Haptic guidance to solve the peg-in-hole task based on learning from demonstration

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***Abstract*— Learning from Demonstration has been successfully used in robotics for trajectory generation. However, this methodology has not been used to solve generic tasks by haptic guidance in teleoperation yet. Therefore, the aim of this paper is to solve the peg-in-hole insertion task using Learning from Demonstration, guiding the operator during the execution of this task in haptic teleoperation.**

I. Introduction

In teleoperation, a human operator performs a task in a distant environment by remotely controlling a robot. To allow efficient operation, the operator needs to receive rich sensory information from the remote site. Despite many years of research on optimizing this feedback, teleoperation is still associated with high workload for the operator. Therefore, methods to provide additional (synthetic) support during task execution are being investigated. Haptic guidance was shown to be a promising method to reduce operator workload and improve performance in teleoperated tasks [1]. This paper explores the use of Learning from Demonstration (LfD) for this purpose. Currently, LfD has been widely used in robotics for generating temporally continuous trajectories based on the manipulator position [3] or contact force measurements [4]. This methodology consists of creating a probabilistic model of a task using Gaussian Mixture Model (GMM) and training it by multiple demonstrations [2]. The trained model is then used to reproduce the task using Gaussian Mixture Regression (GMR).

II. Peg in Hole Problem Statement

We will demonstrate the feasibility of the use of LfD for haptic guidance on a peg-in-hole insertion task. This task, despite being trivial while performed manually, proved to be relatively challenging while carried out by a robot.

To solve this task, when the peg is inserted on the hole, a lever effect arises that will be used to generate the haptic guidance forces. Therefore, when the peg is already in the entrance of the hole, but without a correct orientation (Fig. 2), if 'pushed' down with a force $\vec{F}_m$, a torque $\vec{\tau}$ and force $\vec{f}$ arise because the peg is locked in the hole and there is a lever effect. Thus, a rotation of the peg may be performed in order to align it with the hole.

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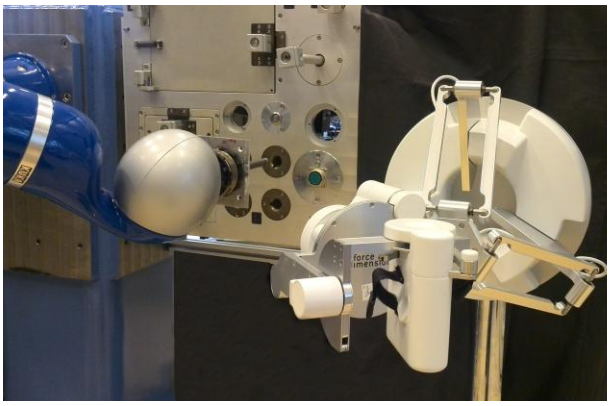

Fig. 1. Manipulator with haptic control device. The system was used to demonstrate the proposed method on a peg-in-hole insertion task.

On the other hand, ideal force references $\vec{h} = (h_x, h_y, h_z)$ are required to train a LfD model that uses interaction forces and/or torques to generate guidance force references. For this purpose, the error $\vec{e}$ between the position of the peg $\vec{s}_j$ every j instant and the final position $\vec{s}_K$, which means the peg has been inserted, has been used. So, the position error $\vec{e}$ has been used to provide an ideal guidance force reference using a spring constant K_H as shown in (1).

$$\vec{h} = K_H \cdot \vec{e}\ ;\ \vec{e} = (\vec{s}_K - \vec{s}_j) \qquad (1)$$

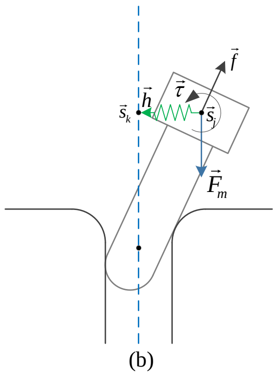

Fig. 2. Lever effect when the peg is already inserted in the hole.

Using a multiaxial Force/Torque sensor placed on the base of the peg, torques on the peg can be measured as $\vec{\tau} = (\tau_x, \tau_y, \tau_z)$. Finally, using this information, a tuple ξ has been defined to represent the relation between the interaction torques, and the ideal force references as:

$$\xi = [\xi^i\ ; \xi^o\ ] = [\tau_x, \tau_y; h_x, h_y] \qquad (2)$$

Once defined this tuple, a dataset $\hat{\xi} = \xi_1, \xi_2, \ldots, \xi_K$ taken every t sample time can be obtained while performing different insertions of the peg.

III. LEARNING FROM DEMONSTRATION APPROACH

To solve the stated problem, a model that learns from the performed insertion movements and generates guidance force references is required. Thus, GMM has been used to encode the relationship between interaction torques and ideal force references. Once encoded, GMR has been used to provide guidance force references.

