

# Human-Agent Shared Teleoperation: A Case Study Utilizing Haptic Feedback<sup>\*</sup>

Affan Pervez<sup>1</sup>, Hiba Latifee<sup>2</sup>, Jee-Hwan Ryu<sup>2</sup>, and Dongheui Lee<sup>1,3</sup>

<sup>1</sup> Department of Electrical and Computer Engineering, Technical University of Munich (TUM), Germany. {[affan.pervez](mailto:affan.pervez@tum.de), [dhlee](mailto:dhlee@tum.de)}@tum.de

<sup>2</sup> Department of Mechanical Engineering, Korea University of Technology and Education, South Korea. {[hibalatifee](mailto:hibalatifee@koreatech.ac.kr), [jhryu](mailto:jhryu@koreatech.ac.kr)}@koreatech.ac.kr

<sup>3</sup> Institute of Robotics and Mechatronics, German Aerospace Center (DLR)

**Abstract.** Even though teleoperation has been widely used in many application areas including nuclear waste handling, underwater manipulation and outer space applications, the required mental workload from human operator still remains high. Some delicate and complex tasks even require multiple operators. Learning from Demonstration (LfD) through teleoperation can provide a solution for repetitive tasks, but in many cases, one task can be a combination of repetitive and varying motion. This paper introduces a shared teleoperation method between human and agent, trained by LfD through teleoperation. In the proposed method, human takes charge of uncertain or critical motion, whereas more mundane and repetitive motion could be carried out through the assistance of the agent. The proposed method has exhibited superior performance as compared to the human-only teleoperation for a peg-in-hole task.

**Keywords:** Teleoperation · Human-Agent Shared Teleoperation · Co-operative Teleoperation · Dynamic Movement Primitive · Learning from Demonstrations · Haptic Feedback.

## 1 Introduction

Imitating a task through observations is inherently easy for humans, but surprisingly challenging for robots. Usually, a robot has to be pre-programmed for performing different tasks. A slight change in a task or the environment requires re-programming of the robot, which can be a tedious and time-consuming process [2]. Learning from Demonstrations (LfD) provides an intuitive way to readily transfer new repetitive skills to the robots [1–3, 9].

On the other hand, in shared teleoperation among multiple operators, the control authority of a slave robot is distributed among multiple operators. This provides a decrease in cognitive workload of each operator and a reliable execution of the task [5]. The issue of dividing the control authority among multiple operators with multiple Field-of-Views (FOVs) is addressed by [11]. That way,

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an operator can always take over partial or full authority over the task, whenever and wherever a need arises. However, utilizing multiple human operators is an economically expensive solution. Autonomous execution of a task on a robot relaxes the workload of a human operator, but the efficiency and safety in critical tasks [4,7], like performing surgeries, are thoroughly ensured when both a human and an autonomous artificial agent leverage from each other’s capabilities in a shared teleoperation setting.

## 2 Human-Artificial Agent Shared Teleoperation

The artificial agent in our study is based on Dynamic Movement Primitive (DMP). DMP is a way to learn motor actions [10]. It can encode discrete and rhythmic movements. A separate DMP is learned for each considered Degree of Freedom (DOF). In the DMP framework, a canonical system acts as a clock. For synchronized motion of multiple DOFs, each DMP is driven by a common clock signal. The canonical system drives the second order transformed system:

$$\begin{aligned}\dot{v} &= \tau\alpha_x(\beta_x(g-x) - v) + \tau a\mathcal{F}(s) \\ \dot{x} &= \tau v\end{aligned}\quad (1)$$

The learning of forcing term  $\mathcal{F}(s)$  allows arbitrarily complex movements. For encoding the forcing terms of the autonomous DOFs, we utilize the learning approach presented in [8], as it can handle the large spatial and temporal variations intrinsic to teleoperated demonstrations for learning.

