Generalization of Task Model using Compliant Movement Primitives in a Bimanual Setting

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***Abstract*— Compliant Movement Primitives (CMPs) showed good performance for a desirable behavior of robots to maintain low trajectory error while being compliant without knowing the dynamic model of the task. This framework uses the integral representation of reference trajectories utilized in a feedback loop together with driving joint torques that represent the feed-forward control term. To achieve the generalization of CMPs, reference trajectories (represented in the form of task space position trajectories) are encoded as Dynamic Movement Primitives (DMPs) while the feed-forward torques are learned through the Gaussian Process Regression (GPR) and are represented as a combination of radial basis functions. This paper extends the existing framework through the generalization of CMPs in *bimanual settings* that can concurrently achieve low trajectory errors in relative task space and compliant behavior in absolute task space. To achieve this behavior of bimanual robotic system, the control terms derived from CMP framework are extended with the symmetric control approach. We show how the task-specific bimanual task dynamics can be learned and generalized to different task parameters that influence the task space trajectory and to a different load. Real-world results on a bimanual Kuka LWR-4 robots configuration confirm the usability of the extended framework.**

I. INTRODUCTION

Although we are witnessing continues progress in collaborative robotics [1], where humans and robots can physically interact to accomplish a common task, this technology has not yet matured to be widely used. The driving wheel for further progress comes from the potential to move the robots from factory floors to everyday human life, and find broad applications in households, hospitals, residential care facilities for the elderly etc... In these scenarios, the list of tasks that require bimanual over single arm configuration is long, mainly because human's everyday homes and work environments are designed with respect to our capabilities.

In environments occupied by humans, safety is of the highest priority. Where physical contact between human and the robot can occur, the compliance of the robot is a necessity. This can be ensured through contact detection [2], passive compliance using elastic elements [3] or active torque control strategies, which rely on comparing the actual torques and the required theoretical torques [4]. However, this requires the precise dynamic model of both the robot and the task (including task variations), but the models of the task dynamics are usually hard or even not possible to determine.

When we look at the humans performing an arbitrary bimanual task, it is clear that we do not possess the knowledge of the dynamical model of the task. Inspired by this human's ability to learn arbitrary dynamical tasks [5], the framework of Compliant Movement primitives (CMPs) is being derived in [6]. The CMP framework is applicable to robots with active torque control. To extend the ability of imitation of just one task, statistical generalization is used to allow some variations in the task definition.

The viability of CMPs was shown in various experiments performed with a Kuka LWR robot. Both the demonstrated and generalized CMPs successfully accomplished different hard-to-model periodic and discrete tasks in a compliant manner and with high tracking accuracy. Explicit dynamical models, which can only be provided by experts, were not required.

One way of mitigating the need to develop dynamical models of tasks is to learn the specifically required torques for the given task with learning by imitation. The learned torques are then applied for the repetition of exact same task. The framework of Compliant Movement primitives (CMPs), utilizes this approach. The method was extended to generalize between a set of learned situations in order to generate the torques for a new task variation, such as a different load or speed. Thus, a single robot was able to perform a wide variety of task variations through direct joint-position and joint-torque control, with low trajectory errors but compliantly in the case of an external perturbation. In this paper, we show that CMPs are useful in bimanual settings and that generalization can be applied to new task parameters defined in task space for bimanual robots.

A. *Problem Statement*

In this paper, we investigate compliant control of a bimanual robotic system, physically interacting with a human (Fig. 1), *without* explicit dynamical models of the task that can handle different task parameters defined in task space.

Therefore, the control of the bimanual system must enable (i) high relative position error rejection and high compliance behavior in absolute task, (ii) generalization with respect to position trajectory execution in task space and (iii) generalization with respect to different loads imposed to the end-effectors. The listed properties should be handled by a robotic

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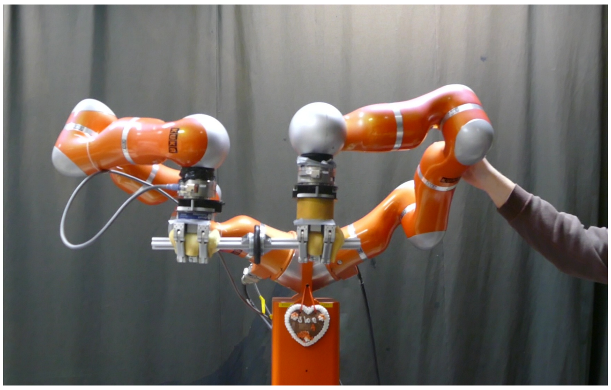

Fig. 1. A person interacting with a compliant robot performing the bimanual task during which the robot holds one object with two arms.

system without knowing the dynamical models of the task, but only with the use of task-specific torques within the framework of CMPs.

B. State of the Art

Compliant behavior is the main advantage of torque controlled robots [7], [8]. These robots should offer precise motion execution and simultaneously the safety in presence of humans in both industrial and human's everyday environment. However, besides the active torque control robots (that are used in this research), there are other approaches to achieve compliance in the joints. One such are artificial muscle-tendon driven systems as presented in [9] where the arm-shoulder system is presented. Other approaches rely on task-specific models. Authors in [10] used tactile sensing to determine the force of contact with the environment on the iCub robot to calculate the joint-torques and used them as a feed-forward signal. In [11] a mapping of external wrenches to a generalized force in the configuration space is used to measured joint-level actuation forces. These measurements are then used as inputs to a compliant motion controller. An example of passive compliance can be found in COMAN that uses joint actuators based on the series elastic actuation principle. In [12] authors presented a method to optimally tune the joint elasticity based on resonance analysis and energy storage maximization criteria to determine the passive compliance. Paper [13] describes the compliance control in the Valkyrie robot, where it demonstrates the robot's ability to accurately track torques with the presented decentralized control approach.

