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Robotic Learning of Haptic Skills from Expert Demonstration for Contact-Rich Manufacturing Tasks

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***Abstract*— We propose a learning from demonstration (LfD) approach that utilizes an interaction (admittance) controller and two force sensors for the robot to learn the force applied by an expert from demonstrations in contact-rich tasks such as robotic polishing. Our goal is to equip the robot with the haptic expertise of an expert by using a machine learning (ML) approach while providing the flexibility for the user to intervene in the task at any point when necessary by using an interaction controller. The utilization of two force sensors, a pivotal concept in this study, allows us to gather environmental data crucial for effectively training our system to accommodate workpieces with diverse material and surface properties and maintain the contact of polisher with their surfaces. In the demonstration phase of our approach where an expert guiding the robot to perform a polishing task, we record the force applied by the human (F_h) and the interaction force (F_{int}) via two separate force sensors for the polishing trajectory followed by the expert to extract information about the environment ($F_{env} = F_h - F_{int}$). An admittance controller, which takes the interaction force as the input is used to output a reference velocity to be tracked by the internal motion controller (PID) of the robot to regulate the interactions between the polisher and the surface of a workpiece. A multilayer perceptron (MLP) model was trained to learn the human force profile based on the inputs of Cartesian position and velocity of the polisher, environmental force (F_{env}), and friction coefficient between the polisher and the surface to the model. During the deployment phase, in which the robot executes the task autonomously, the human force estimated by our system ($\hat{F}_h$) is utilized to balance the reaction forces coming from the environment and calculate the force ($\hat{F}_h - F_{env}$) needs to be inputted to the admittance controller to generate a reference velocity trajectory for the robot to follow. We designed three use-case scenarios to demonstrate the benefits of the proposed system. The presented use-cases highlight the capability of the proposed pHRI system to learn from human expertise and adjust its force based on material and surface variations during automated operations, while still accommodating manual interventions as needed.**

***Index Terms*— physical human-robot interaction (pHRI), haptic skill transfer, autonomous polishing, admittance control, real-time interaction, machine learning (ML), contact-rich tasks.**

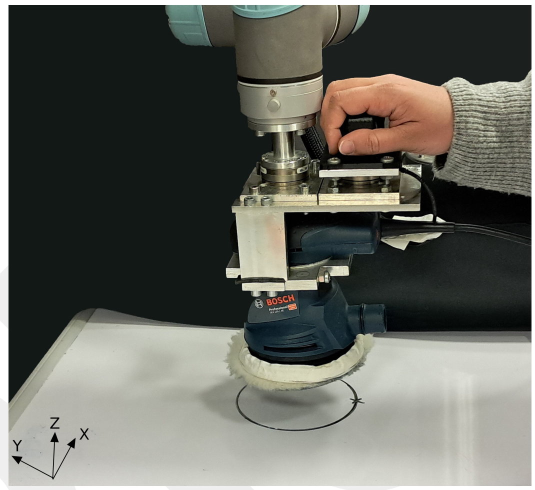

Fig. 1: A scene from our experiments on cleaning a circle drawn on a whiteboard with a board marker, which serves as a model of the scratch removal by polishing in industrial settings. The z-axis represents the direction normal to the surface while the x and y-axes are the tangential directions in which the circular cleaning movement is performed. See video at: `https://www.youtube.com/watch?v=QSn9n6EJ0PE`

I. INTRODUCTION

The introduction of collaborative robots has improved the physical interaction between humans and robots (pHRI) in manufacturing environments. Equipped with force sensors and advanced algorithms, these robots seamlessly integrate into the workforce, complementing human expertise in dynamic production settings. By working alongside human operators, collaborative robots learn from their experience, swiftly adapting to fluctuating demands and evolving environments. This symbiotic collaboration holds particular importance in the realm of small-batch manufacturing, where agility and flexibility are important for meeting diverse customer needs [1]. Small batch manufacturing operations demand adaptability, precision, and quick decision-making from human operators due to frequent changes in products and processes, making full automation challenging due to the need for human ingenuity and flexibility in handling variable tasks and situations.

Consider, for example, the polishing task, traditionally performed manually, which, while precise, is time-intensive and may lead to operator fatigue and ergonomic issues [2], [3]. Conversely, existing fully automated robotic systems face limitations in their adaptability to accommodate workpieces with diverse material compositions and surface characteristics, as well as in their ability to incorporate

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human expertise into the operational workflow [4], [5].

