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The Role Of Human Dynamics In Effective Robot Learning Through Programming By Demonstration

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This extended abstract presents preliminary results from a pilot study on human dynamics within a kinesthetic programming-by-demonstration (PbD) framework, a key method for teaching robots new skills through demonstration. As humans increasingly take on roles as task demonstrators in human-robot collaborative environments, understanding and enhancing these teaching interactions becomes essential (Sosa-Ceron et al., 2022). This ongoing study is a part of "Collaborative Intelligence for Safety-Critical System, Live Lab 1," assesses human teaching dynamics to refine PbD methods. A key effort is refining how robots' learning strategies are communicated to human demonstrators, aiming to optimize how instructors impart skills and evaluate robotic learners, especially considering how variations in demonstration parameters affect the robot's learning process.

We conducted a pilot study at Irish Manufacturing Research's pilot factory line, using a UR10e manipulator and an RGB-D vision sensor to execute two tasks: Object Targeted Placement and Object Sliding (Figure 1). Our PbD algorithm, leveraging dynamic movement primitives and behavior trees (Iovino et al., 2022), and facilitated by an intuitive HMI for efficient data collection. This setup included a Mediapipe-based body motion capture system (Jeong and Kook, 2023) for ergonomic assessments and a Tobii Pro eye tracker to measure cognitive workload at a 100 Hz sampling rate. Subjective data were collected using NASA TLX (Hart and Staveland, 1988) and the System Usability Scale (Lewis, 2018). We gathered exploratory data from 10 participants, divided into knowledge and baseline groups, consisting of 7 males and 3 females with diverse robot interaction experiences—5 with no prior interaction, 3 with over three years of experience but no robot teaching background, and 2 with specific, limited experiences. Each participant provided five demonstrations for both tasks. The gathered data is categorized into four distinct categories of datasets for offline analysis: (a) robot input policy or demonstration data, (b) human teaching postures data, (c) eye tracking data for cognitive workload and (d) participant's subjective feedback. The robot input policy comprises extensive logs detailing the robot's actions and responses throughout the teaching sessions. These logs encapsulate command sequences and operational parameters integral to the robot's learning via kinaesthetic teaching in the PbD framework. The data transfer through the robot involves recording its movement patterns, sensor responses, and behaviours as it learns from human-guided demonstrations. It includes important information about the robot's positional adjustments, and trajectory, offering a view of its interactive learning process.

Here, we present preliminary findings focused exclusively on the efficacy of the transferred skills through demonstration data. This analysis evaluates metrics such as path length, proximity, completion time, and distance-based similarity to an expert's trajectory. We selected one demonstration from each participant for both tasks, analyzing completion time, path length, smoothness, and proximity. Preliminary results show that the knowledge group outperformed the baseline group but did not reach the expert's proficiency, especially in the object sliding task. For instance, the expert completed the object pick and placement task in 22 seconds and the sliding task in 17 seconds, with the knowledge group demonstrating comparable path lengths and smoother motions than the baseline group.

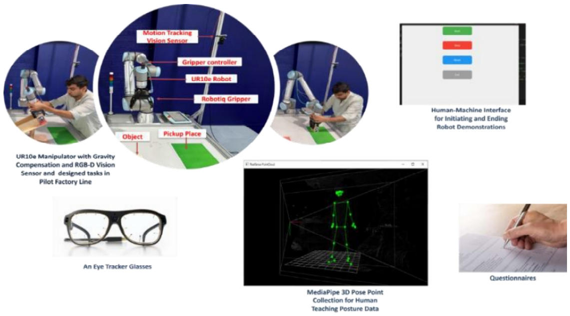

Fig.1. Experimental set-up at the apparatuses used for data collection.

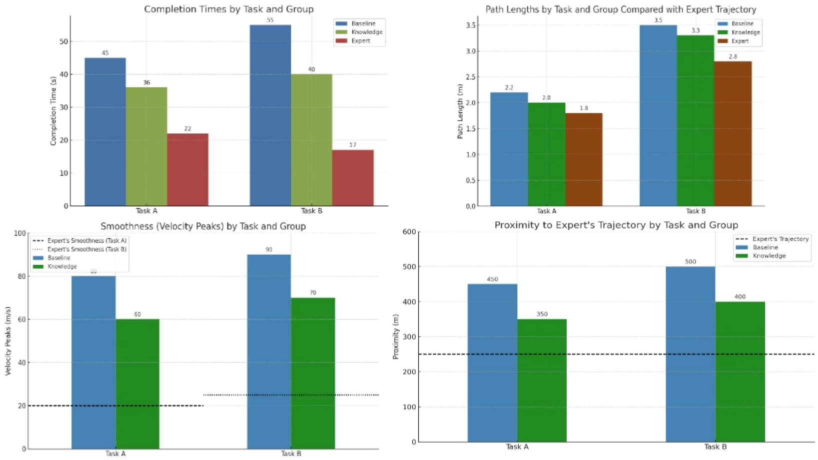

Fig. 2. Preliminary results of teaching performance.

These findings (Figure 2) provide insights into the effectiveness of the collaborative PbD framework and underscore the potential impact of skill transfer on task execution and setting the stage for more detailed future analyses. Future investigations will delve deeper into the demonstration data, focusing on how effectively skills are transferred and adopted by learners, combined with other human factor data.

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