Dynamic Movement Primitives and Force Feedback: Teleoperation in Precision Grinding Process

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Abstract

In this work, the Dynamic Movement Primitives (DMPs) concept for teleoperation on a robotic deburring machine is investigated. The correspondence problem occurs when human link and joint structures are different than target robot. Thus, transferring human movements to robot is generally problematic. Here, a teleoperation scheme is followed where human movements are directly converted to target robot while imposing capabilities of robot to the operator. A single degree of freedom haptic interface which relays the process forces to the human participant is built for controlling the deburring machine remotely. Human participant rotates the knob of the haptic device to keep the normal force constant. The knob motion is converted to the piezoelectric actuator via teleoperation. The DMPs of participants for different experiments are extracted and the ones with the lowest time span are collected in a single database which then used for simulation on different force values.

1. Introduction

In robotics, a scenario, such as a robotic arm playing table tennis, involves perception, path planning, and learning under uncertainties. At each game instant, the arm should position itself to current ball position and velocity in order to react. It also requires strategies to win against an opponent. One way to approach this problem is to use demonstrations such as recorded arm movements of table tennis players. Then, recorded movements of human players need to be casted into a form which is mathematically describable and generalizable. Dynamic Movement Primitives (DMPs) provides a conceivable method for parameterizing human movements and utilizing them on the robot [1].

In industry, there are tasks such as deburring that require skillful human workers. In deburring, a dexterous worker moves a deburring tool (can be motorized or passive like a knife) on the workpiece to remove unwanted burrs or protruding surfaces from a machined part. This is especially a weak spot in Automotive and Aerospace industry where machine parts can be costly and error margin for the workers is small. Programming a machining robot for contact operations, such as deburring, requires great effort. The CAD data of the part provides a general path to follow the edges where burrs usually occur. However, during the operation, this path needs to be altered based on the forces or other sensor information due to changing burr shape, types and hardness [2]. Also, the complicated shape of the burrs makes it difficult to scan and obtain a 3D shape of the edges of the part which would be helpful for both online and offline programming methods [3]. The interaction between the deburring tool and the workpiece is complicated to model in terms of involved system parameters (such as spindle speed, depth of cut, feed rate, material removal rate, etc.). On the other hand, a human operator roughly sees and touches the burrs and utilizes mainly his/her force sensation during the operation. The hand movements required for the deburring are generated based on his/her experience and dexterity.

In order to utilize human skills on the robot, the correspondence problem must be tackled. As described in [4], correspondence problem, if we consider the deburring case, mainly occurs if human hand and arm structure doesn't match with the links and the joints of the robot since we expect the robot to imitate the human movements. We address this issue by enforcing a direct coupling via teleoperation. The teleoperation is a general term vaguely describes the case where an operator remotely controls a robot to perform a task [5]. Instead of recording human movements on its own, for an operator performing a deburring task and converting this information to the robot's end-effector space [1]; this approach requires the operator to move the robot based on the sensory information and movement capabilities available for the robot. Thus it allows only the compatible movements.

In this study, a representative single degree of freedom deburring case with teleoperation is investigated where a setup is built which contains a force/torque sensor to measure normal forces coming from human participant actions and 1DOF haptic device to measure movements of the wrist of human participant. By using this setup, human participant can be able to change movements by considering the force displayed on setup screen during the experiments. Then, the DMP method is used to utilize force sensation and movement information. DMP helps to characterize each human participant with respect to his/her movement primitives for reaction forces.

2. Methodology

2.1. Dynamic Movement Primitives

DMPs are nonlinear differential equations describing an attractor space. Starting from an initial point in space, a DMP attractor generates a trajectory that allows reaching the desired goal point. This trajectory can be recovered from hu-

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man demonstrations. Also, DMPs allows changes in start and goal points which makes them flexible for different trajectories. A DMP parameters gathered from human demonstrations can be used to imitate human motion. Moreover, the start and goal points of the trajectory can be adapted to the task online. The general motivation and the mathematical description of the DMPs can be found in [1].