In contact-rich tasks such as robotic polishing, hybrid position/force control is currently the preferred approach to automate the process [6]. Unlike traditional position-control, commonly used in industrial settings for task automation, which struggles in contact-rich tasks, hybrid position/force control enables control over both robot movements and applied forces, ensuring high-quality polishing on surfaces with known geometry [7], [8]. However, implementing such control schemes for robotic polishing requires predefined movement trajectories for the polisher attached to the end effector of the robot and limits real-time human intervention when, for example, some areas need more polishing than others. Moreover, the force required to maintain the contact and the velocity profile of the polisher on the surface need to be set in advance to accommodate the workpieces with different material and surface properties, which is not trivial and requires expert knowledge.

The indirect force control methods such as impedance or admittance control, also known as interaction control, present a compelling alternative to direct force control. These controllers facilitate the integration of the human operator into the process and seek to regulate the dynamics of interactions between the robot, human, and the environment [9], [10]. The pHRI systems utilizing such interaction controllers (impedance/admittance) have been successfully used in manufacturing tasks involving contacts with the environment. For example, Kana et al. [11] used an impedance control scheme for curve tracing in edge chamfering and polishing. Utilizing a compliant robot for assistance simplifies this process, as it allows the human operator to physically maneuver the tool across the workspace, facilitating the sampling of essential surface points and consequently deriving a mathematical representation of the tool's trajectory. Similarly, an adaptive admittance controller was successfully utilized for collaborative drilling on flat surfaces [12], [13] and also the more challenging case of curved surfaces [14]. The real-time adaptation of the admittance damping during the task in these scenarios based on some predefined rules provides more transparency (minimal resistance to human movement) while driving the robot in free space to the target while ensuring stability during drilling at the target (see more in-depth discussion of the trade-off between transparency and stability in pHRI systems in [15]).

Recognizing the repeatable and tiring nature of contact-rich manufacturing tasks such as polishing, the integration of machine learning (ML) into the pHRI systems opens the door for robots to learn from human demonstrations. We argue that this approach, known as Learning from Demonstration (LfD) can reduce the physical workload of workers. LfD involves learning a mapping between the states and actions, known as policy, from demonstrations provided by an expert, which consist of sequences of state-action pairs. LfD algorithms leverage this dataset to derive a policy replicating the demonstrated behavior [16], [17]. Considerable research has explored this learning paradigm in kinesthetic teaching [18], teleoperation [19], and passive observation [20] in which the robot observes human actions or the environment without actively participating or interacting (see the reviews in [21], [22]). These studies showcase the applications of LfD in robotic pick and place, peg insertion, polishing, welding, and grasping. For instance, Rozo et al. utilized kinesthetic teaching to facilitate impedance-based behaviors in a torque-controlled robot. They employed a collaborative assembly task as a testbed, encoding examples as task-parameterized statistical dynamical systems. This enabled the robot to dynamically adjust impedance during task execution based on demonstrations [23].

Previous research in pHRI concerning LfD has predominantly concentrated on instructing robots to learn the movement trajectories of human user. Nonetheless, in contexts such as small-batch manufacturing, contact-rich tasks like robotic polishing entail the continuous physical interaction between a machine tool, mounted on the robot's end-effector, and the workpiece. In tasks of this nature, effectively counterbalancing the environmental force (F_{env}) is crucial for maintaining contact and ensuring the task is performed in a stable manner. The normal and tangential components of this force provide insights into the environment's stiffness and the frictional properties of the tool-environment interface, respectively. This information can be utilized to transfer human haptic skills to a robot to perform the task autonomously. There are already a few studies in the literature on force learning from an expert to automate the contact-rich tasks such as polishing, but only a single force sensor, measuring the interaction forces between the end-effector tool and the environment, was utilized [24], [25]. However, to extract information about the environment, an additional sensor measuring forces applied by the expert is required.

We propose an LfD approach that utilizes an interaction (admittance) controller and two force sensors to learn the force applied by an expert from demonstrations in contact-rich tasks such as robotic polishing (see Fig. 1). Our primary goal is to equip the robot with the haptic skills and expertise of a human operator via learning. Consequently, by transferring expert skills to the robot, it becomes feasible to automate laborious, contact-intensive tasks requiring repetitive actions and carried out on workpieces with diverse material compositions and surface properties.

Our research makes the following contributions:

- A key aspect of our approach is the use of two force sensors in a pHRI system to extract the characteristics of the environment from expert demonstrations. The normal and the tangential components of this force reveal information about the stiffness of the environment and the frictional characteristics of the tool-environment interface, respectively. This information is then used to learn the profile of force applied by the expert via an ML model. Once the human haptic skills are transferred to the robot, it can autonomously perform the polishing task for a given movement trajectory. We show that the robot can successfully learn the intrinsic changes in the human force profile during the polishing of workpieces having different material and surface properties.