In this paper, we show that if the operator has a distorted visual perspective in certain DOFs, then those DOFs can be encoded by LfD, while the motion of the remaining DOFs can be controlled by the operator. Also, if there are certain DOFs which are highly critical for the execution of a task, then those could be assigned to the operator while the motion of other DOFs can be autonomously generated. The control flow of the proposed human-agent shared teleoperation architecture can be visualized in Figure 1, where, for a given task, a human synchronizes his/her motion with the autonomous agent’s DOFs by utilizing the visual and haptic feedback.

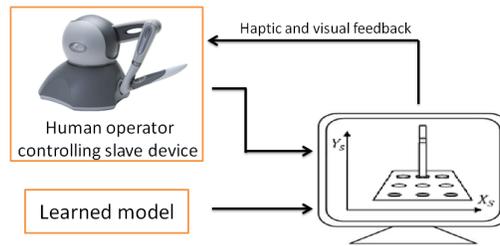


Fig. 1: Human-agent shared teleoperation.

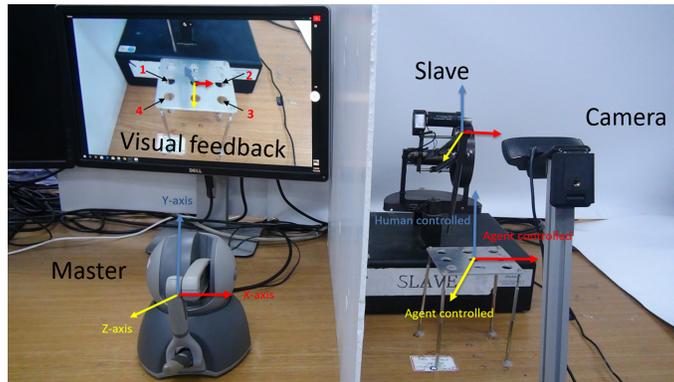


Fig. 2: Perspective distortion due to the camera position on the slave side.

### 3 Results

#### 3.1 Experimental Setup

Our proposed approach is evaluated using a peg-in-hole task rig with a master-slave teleoperation system. It consists of two 3-DOF Phantom haptic devices (Figure 2). A web-camera streams the visual feedback from the slave environment to the human operator with a perspective distortion, thereby inhibiting a clear visual perception to the human. The human operator controls the motion of the slave device in  $y$ -axis, whereas the artificial agent, implemented on the slave device, controls both the  $x$  and  $z$  axes of the motion. One execution cycle constitutes insertion of the slave robot end-effector into the four holes in clockwise direction, while starting and ending above the same hole.

#### 3.2 Discussion

For encoding the DMP, our dataset consists of slave’s Cartesian positions recorded for four teleoperated demonstrations. In order to evaluate the performance of our proposed shared teleoperation approach, nine subjects participated in performing four trials of the two experiments, i.e. human-only teleoperation and human-agent shared teleoperation. In these experiments, we evaluate the execution time, the rate of collision and the overall workload index using NASA-TLX [6] for the two settings. The plots in Figure 3 clearly show that our human-agent teleoperation architecture slightly reduces the total execution time of the task, decreases the rate of collision and eases the mental and physical workload of the operator (NASA-TLX assessment) as compared to the human-only teleoperation.

### 4 Conclusion

In this work, we have proposed a human-agent shared teleoperation architecture. The agent is learned through teleoperated demonstrations. The proposed

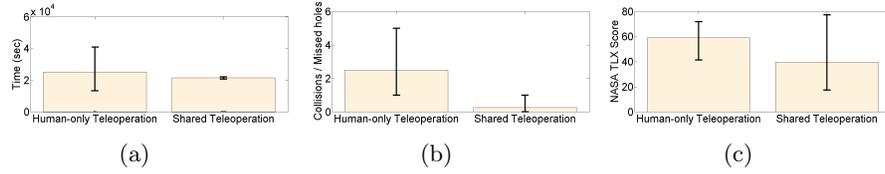


Fig. 3: Average (a) execution time, (b) rate of collision/missed holes, and (c) overall workload index of the peg-in-hole task for the two teleoperation experiments. Error bars indicate the minimum and maximum values in each experiment.

approach shows significant performance improvement in circumstances where FOV deficiency as well as task’s intricacy can deteriorate the efficiency when utilizing the human-only teleoperation.

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