Since the deburring process in local movements is dependent to normal force F_n of the surface of the workpiece, DMPs of the process has to be as a function of F_n. DMP model as a function of F_n is no longer a trajectory model of position, but the trajectory of the force and its derivatives. The point attractor of the system is the desired force which we want to keep constant in order to have desired surface quality.

Therefore, transformation trajectory system of the normal force can be presented as,

$$\tau_F \dot{z}_F = \alpha_F(\beta_F(F_n^{set} - F_n) - z_F) + f_F(x) + P \quad (1)$$

$$\tau_F \dot{F}_n = z_F \quad (2)$$

Here, P is the movement of the piezoelectric actuator. This movement can be obtained from piezo movements or the radial movements of knob during an experiment. F_n^{set} is defined as the intended constant normal force that we need, to have same profile with desired depth of cut.

DMP in this section is changed to force trajectory instead of motion trajectory. This is because of the importance of desired force and the force exerted by the tool tip on the surface of the workpiece. This DMP is not the damper-spring system anymore, however, it is still useful for imitation learning.

For formulating a function approximation problem, we rearrange equations (1) and (2) as

$$\tau_F \ddot{F}_n = \alpha_F(\beta_F(F_n^{set} - F_n) - \dot{F}_n + P + f_F(x) \quad (3)$$

and the learn-able nonlinear term can be obtained from below equation,

$$f_F(x) = \frac{\sum_{i=1}^{k} \omega_i \psi_i(x)}{\sum_{i=1}^{k} \psi_i(x)} x(F_n^{set} - F_n(0)) \quad (4)$$

By using above equations and methods, DMPs can be extracted from the experiments.

2.2. Force Feedback

In machining processes, the exerted force components on workpieces in deburring/grinding have significant influence on surface quality. While performing a deburring/grinding process, the direction which is tangent to the surface of the workpiece is the tangential direction and the force exerted in this direction is tangential force, F_t. Also, the direction which is normal to the tangential direction is normal direction, and the force in this direction is normal force, F_n. Therefore, the forces that are exerted to the tool from surface of workpiece are combination of tangential and normal forces as shown in Fig. 1.

In Fig. 2. red circles represent the cutting tool. Tangential force is shown by F_{t_i} and the normal force is shown by F_{n_i}.

In order to obtain constant depth of cut from variable surface, the key strategy that should be implemented is imposing appropriate normal force and tangential velocity. That is, classical explicit hybrid force/velocity control should be implemented [6]. In order to obtain the actual local normal force from

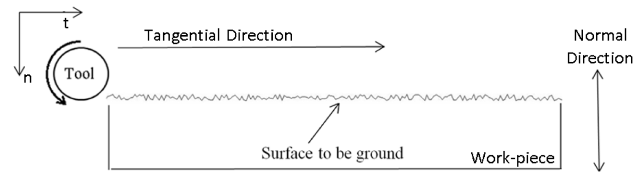

Figure 1. Example of the deburring/grinding operation on a flat surface

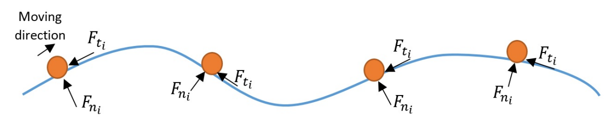

Figure 2. Example of the deburring/grinding operation on a wavy surface

measured X and Y force components, the algorithm which is explained in [7] is implemented.

The local tangential force is as follows:

$$F_t = \frac{M_{zSpindle}}{r_{tool}} \quad (5)$$

Where, $M_{zSpindle}$ the measured moment around the Z axis of the spindle and r_{tool} is the radius of the cutting tool. However, with the used setup, measured moment around Z axis of the force/torque sensor, M_z, is not the moment around the axis of the spindle since the force/torque sensor has an eccentricity with respect to the spindle. Therefore, local tangential force is calculated as follows:

$$F_t = \frac{M_{zSpindle}}{r_{tool}} = \frac{M_z - F_x\Delta_y - F_y\Delta_x}{r_{tool}} \quad (6)$$

where, F_x is the measured force in X direction, F_y is the measured force in Y direction, Δ_y is the eccentricity of the force/torque sensor with respect to spindle axis in Y direction, and Δ_x is the eccentricity of the force/torque sensor with respect to spindle axis in X direction.