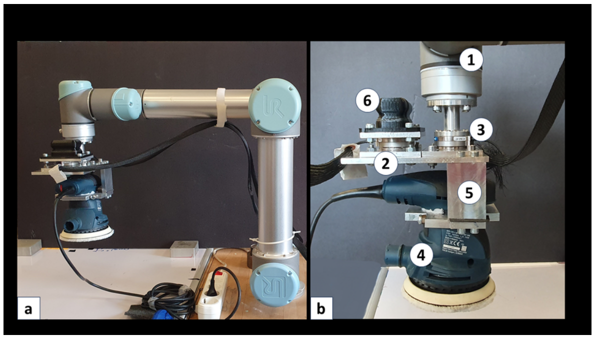


Fig. 2: (a) A picture of our setup and (b) a zoomed view providing its details: the robot arm (1) equipped with two force sensors, one for measuring human force (2) and the other one for interaction force (3), the polisher (4), auxiliary plates (5), and a 3D printed handle (6).

- Employing an interaction (admittance) controller, as opposed to the conventional direct force controller empowers the user to intervene in the polishing task and make adjustments as needed, ensuring alignment between the robot's actions and the desired outcome. By incorporating this shared control approach into our pHRI system, we strike a balance between manual control by user and full robotic execution, leveraging the benefits of both human oversight and automation. To demonstrate the real-time interaction capability of the developed pHRI system, we also present a scenario in which the user intervenes in the robotic polishing task to apply additional force to a region of a workpiece where it requires more polishing.

The remainder of the paper is structured as follows: Section II explains our approach to learning force profile, covering the demonstration, learning, and autonomous phases. Section III describes the experimental use cases, while Section IV presents and discusses the obtained results. Finally, the paper is concluded in Section V.

II. APPROACH

A. Hardware Setup

The components of our hardware (Fig. 2), include a collaborative robot (UR5, Universal Robots Inc.), a powered polisher (GEX 125-1 AE, Bosch Inc.), and two force sensors (Mini45, ATI Inc.). One force sensor (item 2 in Fig. 2) was placed between the polisher and the handle (item 6 in Fig. 2) gripped by the operator, measuring forces applied by human, F_h, while the other force sensor (item 3 in Fig. 2) was placed between the polisher (item 4 in Fig. 2) and the robot's end-effector, measuring the interaction forces, F_{int}. This dual-sensor setup facilitates the extraction of environmental forces, a crucial parameter for contact-rich tasks, and for our approach, as detailed in Section II-C.

In our system, the force data from the sensors are acquired at 125 Hz by an external DAQ card (USB-6343, National Instruments Inc.) connected to a computer. The end-effector position and velocity of the robot are also acquired at the same update rate using the robot's encoders and accessed through its control box. All software code was developed in C/C++ and Python programming language, leveraging multi-threading techniques to guarantee seamless real-time data acquisition and processing.

B. Admittance Control

We employ three decoupled admittance controllers, each dedicated to one of the three Cartesian degrees of freedom (dof), to manage the interactions between the human operator, robot, and the environment. It should be noted that our focus in this study is primarily on polishing flat surfaces to demonstrate the proposed concepts, so we exclusively concentrate on the translational movements, leaving the polishing of curved surfaces via a 6-dof admittance controller to future studies. In the Laplace domain, the expression for the admittance controller $Y_i(s)$ related to each translational degree of freedom, i, can be written as:

$$Y_i(s) = \frac{V_{\mathrm{ref},i}(s)}{F_{\Delta,i}(s)} = \frac{1}{m_i s + b_i} \tag{1}$$

where $V_{\mathrm{ref},i}(s)$ represents the corresponding reference velocity in the Laplace domain, which is provided by the admittance controller to be followed by the robot via its internal motion controller. $F_{\Delta,i}(s)$ denotes the input force along i in the Laplace domain, while m_i and b_i represent the corresponding admittance mass and damping, respectively. The parameters of the admittance controller for each dof are carefully fine-tuned to achieve a balance between transparency for the ease of operator movement and robust stability, especially during contacts with the environment [26].

C. Force Learning from Human Demonstration

1) Demonstration Phase: In this phase, a human operator manually performs the polishing task while grasping the polisher by the handle, with the robot exhibiting compliance to the user's actions. The block diagram explaining the control loop is shown in Fig. 3. Before the polisher guided by human makes contact with the surface, the readings of both force sensors will show the same values ($F_h = F_{int}$). However, after the contact, the human force sensor continues to measure the force applied by the human operator, while the interaction force sensor captures the force arising from the polisher-environment interaction. The interaction force, F_{int}, is essentially the difference between the force applied by the human operator, F_h, and the reaction force from the environment, F_{env}, as described by Eq. 2.

