Learning compliant assembly motions from demonstration

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Abstract— Automating assembly processes outside controlled factory environments is still rare, mostly because of the inherent position uncertainties. The use of compliant motions allows robustness against the uncertainty, but automatic planning of compliant motion sequences is not computationally feasible. In this paper, we show how compliant assembly motions can be learned from human demonstrations. A human teacher will kinesthetically demonstrate compliant motions where the physical shapes of assembled parts guide the motion. From these demonstrations, the proposed method identifies desired direction of movement, the number of compliant axes and their directions. We use this information to construct an impedance controller which can reproduce the assembly motion despite uncertainty in the starting position. The method is studied with a KUKA LWR4+ arm in two test setups with different number of physically constrained degrees of freedom. The experimental study shows that the method is able to correctly identify the motion parameters and allows the robot to successfully perform the demonstrated assembly motion from various unseen starting positions.

I. INTRODUCTION

Although industrial robots have been used for assembly tasks since the 1950s, most of the robots currently used for assembly are using position control only. Consequently, they require a precise, controlled environment, thus limiting their use outside factories. For example, tasks such as pipeline assembly require moving manipulator platforms with associated positional uncertainties, as illustrated in Fig. 1. Compliant motions can be used to increase the robustness of assembly especially towards positional uncertainty [1]. With compliant motions, the physical shape of assembled parts can directly guide the motion towards the intended target (see Fig. 1), thus performing manipulation with the environment rather than considering the environment as an obstacle or a detrimental constraint.

One of the most popular methods for performing compliant motions is impedance control, in which the controller imitates a spring placed between the end-effector and the environment. However, manually constructing the trajectory for an impedance-controlled assembly task is complex and error prone. There has been recently a growing interest towards motion planning under uncertainty [2]. For planning compliant motions, the automatic synthesis of compliant motion strategies using preimage planning was proposed for 2-D already in the 1980’s [3], but the approach is not computationally feasible in 3-D [4], thus highlighting the need for new methods.

Programming by demonstration (PbD) allows the teaching of robots when a human can show an example. This is achieved by creating a generalizable model from one or more demonstrations for the particular task. Mainly used for teaching human skills to robots, PbD can also be useful in assembly tasks. Traditionally PbD has focused on position control, but recently there has been significant effort devoted to force [5] and impedance control [6].

In this paper, we propose a method that allows learning compliant assembly motions from human demonstrations. We assume that each phase of an assembly operation can be specified with a target motion direction along with one or more compliant axes. We focus on the in-contact part of an assembly task in which the motion can be performed by sliding the assembled parts in-contact with each other, as shown in Fig. 1.

We use kinesthetic teaching and measure positions and forces simultaneously using an actively compliant arm with a wrist force/torque sensor, similar to [7]. Each demonstration is used to identify the target motion direction, and up to one compliant axis. By combining multiple demonstrations, we identify the number of compliant axes and their directions, along with the target motion direction. An impedance controller performs the motions with stiffness properties set according to the desired compliance.

The approach is studied experimentally to determine the accuracy of the identified parameters. Two experimental scenarios with different number of intrinsically constrained degrees of freedom are considered. Moreover, the robustness of the identification of number of compliant axes is studied. Finally, experiments are used to demonstrate that a desired motion can be performed successfully with the impedance controlled robot from varying starting positions.

Fig. 1: Illustration of a use case for the proposed method: an assembly task performed on mobile platforms.

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Section II reviews related work in use of compliant motions and learning of robot stiffness from demonstration. In Section III we explain the model used for learning the direction of movement and compliant axes and how they are converted into a stiffness matrix of an impedance controller. Next, experiments with a KUKA LWR4+ robot arm and their results are presented in Section IV. Finally, the results are discussed and future work is outlined in Section V.

II. RELATED WORK

The idea of using compliant motions in assembly is not new [8]. However, few current industrial robots can perform compliant motions, despite their well-known advantages [9]. Compliant motions have been achieved using two main approaches: active and passive compliance. Recently, Variable Stiffness Actuators (VSAs) have received much attention as passive compliance [10]. However, since VSAs can be too imprecise when compliance is high, we consider active compliance via impedance control to be a better alternative. Much research has focused on developing impedance controllers, e.g. [9]. Our method is designed to work with any impedance-like controller.