After the calculation of F_t, the local normal force F_n is calculated by the following equality:

$$\sqrt{{F_x}^2 + {F_y}^2} = \sqrt{{F_n}^2 + {F_t}^2} \quad (7)$$

Therefore,

$$F_n = \sqrt{{F_x}^2 + {F_y}^2 - {F_t}^2} \quad (8)$$

Constant velocity control is performed by the controller of the hexapod robot. However, when the piezoelectric actuator is in action, the resultant feedrate increases since the feedrate is defined as:

$$F_R = \sqrt{{V_{Hex}}^2 + V_{Pzo}^2} \quad (9)$$

where, V_{Hex} is the velocity of the Hexapod, V_{Pzo} is the velocity of the piezoelectric actuator.

However, since the amplitude of the sinusoidal profile of the used workpiece is very low compared to the length of the workpiece, the effect of the V_{Pzo} is neglected. In order to control the normal force, the movement of the piezo actuator is utilized.

3. Experiments and Experimental Setup

3.1. Experimental Setup

The idea of utilizing DMPs in metal cutting and finishing operations is a new concept and humbly we provide the first steps towards this novelty. There are other similar works related to more general tasks such as peg-in-hole placement, grasp-and-replacement etc., that utilize also, teleoperation with DMPs [8]. However, such an approach is not tested on high precision processes such as deburring. Thus, in this study, we developed a teleoperation system utilizing a 1DOF haptic device for deburring operations to prove conceptual viability of this approach.

The haptic device consists of a motor attached to a knob via a timing belt. When the operator rotates the knob, rotation angle is resolved from the encoder embedded within the motor. Also, a torque sensor is mounted between the knob and the setup that allows measurement of the torque applied by the operator. This device is connected to the computer using a Data Acquisition Card (DAQ). A MATLAB/Simulink^{TM} model is developed for receiving and transmitting information between the deburring/grinding robot explained in [9] and the 1DOF haptic device. The workpiece is attached to the piezoelectric actuator within the deburring robot. When the operator rotates the knob, piezoelectric actuator moves back and forth accordingly, thus the workpiece moves. This is the teleoperation part of the setup.

Since the piezoelectric actuator is very fast and withstand fair amount of load, we are free to rotate the knob in a natural way comfortable to human operator physiology (i.e., it doesn't restrict the velocity or acceleration of human hand during the operation). However, we also utilize force feedback mechanism. In the deburring robot, we measure the forces and torques. The cutting forces are fed back to the operator via the motor of the haptic device. This way, the operator is aware of the cutting forces, thus provides better cutting action. On the Simulink^{TM} model, a display shows the instantaneous cutting force. The operator both looks at the cutting force shown in the monitor and feels the force from the haptic device simultaneously.

Knob is at zero angle (relative) when starting an experiment. A 60° counterclockwise rotation of knob corresponds to 1 mm (The limit of elongation of the piezoelectric actuator) movement of piezoelectric actuator towards the tool. At zero angle, a clockwise rotation does not result in movement of piezoelectric actuator since the actuator is at its minimum elongation, Fig 3.

During the operation, for the purpose of post-processing and DMP model extraction, we recorded the knob movements, piezoelectric actuator movements, time in nanosecond, and the force data in a dataset.