The difference between the reference force, F_{ref}, and the measured interaction force, F_{int} is then utilized as input, F_Δ (see Eq. 3), for the admittance controller, which, in turn, generates a reference velocity command to be followed by the internal motion controller of the robot to comply with the desired human movements on the surface. In the demonstration phase, we set the reference force to zero ($F_{ref} = 0$), and hence the force inputted to the admittance controller is the interaction force ($F_\Delta = -F_{int}$).

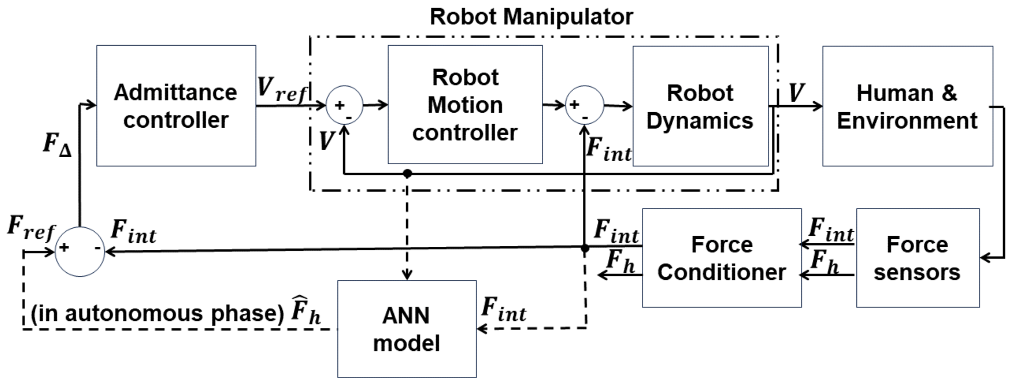


Fig. 3: Block diagram of the proposed pHRI system for robotic learning of human forces from expert demonstration to perform contact-rich tasks autonomously.

$$F_{int} = F_h - F_{env} \tag{2}$$

$$F_\Delta = F_{ref} - F_{int} \tag{3}$$

During the polishing under human guidance, the data acquisition system is in operation, acquiring the system "state", including the movement trajectory (Cartesian position and velocity of the polisher after the initial contact) and the forces measured by two force sensors (F_h and F_{int}). Following data collection, the acquired sensory data undergoes several preprocessing steps including filtering and outlier removal, to prepare it for the learning phase. Additionally, we compute the environment force (Eq. 2) and the friction coefficient using its tangential and normal components ($\mu = F^t_{env}/F^n_{env}$), which provide information about the material and surface properties of the workpiece being polished.

2) Learning Phase: The goal of the learning phase is to transfer the haptic skills of the human expert to the robot for autonomous robotic polishing. In our approach, we adhere to the supervised ML paradigm, treating the learning task as a regression problem. Unlike the record-and-play approach, the ML approach endows our robot with dynamic learning and adaptive capabilities, essential for mastering the intricacies of the polishing task. Building upon this approach, our designed multilayer perceptron (MLP) model aims to understand the complex coupling between various parameters (called state) acquired from the expert during the demonstration phase. By learning these relationships, the model can estimate the corresponding human force, which is crucial for the robot's autonomous polishing phase for achieving expert-level polishing performance.

The MLP architecture was designed for performing regression, aiming to predict continuous values (human forces) directly from the 10 input features (Cartesian position and velocity of the polisher, environmental force, and the friction coefficient between the polisher and the surface). The architecture, shown in Fig. 4, begins with an input layer of 10 neurons, followed by a dense (fully connected) hidden layer with 40 neurons. Employing the Rectified Linear Unit (ReLU) activation function, this layer introduces non-linearity to capture complex patterns. Another hidden layer with 30 neurons was added after the first hidden layer, again utilizing ReLU activation. This layer further refines the learned representations. The output layer consists of three neurons, representing the components of human force. Before training, the input features and target values underwent min-max scaling for normalization. The dataset was then split into training and validation sets with an 80:20 ratio, ensuring the evaluation of unseen data. In addition, hyperparameters of the model were tuned through cross-validation to optimize performance. The model was trained by using Mean Squared Error (MSE) as the loss function, and Stochastic Gradient Descent (SGD) algorithm as the optimizer. Over 200 epochs with a batch size of 32, careful monitoring of the performance ensured that the model was learning effectively without falling into the trap of overfitting.