One of the classic approaches to plan a task consisting of compliant motions is preimage planning [11], which considers the task as a combination of motion command subtasks. However, preimage planning has been shown to be computationally infeasible in 3-D [4], leading to the need for a computationally simpler approach.

Tedrake et al. [12] developed a method based on successive Linear Quadratic Regulators, with piecewise linearization creating figurative funnels for the trajectory, as originally devised by Mason [13]. Therefore, for an assembly task, having an actual funnel as a guidance in the spirit of manipulation with the environment is appealing and demonstrated in this paper.

For learning stiffness from human demonstrations, Kro- nander and Billard [14] proposed a method which halts the demonstration at regular intervals and sets the robot to gravity compensation. Thereafter, the teacher moves the robot in the directions of the desired compliance. Subsequently, they built an interface allowing the teacher to also increase compliance [15]. In contrast to their work, in this paper the directions of compliance are learned automatically from the demonstration of a motion.

Automatic learning of the full stiffness matrix from demonstrations has been accomplished by using the variance in the demonstrated trajectories as an implicator of the degree of precision required, related to the stiffness needed [16]. That approach is primarily applicable to non-contact motions. A similar approach has been further studied by Rozo et al. [17], who used a weighted least squares estimation to estimate the stiffness matrix in a co-operative manipulation scenario. The scenario considered in this paper differs from Rozo et al. significantly in that our approach intentionally causes interaction forces with the environment to cause sliding motions that align parts while in their case the interaction forces are due to the active collaboration partner.

III. METHOD

This section is structured as follows. We begin with the analysis of demonstrations, first explaining how the target motion direction and a compliant axis can be identified from a single demonstration. We continue by showing how multiple demonstrations are combined. Finally, we explain how the stiffness matrix and the target motion direction vector are constructed and the reproduction is performed.

A. Teaching

The learning process requires a robot arm that has a gravity compensation mode. A force-torque sensor is necessary to measure the force applied by the teacher during demonstrations. In the teaching process, the teacher performs the required task several times using in-contact trajectories with the desired compliance. In the following, we assume that the task has been segmented into in-contact and non-contact phases using the force measurements and the analysis is performed solely on the in-contact measurements.

We assume that there is a single target motion direction for a phase. The motion is fully described by direction, compliance and the starting pose. In this work the direction and compliance are defined in the world coordinate system for convenience, but they can be defined with respect to the starting pose if necessitated by the application.

1) Processing single demonstrations: For each demonstration, the measured forces $\mathbf{f}$ and positions $\mathbf{x}$ of the contact phase are transformed into the world coordinate system. The position data is used to estimate the velocity $\mathbf{v}$ of the robot at each time step by backward difference, i.e. $\mathbf{v}(i) = \frac{\mathbf{x}(i) - \mathbf{x}(i-1)}{\tau}$, where $\tau$ is the duration of a time step. The means of both speeds and forces within the contact phase are then calculated and labelled $\bar{\mathbf{v}}$ and $\bar{\mathbf{f}}$, respectively.

The key idea is that the direction of the force indicates the direction towards which the teacher wants the robot’s end-effector to move, even if the contact force may prevent that motion. To determine that, the force vector is first normalized to unit length

$$\hat{\mathbf{f}} = \frac{\bar{\mathbf{f}}}{|\bar{\mathbf{f}}|}. \quad (1)$$

Then the component (projection) of the velocity along $\mathbf{f}$ is calculated

$$\mathbf{v}_f = (\bar{\mathbf{v}} \cdot \hat{\mathbf{f}}) \hat{\mathbf{f}}. \quad (2)$$

$\mathbf{v}_f$ is then the identified target motion direction.

The compliant direction is then the direction perpendicular to the applied force, i.e. the velocity component in a direction where no force is applied,

$$\mathbf{v}_c = \bar{\mathbf{v}} - \mathbf{v}_f. \quad (3)$$
2) Combining demonstrations: With multiple demonstrations, the number of compliant axes in a current task and their directions can be learned. We do this by using Principal Component Analysis (PCA) [18] on the determined target motion and compliance directions.