To encode the previously described task, we can define a GMMs λ composed by N Gaussians distributions that are represented by $\lambda = \{\pi_n, \mu_n, \Sigma_n\}_{n=1}^{N}$ whose parameters are the prior probabilities $\pi_{q,n}$, the centers $\mu_{q,n}$ and the covariance matrices $\Sigma_{q,n}$. Using a tuple ξ, the probability that this tuple belongs to a GMM is:

$$\mathcal{P}(\xi) = \sum_{n=1}^{N} \mathcal{P}(n)\mathcal{P}(\xi|n) \tag{3}$$

where $\mathcal{P}(n)$ is the prior probability (4) and $\mathcal{P}(\xi|n)$ is a conditional probability density function whose parameters are defined in (5).

$$\mathcal{P}(n) = \pi_n \tag{4}$$

$$\mathcal{P}(\xi|n) = \mathcal{N}(\xi; \mu_n, \Sigma_n) \tag{5}$$

Using these equations, the log-likelihood of a λ GMM for a dataset $\hat{\xi}$ is obtained by:

$$\mathcal{L}(\hat{\xi}) = \sum_{j=1}^{K} \log\left(\mathcal{P}(\xi_j)\right) \tag{6}$$

where $\mathcal{P}(\xi_j)$ is obtained by (3). Therefore, the objective is to find a set of parameters for each GMM that maximize (6) for a training dataset $\hat{\xi}$ of K elements. To do this, the Expectation-Maximization (EM) algorithm has been used. This algorithm is an iterative method that estimates the GMM parameters to maximize the likelihood of a set of observed data belongs to this GMM.

Once trained the GMM λ, GMR is used to generate the haptic guidance forces $\overline{\xi^o} = (\overline{h_x}, \overline{h_y})$. For this purpose, the parameters of a GMM can be represented as:

$$\mu_n = \begin{bmatrix} \mu_n^i \\ \mu_n^o \end{bmatrix}, \Sigma_{i,n} = \begin{bmatrix} \Sigma_n^i & \Sigma_n^{io} \\ \Sigma_n^{oi} & \Sigma_n^o \end{bmatrix} \tag{7}$$

It is used to represent the GMR function as (8). In this equation, $\overline{\xi^o}$ is the estimated output reference and $h_n(\xi^i)$ is the probability of an observed input belonging to each of the Gaussians n as defined in (9).

$$\overline{\xi^o} = \sum_{n=1}^{N} h_n(\xi^i)\left[\mu_n^o + \frac{\Sigma_n^{io}}{\Sigma_n^i}(\xi^i - \mu_n^i)\right] \tag{8}$$

$$h_n(\xi^i) = \frac{\mathcal{P}(n)\mathcal{P}(\xi^i|n)}{\sum_{m=1}^{N}\mathcal{P}(m)\mathcal{P}(\xi^i|m)} \tag{9}$$

IV. IMPLEMENTATION & EXPERIMENTS

The LfD approach is then applied to the peg-in-hole problem on a real experimental teleoperation master-slave system (Fig. 1), which consists of a KUKA LWR slave robot and a Sigma.7 haptic master device. Moreover, a 155 mm long titanium peg was rigidly mounted on a 6-DOF force/torque (F/T) sensor on the end-effector of the arm. The proposed approach was developed using *Simulink Coder* and deployed into a 3GHz CPU embedded computer, which communicates with all the devices, reaching up to $t = 1ms$ sample time.

To obtain the training dataset $\hat{\xi}$, the robot was configured in kinesthetic mode and manually guided to insert the peg from two different initial positions. Once obtained the training dataset and encoded it into a GMM, two teleoperated peg-in-hole insertions from different initial positions, using haptic guidance, were carried out in order to validate the proposed approach. Fig. 3 represents the reproduction of these insertions, where only relevant information is shown. As it is appreciated, during the insertion (left plot) when a torque τ_x is measured due to the lever effect of the peg, a haptic guidance force $\bar{h}_y$ is generated using GMR.

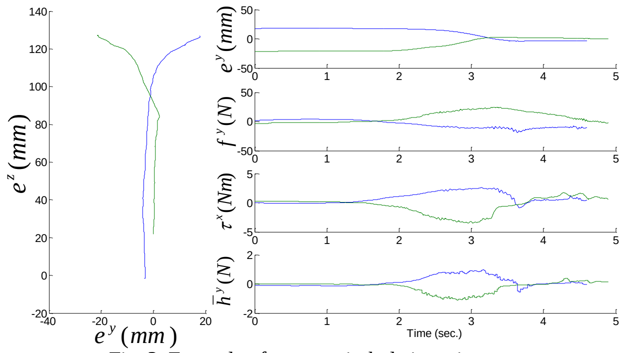

Fig. 3. Example of two peg-in-hole insertions.

V. CONCLUSION

The paper has confirmed the feasibility of using Learning from Demonstration for constructing torque measurements based haptic guidance to aid a teleoperated peg-in-hole insertion task.

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