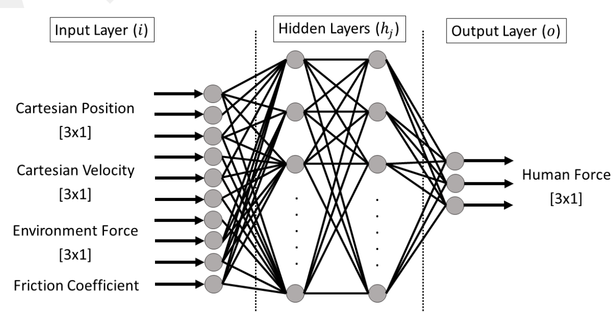


Fig. 4: The architecture of our MLP model consists of an input layer with 10 neurons, two hidden layers containing 40 and 30 neurons respectively, and an output layer designed for estimating human force.

3) Autonomous Polishing Phase: In this phase, we deploy the proposed model, which estimates human force in real-time, to empower the robot with the capability to autonomously execute the polishing task. The control architecture used for this purpose is shown in Fig. 3. Notably, the absence of human involvement within the loop ($F_h = 0$) means that the interaction force sensor exclusively measures environmental forces (see Eq. 2). Nevertheless, the human force estimated by the MLP model, $\hat{F}_h$, is introduced into the system, serving as the reference force ($F_{ref} = \hat{F}_h$), as depicted by the dashed line in Fig. 3. Subsequently, the measured interaction force, F_{int}, is subtracted from the reference force to compute the force inputted to the admittance controller ($F_{\triangle}$).

D. Real-Life Application

Our quest for insight into the challenges involved in polishing led us to visit various industries involved in manual polishing, from white goods to car surface finishing. A common thread in these visits was the repetitive nature of the polishing task, leading to physical and mental fatigue in the workers. During these interactions, we also learned more about the factors affecting the quality of polishing such as a) the magnitude of force applied to the workpiece by the human operator, b) the circular trajectory followed by the human operator, and c) the complex coupling between them as it is also emphasized in [6]. Additionally, throughout these visits, the first author of this study acquired essential manual polishing skills and assumed the role of the expert in the controlled experiments conducted within our laboratory.

During our discussions with industry experts, we learned that ”scratch removal” is one of the common applications of polishing, which involves either eliminating or reducing surface scratches. For example, in the context of car polishing, the primary focus is on surface-level scratches affecting the outermost layer known as ”clearcoat” or ”paint layer”, while deeper scratches may necessitate additional steps like sanding and filling.

III. Use-Cases

Our use-case scenarios aim to showcase the efficacy of the proposed pHRI system and the ML approach in transferring the haptic skills of an expert to a collaborative robot for polishing. Since the quantitative assessment of surfaces after polishing requires sophisticated measurement techniques, we devised a relatively simple approach to simulate scratch removal through polishing in our laboratory and assess the quality by visual inspection. Initially, a circle was marked with a board marker on a flat surface, serving as a simulated scratch. Subsequently, the proposed pHRI system was deployed to erase (clean) the marked circle from the surface employing the polisher’s rotating pad while no polishing compound was applied to the interface. To this end, we designed three use-case scenarios. In the first one, our goal was to highlight the importance of haptic skills in the polishing process by conducting a comparative analysis of the performances between an expert and a novice user. In the second use-case, we collected data from an expert user applying polishing to different workpieces. The objective is to demonstrate that the proposed approach can effectively extract force response characteristics from workpieces having different material and surface properties to train a MLP model, enabling accurate estimation of human force for autonomous robotic polishing. The third use-case was designed to demonstrate the real-time interaction capability of the developed pHRI system, where we study a scenario in which the user intervenes in the autonomous polishing performed by the robot to apply additional force to a region of a surface where it requires more polishing.

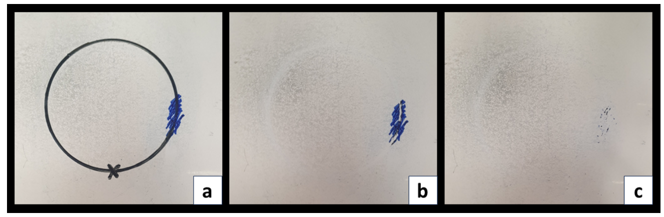
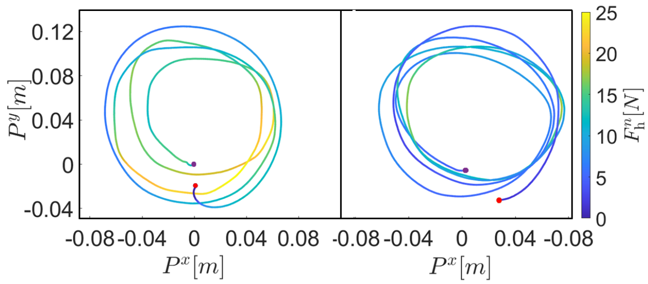


Fig. 5: The states of a circle drawn on a whiteboard with a marker in Use-Case 3: (a) the initial state of the circle containing a densely marked region, imitating a deep scratch in polishing (b) the circle after autonomous robotic cleaning, and (c) the circle after user intervention during autonomous robotic cleaning.