The covariance matrices of the target motion and compliant direction vectors are first found from \( N \) demonstrations as follows:

\[
\begin{align*}
\mu_f &= \frac{1}{N} \sum_{i=1}^{N} \mathbf{v}_{f,i} \\
\mu_c &= \frac{1}{N} \sum_{i=1}^{N} \mathbf{v}_{c,i} \\
\Sigma_f &= \frac{1}{N-1} \sum_{i=1}^{N} (\mathbf{v}_{f,i} - \mu_f)(\mathbf{v}_{f,i} - \mu_f)^T \\
\Sigma_c &= \frac{1}{N-1} \sum_{i=1}^{N} (\mathbf{v}_{c,i} - \mu_f)(\mathbf{v}_{c,i} - \mu_f)^T
\end{align*}
\]

The PCA corresponds then to the eigenvalue decomposition of the covariance matrices

\[
\begin{align*}
\Sigma_f &= W_f \Lambda_f W_f^{-1} \\
\Sigma_c &= W_c \Lambda_c W_c^{-1}
\end{align*}
\]

where the columns of matrices \( W_f \) and \( W_c \) are the eigenvectors and the values on the diagonals of the diagonal matrices \( \Lambda_f \) and \( \Lambda_c \) the eigenvalues. Because the covariance matrix is symmetric, the eigenvectors form an orthogonal basis. Moreover, each eigenvector tends in the direction of maximal variance w.r.t. the original data with the orthogonality constraint.

The target motion direction \( \mathbf{d} \) is then the direction of maximum variance of \( \mathbf{v}_c \), that is,

\[
\mathbf{d} = \mathbf{e}_{f,1}
\]

where \( \mathbf{e}_{f,1} \) is the column of \( W_f \) corresponding to the largest eigenvalue.

As the eigenvectors \( W_c \) describe the directions where the end-effector moves without force being applied by the human teacher, they are the directions where compliance is required in order to complete the motion. The eigenvalues \( \Lambda_c \) describe the degree of compliant movement in the corresponding direction. Hence, if most of such unintended movement is towards a single direction, only one axis of compliance is required. This can be analyzed from the ratio

\[
\theta = \frac{\lambda_{c,1}}{\lambda_{c,2}}
\]

where \( \lambda_{c,1} \) and \( \lambda_{c,2} \) are the largest and second largest eigenvalues of \( \Lambda_c \). Experimental analysis in Sec. IV shows that the threshold value for \( \theta \) can be chosen robustly.

B. Reproduction

An impedance controller is used for the reproduction. It is a feedback controller defined as:

\[
\mathbf{F} = K(\mathbf{x}^* - \mathbf{x}) + D\mathbf{v} + f_{dyn}.
\]

where \( \mathbf{x}^* \) is the desired position, \( \mathbf{x} \) the current position, \( K \) the gain matrix, \( D\mathbf{v} \) a linear damping term and \( f_{dyn} \) the feed-forward dynamics of the robot. In our controller, the stiffness is set according to \( K = RV R^T \), where \( R \) is a rotation matrix which defines the directions of compliance learned. The set of eigenvectors \( W_c \) can be used directly as the \( R \) matrix if the coordinate system they span is right-handed; otherwise it must be converted into one. This can be done by calculating the determinant of \( W_c \).

\[
R = \begin{cases} 
W_c & \text{if } |W_c| = 1 \\
\begin{pmatrix} 1 & 0 & 0 \\
0 & 1 & 0 \\
0 & 0 & -1 \end{pmatrix} & \text{otherwise.}
\end{cases}
\]

The matrix \( V \) is a 3-by-3 diagonal matrix defining the stiffness values for each direction in \( W_c \). The values of \( V \) corresponding to compliant directions are set to 0 and the others to \( \frac{k}{N_m} \), where \( k \) is the stiffness of the non-compliant direction or directions. For one compliant axis,

\[
V_1 = \begin{pmatrix} 0 & 0 & 0 \\
0 & k & 0 \\
0 & 0 & k \end{pmatrix}
\]

for two compliant axes,

\[
V_2 = \begin{pmatrix} 0 & 0 & 0 \\
0 & 0 & 0 \\
0 & 0 & k \end{pmatrix}
\]

The choice of \( k \) depends on the task and the user’s preferences. Higher stiffness values allow more accurate control of position trajectory, whereas lower stiffness leads to increased safety.

The desired positions for each time step are calculated in a feed-forward manner from the learned direction vector and the desired velocity as

\[
\mathbf{x}_t = \mathbf{x}_{t-1} + d \mathbf{v}_{des} \Delta t
\]

where \( d \) is the unit vector of the desired direction, \( \mathbf{v}_{des} \) the desired speed and \( \Delta t \) the update cycle of the control loop. \( \mathbf{v}_{des} \) can either be specified manually or learned from the demonstrations by calculating the average of the demonstration velocities, i.e. \( \mathbf{v}_{des} = \frac{1}{N} \sum_i^n \mathbf{v}_i \). The choice of using feed-forward over feedback is to prevent possible drifting caused by external forces.

