Towards a geometric identification of compliant motions in learning from demonstration

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I. INTRODUCTION AND RELATED WORK

We propose a method to learn compliant motions from demonstration to reduce the need for positional accuracy in an assembly task. An example of compliant motion in workpiece alignment is depicted in Fig. 1. Impedance control is a natural control method to realize compliant motions, but the drawback is that it makes motion planning difficult. Preimage planning [1] can be used for planning compliant motions in two dimensions. However, in 3-D preimage planning has been shown to be computationally infeasible [2].

In contrast to automatic planning, learning from demonstration (LfD) [3] can be used to transfer skills from a human expert to a robotic system. Most LfD research has focused on position control and only recently LfD has been extended to in-contact tasks and force control [4]. However, the existing methods are unable to learn compliant motions for aligning workpieces.

We propose a method for learning compliant assembly motions from demonstrations. The intuition of our method stems from geometry: there is always a certain range of angles from which a human can push an object to make it slide along a surface. Most LfD methods try to reproduce any kinds of motions, and use tools such as dynamic movement primitives [5] or hidden semi-Markov models [6]. However, they are not well equipped to handle motions where interaction forces can appear from a variety of directions, such as inserting a tool into a funnel.

We use kinesthetic teaching to collect both position and force data from demonstrations. From one or more recordings we learn a direction which will lead the end-effector through the motion, either directly in free-space or in contact. In addition, we learn the necessary compliant axes for performing the demonstrated task.

Our earlier work [7] considered a similar problem under the assumption that the forces exerted by human during demonstration can be directly measured, as is the case for example in teleoperation. In contrast, this work provides a solution to a more general problem where only the interaction forces can be measured.

Kronander and Billard [8] proposed learning compliance parameters from human demonstration by halting a trajectory demonstration at intervals and wiggling or tightening the grip on the robot to demonstrate the correct compliance. However, this is not a suitable method for in-contact tasks.

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Automatic learning of the stiffness matrix has been proposed by Carrera et al. [9] and Rozo et al. [10]. However, Carrera et al. used DMPs for the learning, which are unsuitable for our use case. Rozo et al. learned the stiffness matrix from positional deviation using least squares estimation in a cooperative assembly scenario. The main difference between our method and Rozo et al. is that we require the interaction forces to complete the task, whereas in their work the forces were an unnecessary consequence of the collaborative partner’s actions.

More detailed description of the method presented in this paper can be found in [11].

II. METHOD

When sliding the end-effector along a surface with a constant velocity, the force measured by the force/torque sensor ($F_m$ in Fig. 2) is the combination of normal force of the surface $F_N$ and Coulomb friction working against the motion. Assuming the human demonstrator exerts a constant force, a particular motion direction $v_a$ can result from any of a set of force directions $v_d$, which we call the desired directions (see Fig. 2). The set of desired directions, $v_d$, include all directions between $-F_m$ and $v_a$, because a force applied along any of those would cause sliding in the direction $v_a$.

A. Learning desired direction

We define the desired position of a motion as a point or a set of points where the demonstrator wants the end-effector to move to. The desired direction of motion $\hat{v}_d$, chosen from the set of possible desired directions $\hat{v}_d$, is a direction vector in 3-D Cartesian space. Because a human cannot demonstrate a desired trajectory perfectly, we also add error in the direction perpendicular to the desired direction, illustrated in Fig. 3a.

Now for each measured data point along the demonstrated trajectory, we can construct a polyhedron consisting of four vectors originating from the measured point. We add the error vector and it’s opposite vector to both $\hat{v}_d$ and $\hat{F}$. Thus we have a polyhedron in 3-D space which constrains the motion, illustrated in Fig. 3b.

To find the set of feasible desired directions for the whole motion, we must satisfy all the constraints through the trajectory represented by a set of polyhedra. To simplify the
Fig. 2: Force/torque sensor configuration, the position where external force by the human teacher $F_{ext}$ is applied and the forces which sum up to the reading of the force/torque sensor.

![Force/torque sensor diagram](image)

Fig. 3: Possible desired directions $v_d$ on a single time step.

(a) Human variation in 2-D (b) $v_d$ in 3-D

computation, we transform the direction vectors to a 2-D angular space. Thus we project the 3-dimensional polyhedra into 2-dimensional polygons. With suitable outlier detection, we then calculate the intersection of these polygons, which is a set of all feasible desired directions $\hat{v}_d$. To choose a single direction, we calculate the Chebyshev center of the polygon and transform it back to 3-D Cartesian space to get $\hat{v}_d$.

If we have multiple demonstrations, the method works exactly the same way. The polygons are concatenated and an intersection is calculated. If there are multiple viable approach directions, a sufficient number of them should be demonstrated such that all viable approach directions are a positive linear combination of the average directions of each individual demonstrated motion. For example, in the case of the funnel, the demonstrations should come from parallel directions for the method to learn to slide along any side, and in the valley setup in Fig. 5a demonstrations must be performed along both sides. No more than one demonstration from each such direction is required if the demonstration is well performed.