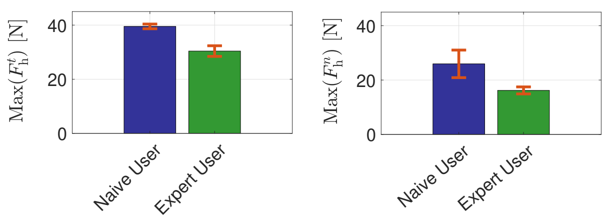
Use-Case 1: Haptic Skills of Expert vs. Naive Users: The goal of this use-case is to show the added value of haptic skills gained by experience in executing a polishing task by comparing the performances of an expert (the first author of this paper who learned the task from expert industrial workers by practicing it several times) and naive (a graduate student in our laboratory with no prior experience in robotic polishing) user. The participants were asked to clean a circle, drawn by a black-colored marker, from the surface of a whiteboard, which is placed on a workbench horizontally, as shown in Fig.1. The naive user was informed about the procedures of the task and performed one test trial before the actual experimentation.

Use-Case 2: Learning Force Response Characteristics of Environment: One of the key contributions of this study is the ability of the proposed pHRI system to learn the force response characteristics of the environment. By incorporating two force sensors into the pHRI system, we can effectively isolate the environmental forces. This enables the MLP model to accurately discern and adapt to the human-generated forces specific to the polishing task within that particular environment. To demonstrate that the proposed pHRI system can differentiate different environments in which the polisher makes contact and also learn the corresponding human forces, we experimented with two surfaces (whiteboard and chipboard) having different material and surface characteristics. Again, a circle was drawn on each surface using the board marker, and the expert user was tasked to clean it using the proposed pHRI system in demonstration mode. The recorded data was then used to train the MLP model to estimate the human force for each surface.

Use-Case 3: Real-time User Intervention During Autonomous Polishing: We set up a scenario where the user steps in while the robot is polishing a surface autonomously. The user applies additional force to a particular area of the surface that needs more polishing. To demonstrate this scenario, we drew a circle on the whiteboard as in the



(a)



(b)

Fig. 6: (a) A sample trial demonstrating the normal force applied by naive (left) and expert (right) users as they follow a circular trajectory to clean the surface of a whiteboard. The start and end of the trajectory are marked by purple and red dots, respectively. (b) The mean values and standard deviations of the maximum tangential and normal force applied by the naive and expert users over three trials, with each trial encompassing roughly 5 cycles to clean the surface.

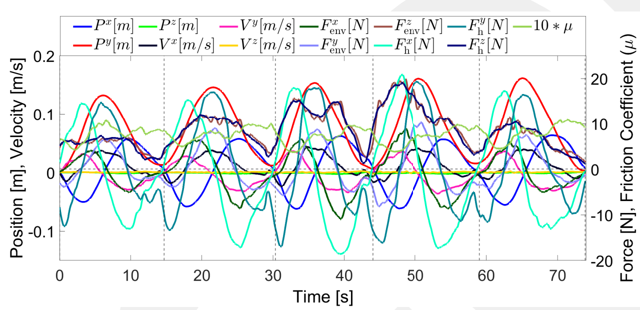


Fig. 7: Movement trajectory (Cartesian position and velocity) of the polisher, the environmental force, the human force, and the friction coefficient between the polisher and the whiteboard for the circular trajectory followed by the expert user in an exampler trial. Vertical dashed lines indicate the beginning and end of each cycle of the trial.

first and second use-cases but applied marker more strongly and densely to a certain region on the circle (Fig. 5), simulating deep scratches that necessitate increased force in the direction normal to the surface during polishing.

IV. Results

In the first use-case, both an expert and a naive user were asked to erase a marked circle from a whiteboard surface. Both users repeated the task three times (i.e. 3 trials). It took approximately 5 cycles (i.e. circular trajectories) in each trial to entirely erase the marked circle.

Fig.6a presents an exemplary trial for the naive user (on the left) and the expert (on the right). The normal forces exerted by each user while following the circular trajectory are illustrated in the form of colormaps. The colors indicate the magnitude of the exerted normal forces.

Fig. 6b presents the mean values of maximum tangential and normal forces applied by the naive user and the expert across 3 trials. To effectively analyze the collected data, we partitioned each trial based on the starting and ending position of each cycle. Hence, the height of the bars represents the mean values of all cycles of 3 trials while the error bars are the standard deviations. As shown in the figure, the expert user exerted lower tangential and normal forces than the naive user to erase the circle, demonstrating the importance of haptic skills in contact-rich tasks.