Finally, we analyze the robustness of the method. There are two main types of uncertainties which can cause the reproduction to fail: gross errors in the starting position in which the motion starts outside the region of convergence of the compliant motion, and estimation errors in the desired direction \( \mathbf{d} \). The error tolerance of the starting position depends on the setup. For example in the case of a funnel, the trajectory must lead to within the funnel. In general the robustness to starting position errors depends on the particular task.

The error tolerance of the desired direction depends on two things: the angle \( \alpha \) between the force and the contact...
surface and the static friction coefficient between the end-effector and the surface $\mu$. The dynamics of friction define that for an object to slide, $\mu$ and $\alpha$ must satisfy

$$\tan(\alpha) > \mu \quad (13)$$

Because of this, the choice of stiffness in the non-compliant direction does not affect the performance of the compliant motions. Again the key is the physical design of the task such that once the end-effector makes contact with the surface, it slides to the correct position.

IV. EXPERIMENTS AND RESULTS

A. General setup and experiments

The first research question is to determine from demonstrations the number of compliant axes and their directions required for the current assembly task. The second is to determine the desired direction of movement and therefore gain the ability to robustly reproduce the task with an impedance controller.

To address these questions, we implemented the methods on a 7DOF KUKA LWR4+ lightweight arm with an ATI mini 45 force/torque sensor attached between the robot’s flange and tool. Instead of gripping a tool as in Fig. 1, a regular pen was directly attached to the flange. The task was therefore a simple insertion task with a fixed tool. To implement our controller on the robot, we used the Fast Research Interface (FRI) [19] with control frequency of 100Hz. The objective was to verify the methods explained in Section III, i.e. to show that the robot can really learn and reproduce various compliant motion tasks with physical guidance.

The control law for the Cartesian impedance control of the KUKA LWR4+ through FRI is

$$\tau = J^T (\text{diag}(k_{FRI})) (x^* - x) + D(d_{FRI})v + F_{FRI} + f_{dyn} \quad (14)$$

where $\text{diag}(k_{FRI})$ is a diagonal matrix constructed of the gain values of $k_{FRI}$. We implemented our controller through the $F_{FRI}$ by setting $k_{FRI}$ to 0. Then by setting $F_{FRI} = K(x^* - x)$ we have a similar controller as in Equation 8 where $K$ and $f_{dyn}$ are managed by the KUKA’s internal controller. In these experiments we set the value $d_{FRI}$ to $0.7 \frac{N\cdot m}{m}$ and $k$ in Equation 10 to 500 $\frac{N\cdot m}{m}$ for safety reasons.

We experimented on three different setups. The first setup was a valley consisting of two aluminium plates set on 45 degrees angle on the table, as seen in Fig. 2. The second one was a funnel rigidly attached to the table on an upward position as seen in Fig. 3. The third setup was the funnel tilted 19 degrees sideways.

In both of the funnel setups, 30 demonstrations were performed sliding the end-effector to the bottom of the funnel using various trajectories along the side the funnel. On the valley setup, 30 demonstrations were performed sliding the end-effector to the bottom of the valley on a direct trajectory from varying starting positions on both sides of the valley. Another 30 demonstrations were performed sliding the end-effector on an indirect trajectory to the bottom of the valley, as illustrated in Fig. 4.

B. Desired motion direction

To validate the desired directions calculations, we wanted to evaluate two possible sources of error. Firstly, how consistent are the directions of force measurements from the teacher. Secondly, we wanted to verify our assumption that the measured forces point towards the desired direction. This was achieved by assuming that the ground truth for desired direction is straight down for the valley setup and the upward funnel.

The 30 demonstrations were divided into groups of 4 demonstrations, such that in the valley setup, there were 2 demonstrations from both sides of the valley in each group. The desired direction was calculated as explained in Section III. The results are in Table I.
Fig. 4: Two experiments on the valley setup. The black trajectory on the left side is an example of a direct trajectory (with noise caused by the human demonstrator) and the red trajectory on the right is an example of an indirect trajectory. In both experiments the trajectories were performed on both sides of the valley.