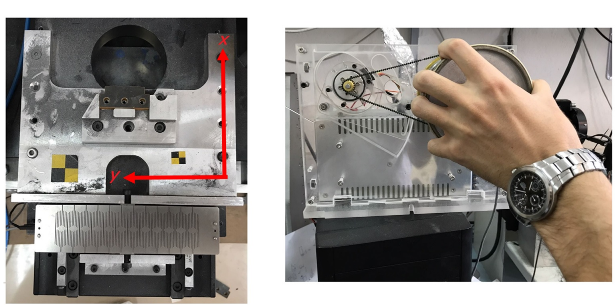

Figure 3. Relative clockwise or counterclockwise 1DOF haptic motion with respect to piezoelectric actuator. Left: Workpiece and piezoelectric actuator top-view, Right: 1DOF haptic device.

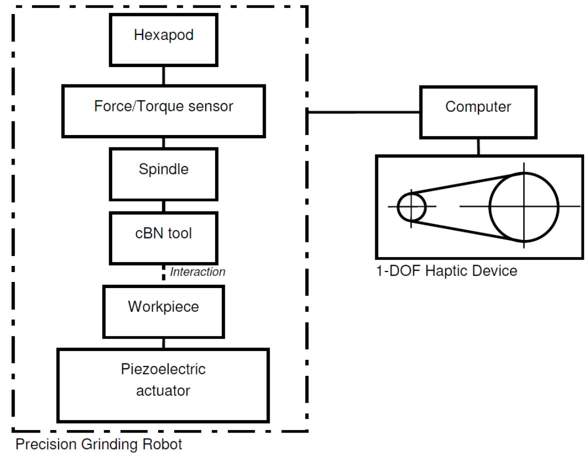

Figure 4. The connectivity diagram of the overall system

3.2. Experimental Procedure

In this study the following main devices are utilized:

1. An experimental precision grinding robot (utilizing a 6DOF Hexapod from PI company) with 6DOF force/torque sensor, (Fig. 5)
2. A 1DOF haptic system with force feedback,
3. A piezoelectric actuator with 1-mm stroke for moving the workpiece,
4. Workpiece (St37) with known geometry,
5. A high speed spindle.
6. A 4-mm diameter cBN tool from Pferd company

In Fig. 4, the connection of the devices is summarized. In order to combine all these devices, a prototypical MATLAB/Simulink^{TM} model is developed (with Windows target machine, at 1000 Hz sampling frequency for all measurements and control action in pseudo-real-time).

As it is mentioned before; during the experiments, human operator rotates the knob of the haptic device. This rotation is translated into motion of piezoelectric actuator. Since piezoelectric actuator is connected to the workpiece, human knob rotation actually moves the workpiece back and forth. Simultaneously, the hexapod moves the spindle from left to rigth in a constant speed. By default, the tool doesn't touch the workpiece. The cutting action is only possible if the operator moves the workpiece towards the tool. Due to the sinusoidal geometry of the workpiece, the operator has to follow the geometry (otherwise the forces will become too small or too large for cutting) while tracking the cutting forces from the monitor and feeling them from the force feedback of haptic device.

The hexapod only moves in Y-axis and carries force/torque sensor, spindle and the cBN tool. Since hexapod can only move with 1 mm/s speed, it is not suitable to track the human hand motion. However, piezoelectric actuator is fast enough, so that it can follow even the fastest hand movements.

Forces coming from the cutting operation are translated to the voltages for the motor in the 1DOF haptic system. If the

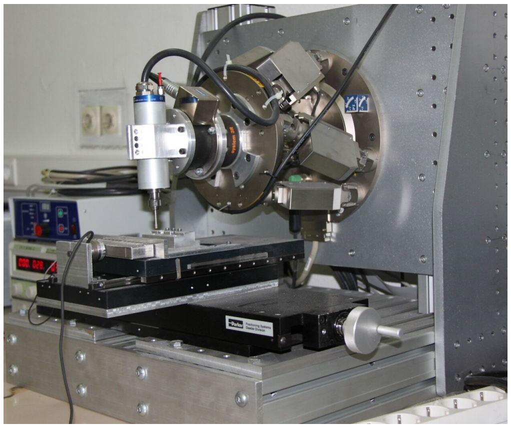

Figure 5. Deburring robot setup.

operator moves the workpiece towards the tool and a force is occurred, this force is converted to the knob motion for operator to feel. Note that, this force is not the actual force resulting from the operation, but proportional (increased) to it. Moreover, if forces are too high, operator either cannot move the knob or moves it in the reverse direction to reduce it.