In Use-Case 2, we conducted experiments with the expert user on two surfaces (whiteboard and chipboard) having different material and surface characteristics to demonstrate the ability of our system to distinguish between different environments and learn the corresponding human forces. Starting with the whiteboard surface, we first show the complex relation between the parameters contributing to the polishing process, including the movement trajectory (Cartesian position and velocity) of the polisher, the human and environmental forces, and the friction coefficient (Fig. 7). This complex relation is not surprising due to the inherent complexity of physical coupling between the tangential movements necessary on the surface for polishing and the force required to maintain contact with the surface.

In our comparative analysis of the whiteboard and chipboard surfaces, the expert user repeated the polishing process three times on each surface (i.e. three trials). It took approximately 5 cycles in each trial on both surfaces to entirely erase the marked circle. To effectively analyze the collected data, we partitioned each trial based on the starting and ending position of each cycle. We calculated the maximum normal and tangential forces, tangential velocity, and also the coefficient of friction for each cycle. The results are reported in Fig. 8. From the figure, we observe that the maximum human force in the normal direction (F_h^n) is higher for the chipboard (16.9 ± 5.9 N) compared to the whiteboard (11.1 ± 3.8 N). This difference can be attributed to the chipboard's porous nature which requires greater pressure to clean its surface effectively, compared to the smoother and non-porous surface of the whiteboard. Regarding the friction coefficient values (μ), we observed that the maximum friction coefficient was larger (1.2 ± 0.3) for the whiteboard compared to the chipboard (0.7 ± 0.1). Considering the similarity in the magnitude of the environmental forces applied tangentially (F_{env}^t) to the polisher by both surfaces, as illustrated in Fig. 8, the resulting friction coefficient findings are as expected.

The MLP model was trained by the experimental data collected from the expert user for the whiteboard and chipboard. Hence, a total of 6 trials, with each trial containing roughly 5 cycles were used for training and testing. For cross-validation, we employed a leave-one-out strategy across the

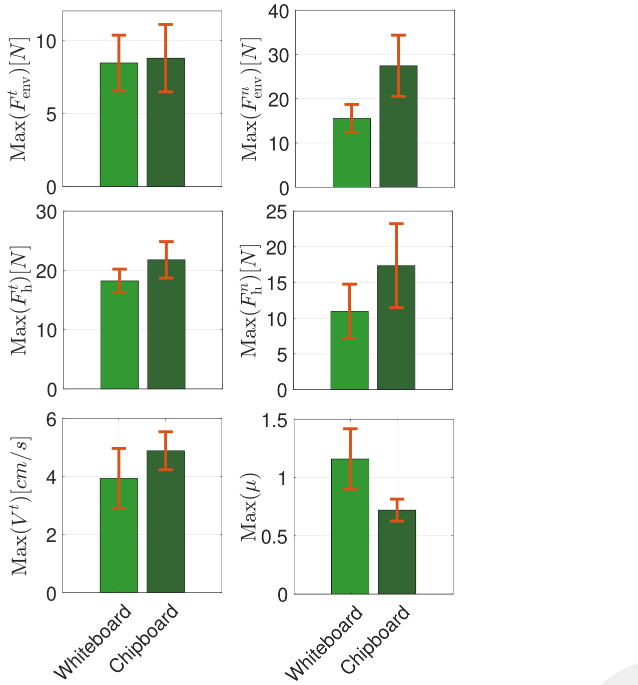


Fig. 8: The mean values of maximum human force, environmental force, velocity and the friction coefficient (μ) for the whiteboard and chipboard surfaces. The height of the bars represents the mean values for all cycles of 3 trials, while the error bars represent the standard deviations.

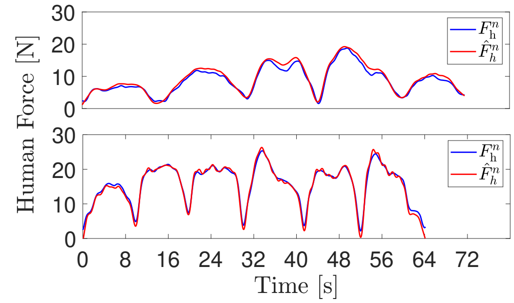


Fig. 9: The human force predicted by the MLP model ($\hat{F}^n_h$) and measured by the force sensor (F^n_h) for one testing trial of the whiteboard (top) and chipboard (bottom).

