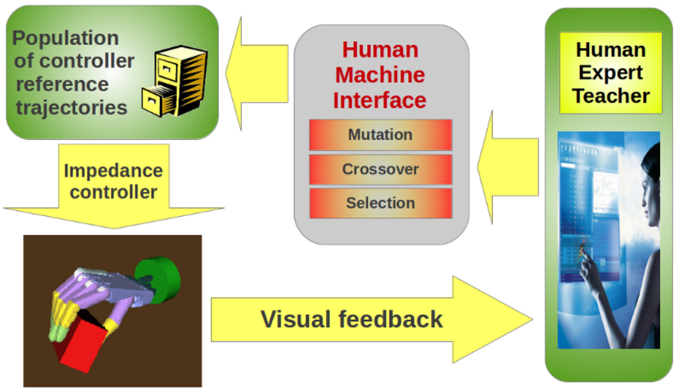

Fig. 1. Overview of human-based computation framework applied to the teaching of in-hand manipulation tasks

Each of the impedance controller reference commands are formed by two parametrized curves, in this case third order splines. One of the curves corresponds to position reference commands and the other one to the allowed maximum torque reference command. The human supervisor can add new individuals to this population by creating them randomly, by using a slider interface, by mutating one of the individuals and also by crossing two preexisting individuals. One of the key aspects in the design of the GUI is that it enables a natural interaction between the expert teacher and the robot. An example of such natural interaction is that the control of the human expert teacher over the recombination operations (mutation and crossover) is only possible at a finger level. Furthermore, it is not necessary to tell the system to perform modifications finger by finger. It is possible to manage various modifications at the same time. Behind the interface, these operations are translated to the joint level (i.e. a mutation over one finger would lead to mutating each of the joints controller reference trajectories belonging to that finger). Another natural aspect is that the human expert teacher can specify the mutation degree using fuzzified quantity commands (i.e. a ”low quantity”, a ”medium quantity” o a ”high quantity”). These commands associate a specific variance to the mutation operator, in such a way that the randomness of the candidate solution is kept. The randomness of the new solutions is also kept in the case of the crossover operations. In this case, a weighted average with random weighting factors creates a new individual by combining the finger (or various at the same time) movement of two different source individuals.

Each time the expert teacher creates a new individual, it evaluates it by telling the system to reproduce the movement associated to that individual. If the generated movement is good, or at least useful for the future teaching process, the expert teacher can tell the system to save it in the population database. Otherwise, the human supervisor can delete that individual. It is necessary to realize that no explicit fitness evaluation is performed. It is also interesting to remark that as long as the database with in-hand manipulation primitives grow, it results much easier for the human expert to teach newer complex in-hand manipulation primitives, as these primitives can be easily reused.

III. EXPERIMENTAL RESULTS

The experiments have been carried out at simulation level using the Shadow Dexterous Hand, an anthropomorphic robotic hand developed by the ShadowRobot Co. OpenRAVE has been used as the simulation software [5]. The employed motor physics engine was ODE (Open Dynamics Engine). A modified version of the controller plug-in was used. This controller allows to send reference commands which do not only take into account the position of the finger joints, but also to specify the maximum torque.

Figure 2 illustrates an in-hand manipulation sequence corresponding to the end of the learning process in one of the experiments that were carried out. The sequence is shown from three different perspective views corresponding to the three rows of the figure. A rectangular prism was initially laying on top of the table. The experiment began with an initial grasp corresponding to the first sequence image. The figure illustrates the robot hand lifting the object in the air and at the same time performing a rotation of the object with respect to the palm coordinate frame.

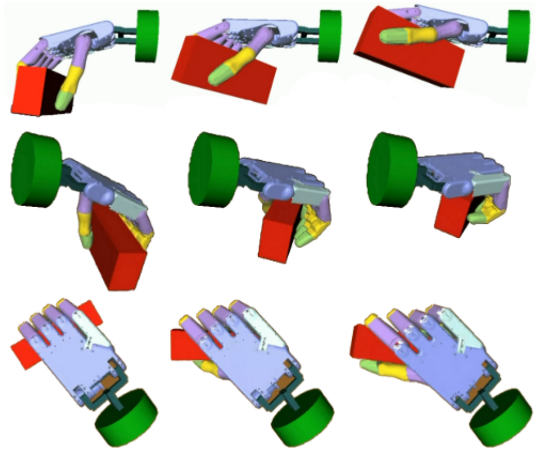

Fig. 2. A sequence of one of the in-hand manipulation solutions is shown from three perspective views. Each of the perspecitve views corresponds to each of the rows

IV. CONCLUSIONS AND FUTURE WORK

This work proposes the use of human-based genetic algorithms to teach object in-hand manipulation motor primitives with an anthropomorphic robotic hand. A human machine interface implements the core idea of the algorithm. The algorithm allows for a natural bidirectional interaction between the human expert teacher and the robot. Preliminary experimental results demonstrate that it is possible to teach the in-hand manipulation of simple objects in a relatively short period of time.

V. ACKNOWLEDGMENTS

The research leading to these results has been partially supported by the HANDLE project, which has received funding from the European Communitys Seventh Framework Program (FP7/2007-2013) under grant agreement ICT 231640

REFERENCES

[1] H. Scharfe, N. Hendrich, and J. Zhang, “Hybrid physics simulation of multi-fingered hands for dexterous in-hand manipulation,” in *Robotics and Automation (ICRA), 2012 IEEE International Conference on*, may 2012, pp. 3777 –3783.

[2] A. Fernandez, J. Gazeau, S. Zeghloul, and S. Lahouar, “Regrasping objects during manipulation tasks by combining genetic algorithms and finger gaiting,” *Meccanica*, vol. 47, pp. 939–950, 2012, 10.1007/s11012-011-9486-1. [Online]. Available: http://dx.doi.org/10.1007/s11012-011-9486-1

[3] N. Hendrich, D. Klimentjew, and J. Zhang, “Multi-sensor based segmentation of human manipulation tasks,” in *Multisensor Fusion and Integration for Intelligent Systems (MFI), 2010 IEEE Conference on*, sept. 2010, pp. 223 –229.

[4] A. Kosorukoff, “Human based genetic algorithm,” in *IEEE Transactions on Systems, Man, and Cybernetics*, 2001, pp. –.

[5] R. Diankov and J. Kuffner, “Openrave: A planning architecture for autonomous robotics,” Robotics Institute, Pittsburgh, PA, Tech. Rep. CMU-RI-TR-08-34, July 2008.