4. Model Verification

It is asked to each participant to hold the knob of the 1DOF haptic device and try to move it clockwise or counterclockwise in order to keep the normal force at a safe range. Safe range is the normal force limitation that implies acceptable depth of cut. In this study, it is asked from participants to keep the normal force at $10N$.

Each participant perceives the target $10N$ goal not as an exact target but (unconsciously) as a range (safe range). Since it is very difficult for the participants to keep the normal force exactly at $10N$. We assumed this range to be from $9.9N$ to $10.5N$ by observation. Participants unconsciously try to be inside this range during the experiments. If participants see or feel a force outside of this range, they rotate the knob to increase or decrease the forces accordingly to be in the range.

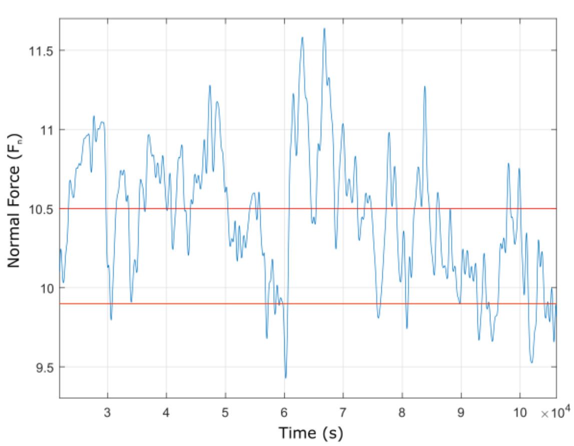

Figure 6. Force response of knob motions of one of the participants while trying to keep normal force at $10N$

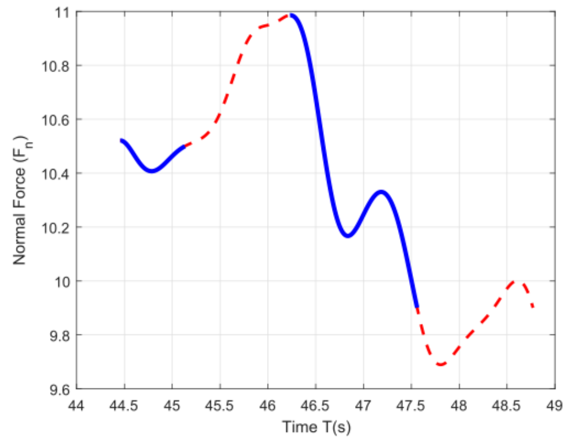

Figure 7. Example of the segmentation for the 1st participant in a random normal force of experiment

We observe from the data that, if the participant is outside of the safe range, he/she returns to safe range by a continuous complete motion. We performed a segmentation on the recorded data based on the determination of these continuous complete motions (a complete experiment force response is shown in Fig. 6). These segmented portions of the data represent the DMP force trajectories. Each participant has his/her own set of reactions, i.e. DMPs, as the set of these segmented portions. An example of one of these segmentation results is shown in Fig. 7.

Fig. 8 shows a set of DMPs for one of the participants. As the reader can observe, each DMP starts from a different force value, but goes inside the safe range.

Each participant has specific reactions in the experiments, that the characteristics to him/her. By using the segmentation of the reaction of 1 participant in 3 experiments, we can use transformation trajectory system of DMP to compare different reactions and choose the best one. In addition, we can learn the best reaction of each participant for different normal forces. The best reaction is the reaction which has minimum time span to reach the desired normal force (Fig. 9).