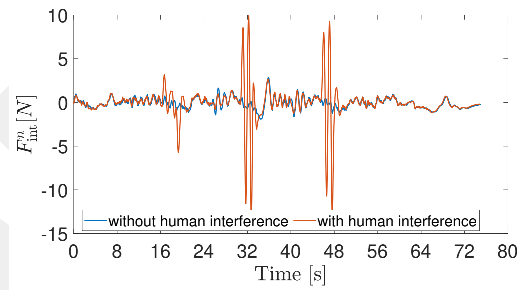


Fig. 10: The interaction force in the direction normal to the surface of whiteboard during autonomous robotic cleaning without (blue) and with (red) human intervention. The expert applied more force to the surface as the polisher passed through the densely marked area on the circle. The high magnitudes in the force profile (red-colored) mark the times of human intervention.

6 trials, where each trial was sequentially used as the test set while the remaining 5 trials served as the training set. The root mean square error (RMSE) for the whiteboard and chipboard were (1.79 ± 0.32 N) and (1.73 ± 0.28 N), respectively. Fig. 9 compares the predicted and measured human forces in the normal direction for one trial of the whiteboard and the chipboard. As shown in this plot, the expert performs 5 and 6 cycles for the whiteboard and chipboard, respectively. The magnitude of measured human force is not constant and varies within each cycle. Due to the circular trajectory, it fluctuates as the polisher is accelerated and decelerated by the expert. The robot, utilizing the trained model to estimate the human force and operating in autonomous mode (i.e. no human intervention) successfully cleaned the surface of the whiteboard and chipboard.

In the third use-case, we worked on a scenario where the user intervenes into the operation of robot while it cleans a circle on whiteboard autonomously. A part of the circle demanded increased application of normal forces for effective cleaning due to its heavy marking (Fig. 5a). We utilized the learned force profile of the whiteboard from the second use-case without making any modifications. As anticipated, the system was unable to completely erase the densely marked region on the circle in autonomous polishing mode (Fig. 5b). However, the user applied more force to the surface in the normal direction while the polisher passed through the densely marked region, resulting in a better cleaning as shown in Fig. 5c. This use-case highlights the limitations of using a constant force in automated robotic polishing, especially when the workpiece has areas needing varied levels of polishing attention.

Fig. 10 displays the variation in interaction force along the z-direction (F^n_{int}) during autonomous robotic polishing of the whiteboard without and with human intervention. In the former case, the interaction force fluctuates around zero, indicating that the human forces estimated by our model effectively counterbalance the reaction forces originating from the whiteboard. In the latter case, additional forces were applied by the expert in the normal direction to the surface for better cleaning of densely marked region on the circle.

V. CONCLUSIONS

In this study, we addressed the problem of automating small-batch manufacturing tasks, particularly robotic polishing, which involves continuous physical contact with a workpiece. We proposed an ML approach that integrates an interaction controller (admittance controller) and two force sensors, enabling the robot to learn human haptic skills from expert demonstrations and adjust its behavior in real-time based on environmental feedback. We defined two phases to implement this approach: an expert guides the robot through the polishing process in the first phase, allowing us to record force sensors data and extract information about the environment. This information, along with the Cartesian position and velocity of the polisher relative to the first contact point, is then used to train an MLP model, to learn the human force required for the robot to keep the polisher in contact with the surface and perform the polishing task autonomously in the second phase. To assess the effectiveness of our proposed pHRI system and ML approach in transferring expert haptic skills to a collaborative robot for polishing, we designed experiments to clean a circle drawn on a surface with a board marker in our laboratory, as a model of scratch removal through polishing in industrial settings. Our assessment of the pHRI system involved three use-case scenarios. First, we conducted a comparative analysis between an expert and a naive user to highlight the significance of haptic skills in the polishing process. Second, we collected data from the expert user polishing two different workpieces (whiteboard and chipboard). By analyzing the data captured by human and interaction force sensors, we were able to compute both the reaction force exerted by the environment and the coefficient of friction between the polishing tool and the workpieces, providing insights into the material properties and surface characteristics of the workpieces. We then trained our proposed MLP model to predict the human force required to perform the task for each workpiece based on those extracted characteristics. Our findings demonstrate successful learning of human force dynamics across various materials and surfaces. Finally, we designed a use-case scenario to demonstrate the real-time interaction capability of our pHRI system. In this scenario, the user intervened during autonomous robotic polishing to apply additional force to a specific region of the surface requiring further polishing, imitating the removal of a deeper scratch in that area. These use-cases illustrate the potential of our system in automating and improving the polishing process through human-robot collaboration. In future work, we plan to extend our system's capabilities to handle curved surfaces by implementing a 6-dof admittance controller. This enhancement will enable the robot to adapt its motion not only in the plane of the curved surface but also in the perpendicular direction to maintain the contact, allowing polishing on complex geometries.

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