<table>
<thead>
<tr>
<th>Setup</th>
<th>Error mean [Deg]</th>
<th>Error std [Deg]</th>
</tr>
</thead>
<tbody>
<tr>
<td>Funnel upward</td>
<td>12.3</td>
<td>7.9</td>
</tr>
<tr>
<td>Valley, direct</td>
<td>4.6</td>
<td>1.3</td>
</tr>
<tr>
<td>Valley, indirect</td>
<td>6.6</td>
<td>1.5</td>
</tr>
</tbody>
</table>

TABLE I: Error (angle, deg.) of of a desired direction learned from sets of 4 demonstrations compared to the assumption that the desired direction is straight down, as it is in other setups besides the tilted funnel.

The error variance is small enough that human demonstrations can be considered consistent. However, error variances being smaller than error means implies that there is a systematic error present. Although it is not significantly large, the issue will be thoroughly examined. Nevertheless, the error mean is small enough to accept the assumption.

C. Compliant axes

To estimate the number of compliant axes, we inspected the eigenvalues of the PCA as described in Equation 7 from the 30 demonstrations on both the direct and indirect trajectories on the valley setup (Fig. 4). The idea is that with the direct trajectories we simulate the case where a certain point at the bottom of the valley must be reached. In contrast, with the indirect trajectories the target is to reach any point at the bottom of the valley.

The demonstrations were divided into groups of 4. We examined the ratios between the first and second PCA score. The results of those ratios can be seen from Fig. 5. The largest indirect value was 5.4 and the smallest direct value 11.4, thus there is a distinction between the demonstrations with direct and indirect trajectory. \( \theta \) value in Equation 7 is chosen to maximize the distance to both data sets and therefore \( \theta = 8.4 \). 

D. Reproduction

The robot performed the reproduction tasks as expected. With both the upward and tilted funnel, the compliant directions were correctly identified to form a plane perpendicular to the desired trajectory which pointed towards the bottom of the funnel in both cases. The robot moved the end-effector to the bottom of the funnel from any chosen starting position where the trajectory lead through the opening of the funnel. Examples of possible starting positions are depicted in Fig. 6. Screenshots from a video showing one completed reproduction are shown in Fig. 7.

On the valley setup with direct trajectories, the end-effector was stiff along other directions except the one leading towards the bottom. With the indirect trajectories, the compliant directions formed a plane such as in the funnel setup.

V. CONCLUSIONS AND FUTURE WORK

In this work, we developed a new method for learning the desired direction and compliant axes for an impedance controller used in an assembly task. Kinesthetic teaching is used for the learning. The key target was to increase the robustness of an assembly task to take place using mobile platforms.

Experiments from the valley setup (Fig. 4) show that the proposed method can identify the number of compliant axes in an assembly task, as depicted in Fig. 5. However, further experiments are needed to study the robustness of the choice over different tasks.

In theory two non-parallel demonstrations are sufficient to find two axes of compliance for a certain motion. In practice problems can arise if the demonstrations are too similar, especially when two compliant axes are needed, because the human demonstrations include unintentional motions. If, for example, in the funnel setup all demonstrations were performed from a single direction, the method would learn only a single compliant axis even though there are most likely two.

The number of demonstrations in a batch was chosen as four. However, the question whether this depends on the setup warrants further research. If the motion is physically very limited, a smaller number of demonstrations in a batch is likely to be sufficient.
environments where a human cannot perform the demonstration, from teleoperated demonstrations is an appealing direction. Another problem for future research. A state machine would be a natural solution, but the construction of such a state machine is treated accordingly. A state machine was almost flat near the bottom. However this demonstrates that the method can also be applied to varying shapes, since the error was still acceptable.

The proposed method is targeted to learning of a single phase of an assembly task. The transfer from one phase in an assembly to another has been studied, for example, by Stolt in [20]. The segmentation for the experiments in this paper was done manually, but the application of segmentation methods for programming by demonstration is an important research topic for the future. Also generalizing the method from translational to rotational motions and forces/torques is an intriguing research problem.

Another important research topic related to a complete assembly task is error detection and recovery. If a part is somehow misplaced, the misplacement must be detected and treated accordingly. A state machine would be a natural solution, but the construction of such a state machine is another problem for future research.

Besides kinesthetic teaching, a generalization to learning from teleoperated demonstrations is an appealing direction. This would enable the usage of larger robots even in environments where a human cannot perform the demonstration, for example underwater.

**REFERENCES**