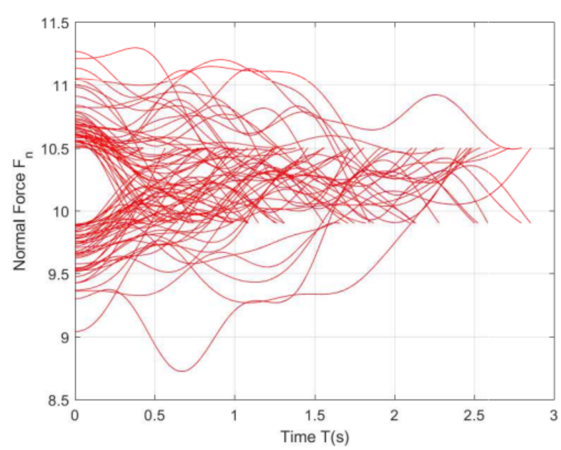

Figure 8. All normal force reactions of 1st participant

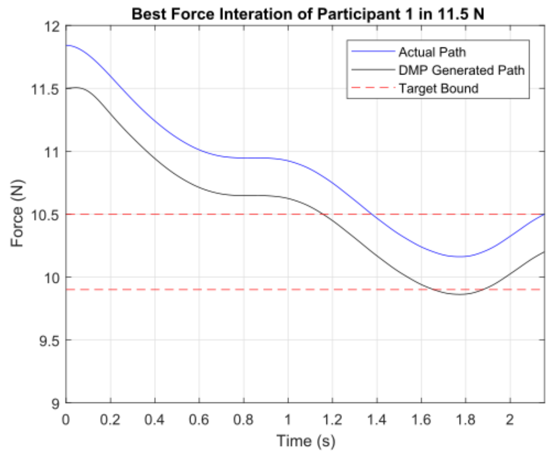

Figure 9. Best reaction of one of the participants for 11.5 N force disturbance

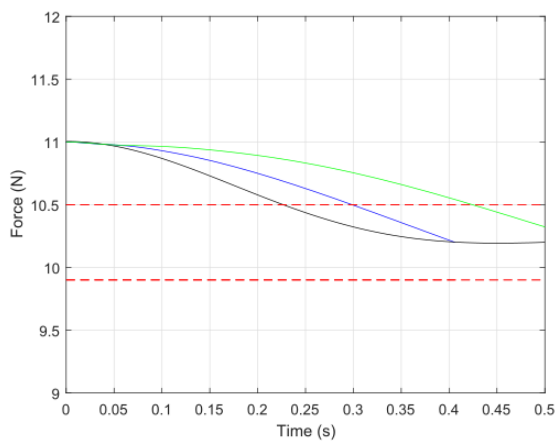

Figure 10. The best responses of three participants from all experiments, for a specified force in the simulation

We can obtain the best responses and respective DMP parameters of the participants automatically, considering their time span. A database based on best DMP responses of experts can serve as a building block for a human active controller. This controller can work as an outer loop (a supervisory controller) for a Proportional Integral Derivative (PID) controller and may make it robust for sudden high and low force cases. In other words, such a controller would be important for automated deburring robots since, it creates human-like reactions for sudden changes that a PID controller cannot handle. Our findings can be used to build such a controller. However, the purposes of this study are the extraction of the primitives, creating a database and simulation of human responses.

5. Conclusion

We successfully extracted force trajectories of human participants in DMP form. Our approach allows automatic segmentation of force data to obtain individual DMPs used by participants. These DMPs are collected in a database. Also, a simulation environment utilizing the DMPs is built. In simulations, a force specified outside the safe range is moved inside the range using a suitable DMP pattern drawn from the DMP database. This corresponds to a reaction of one of the participants around that specific force. Note that, the chosen pattern is the best DMP among all of the participants. Mainly, each participant has potential to react to a random force better than others. Since, a participant sometimes react better than others for a specific force; even though, his/her overall performance may be poor compared to others.

Using a teleoperation scheme for the experiments, we eliminated the correspondence problem. Participants were able to follow the sinusoidal initial form of the workpiece during the experiments. This is only possible by the normal force calculation method we presented. We will use our DMP controller as supervisory control scheme steering a PID controller to perform deburring in the future.

6. References

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