**B. Learning axes of compliance**

To successfully complete a motion, the compliant axes need to be identified. If the motion occurs only in free space, no compliance is required. In-contact tasks require at least one compliant axis. Certain tasks, such as inserting a tool to a funnel, require a second compliant axis to take full advantage of the funnel’s geometry and allow sliding along any side of the funnel. We assume that if compliance is required, the axis should be totally compliant.

The compliant axes must be perpendicular to the desired direction $\hat{v}_d$ due to our definition of no stiffness along a compliant axis—the end-effector would not move in that direction even if commanded. The key idea is that if there is movement along other directions besides the desired direction, this movement must be generated by interaction forces. When the environment interaction is causing forces on the end-effector, compliance is needed to reproduce the demonstrated motions.

To exploit this idea, we first calculate the mean direction of actual motion $\bar{v}_a$ separately for each demonstration used in calculation of corresponding $\hat{v}_d$. Then we rotate all $\bar{v}_a$ such that in the new coordinate system $\hat{v}_d$ is along the z-axis, after which we transform the values to 2-D angular space. As a result, the corresponding values in the angular coordinate system, $\phi_a$, will be within a unit circle, where origin represents $\hat{v}_d$ and the values on the unit circle are directions perpendicular to $\hat{v}_d$. As we assume compliance is required in the direction where we observe motion without human initiative, we can see that the direction of compliance should be towards $\phi_a$ and lie on the unit circle to fulfill the orthogonality requirement. This is illustrated in Fig. 4.
To choose the correct number of compliant axes, we need to measure how well each model (number of compliant axes) explains the observations, but also discourage the choice of an overly complicated model. We use a modification of Bayesian Information Criterion (BIC) [12]. Assuming the error a human makes while demonstrating a task is normally distributed with variance $\sigma$, we calculate the likelihoods for each model from a 2-D normal distribution. Then we use the likelihoods for calculation of the information criterion to choose the model. The likelihoods are calculated from Fig. 4, where the blue line represents a single compliant axis and origin represents 0 compliant axes. For two compliant axes, we assume a linear combination of two straights, which perfectly explains any data.

If the model with a single compliant axis is chosen, we choose the direction of compliance as the intersection between the blue line and the unit circle, marked with red x in Fig 4. If no compliance is needed, a position controller is sufficient. If two compliant axes are needed, any pair of vectors which form an orthonormal base with $\hat{v}^*$ are adequate as the compliant axes. Reproduction of the task is performed similarly as in [7].

III. EXPERIMENTS AND RESULTS

We used KUKA LWR4+ lightweight arm to verify our method on two different setups presented in Fig. 5. To validate that we can learn the desired direction from both curved and straight surfaces and multiple directions, we performed a number of experiments on the physical setups presented in Fig. 5. Unfortunately, no alternative methods exist in the literature that could be used for comparison, the closest alternative being our earlier work [7] which assumes direct measurement of demonstrator forces.

Figure 6a shows in 2-D angular space two trajectory demonstrations performed by sliding along different sides of the valley. The difference in the orientation of the polygons is due to the normal forces being in opposite directions, therefore constraining the final intersection. Figure 6b shows two perpendicular funnel demonstrations. Now we can see that the polygons are almost perpendicular as were the demonstrations.

![Diagram of robot and valley](image1.png)
(a) Robot and valley

![Diagram of funnels](image2.png)
(b) Funnels

Fig. 5: Our test equipment, the KUKA LWR4+ lightweight arm, the valley setup, and the two funnels, curved and straight.

![Diagram of setup](image3.png)
(a) Valley setup
(b) Funnel setup

Fig. 6: 2-D angular coordinate system polygons of two demonstrations: (a) down different sides of the valley and (b) perpendicularly into the funnel. The red and blue rectangles represent the $\Theta$ of separate demonstrations, and the black polygon is the set of desired directions in angular coordinate system, $\Phi$.

![Box plot](image4.png)

Fig. 7: Box plot of the error angle with different number of demonstrations used to calculate $\hat{v}^*_d$. The edges of the blue boxes are the 25th and 75th percentiles of the data.

The intersection, i.e. the set of $\hat{v}_d$ in the current space, is highlighted in black.

To verify our assumption that one demonstration from each approach direction is enough to calculate $\hat{v}^*_d$, we performed 32 demonstrations of the funnel motion, such that all the demonstrations were either perpendicular or opposite to each other. We divided the demonstrations into groups of 2, 4, 8 and 16 demonstrations, calculated the $\hat{v}^*_d$ and its error. Box plot of the results is in Fig. 7. We can see that the error was significantly below our assumption of maximum human error (20 degrees) already on 2 demonstrations and did not decrease when more demonstrations were added. Therefore we conclude that one demonstration along each viable approach direction, as described in section II-A, is enough to learn a valid $\hat{v}^*_d$.

To verify our method for finding the degrees of freedom, we performed 30 demonstrations of the following tasks: free space motion with a straight downward trajectory, sliding down the valley and sliding into the funnel, which require, 0, 1 and 2 degrees of freedom, respectively. Our version of the BIC calculation successfully chose the correct number of compliant axes for each task. Finally, we taught the parameters
of the motion with the left funnel in Fig. 5b. We successfully
reproduced the motion with both funnels from anywhere above
the projection of the funnel, even when the funnel on right
hand side in the figure was tilted 15 degrees.

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