Another aspect of this paper is bimanual control. In an asymmetric control scheme, each robot acts independently. An example using dynamic motion primitives can be found in [14]. A method of implementing impedance control on a dual-arm system by using the relative Jacobian technique is given in [15]. The symmetric control scheme assumes the two robotic arms are executing the common task, and thus the motion of the bimanual system can be represented by a common coordinate frame. In the symmetric control, the task can be defined in both relative and absolute coordinates. In [16] is introduced a kinematic control of a dual arm system. An example of bimanual robot controller for safe interaction with humans is presented in [17]. It relies on different gains for absolute and relative motion. This approach, however, did not offer a solution for low trajectory tracking errors when the absolute gains are set low.

To address the problem of handling different task parameters we rely on generalization. Generalization has been extensively applied in robotics, with methods such as Locally Weighted Regression [18] and Gaussian Process Regression (GPR) [19] at the forefront. We refer the reader to [20] for an extensive overview of generalization of kinematic behavior. However, not so many approaches deal with dynamic variables. An example of generalization of force trajectories for peg-in-hole operation is given in [21]. In this paper we, rely on GPR to generate new CMPs for a bimanual system.

The rest of the paper is organized as follows. In Section II, is introduced the CMP framework. Section III describes the procedure for obtaining the model that will provide CMPs based on the varying parameters of the trajectories and the load. Experimental results conducted on a bimanual KUKA LWR-4 robotic system are presented in Section IV and the final conclusion is given in Section V.

II. COMPLIANT MOVEMENT PRIMITIVES

A. Robot arm controller and Single arm CMPs

The active torque controller, such as the one governing the motion of Kuka LWR-4 robot arms [22], is defined by

$$\boldsymbol{\tau}_u = \mathbf{K}_q(\mathbf{q}_d - \mathbf{q}) + \mathbf{D}_q(\dot{\mathbf{q}}_d - \dot{\mathbf{q}}) + f_{dyn}(\mathbf{q}, \dot{\mathbf{q}}, \ddot{\mathbf{q}}), \quad (1)$$

where $\boldsymbol{\tau}_u$ are the driving joint torques, $\mathbf{K}_q$ is a diagonal joint-stiffness matrix, $\mathbf{q}_d$ and $\mathbf{q}$ are the vectors of the desired and measured joint positions, respectively, $\mathbf{D}_q$ is a diagonal damping matrix, ($\dot{\mathbf{q}}_d$ and $\dot{\mathbf{q}}$ are the desired and measured vectors of joint angular velocities, respectively, and $f_{dyn}(\mathbf{q}, \dot{\mathbf{q}}, \ddot{\mathbf{q}})$ represents the torques calculated from the dynamic model of the robot together with all the non-linearities in the robot emerging from Coriolis effect, friction, ...

The compliance of the robotic arm is being adjusted by changing the stiffness matrix ($\mathbf{K}_q$). Smaller values lead to more compliant behavior, but on the other hand, it affects the trajectory tracking capability of the robot. One of the ways to keep the low tracking error simultaneously with compliant behavior is to introduce feed-forward joint torques $\boldsymbol{\tau}_{ff}$. Thus, the eq. (1) can be rewritten in the following form:

$$\boldsymbol{\tau}_u = \mathbf{K}_q(\mathbf{q}_d - \mathbf{q}) + \mathbf{D}_q(\dot{\mathbf{q}}_d - \dot{\mathbf{q}}) + f_{dyn}(\mathbf{q}, \dot{\mathbf{q}}, \ddot{\mathbf{q}}) + \boldsymbol{\tau}_{ff}. \quad (2)$$

Typically, feed-forward torques $\boldsymbol{\tau}_{ff}$ are calculated from explicit dynamical models or can be obtained from the frameworks such as CMPs.

Compliant movement primitives are defined as a combination of desired motion trajectories and corresponding torque signals

$$\mathbf{h}(t) = [\mathbf{q}_d(t), \boldsymbol{\tau}_f(t)]. \quad (3)$$

with

$$\mathbf{q}_d(t) = [q_{d1}(t),\ q_{d2}(t), \dots,\ q_{dN}(t)], \quad (4)$$

$$\boldsymbol{\tau}_f(t) = [\tau_{f1}(t),\ \tau_{f2}(t), \dots,\ \tau_{fN}(t)], \quad (5)$$

where N represents the number of degrees of freedom (DOF) of the robot. In the proposed approach, joint trajectories $\mathbf{q}_d$ are obtained by human demonstration and encoded as Dynamic Movement Primitives (DMPs) [23], [24]. The corresponding torques $\boldsymbol{\tau}_f$ are recorded during the stiff execution of demonstrated task, i.e. with a high-gain feedback controller. An example of the use of CMP framework for single arm robot is given in [6].

B. CMPs in bimanual configuration with symmetric controller

The single arm CMP control method was designed for joint-space control of the robot. It is thus not applicable for a bimanual setting, where the control has to be implemented in the task space. Otherwise, it is impossible to maintain the bimanual task. The paper [25] describes in detail the kinematics of the bimanual configuration and derivation of the compliant bimanual symmetric controller, based on [16]. For the completeness of this paper, the following text provides and comments the final derived equation for the CMP-based symmetric compliant controller. Relying on (2), in this controller we are using the feed-forward $\boldsymbol{\tau}_{ff}$ while reducing values in stiffness and damping matrix to achieve compliance, but still preserve accurate trajectory tracking for specific, learned tasks.

Feed-forward torques $\boldsymbol{\tau}_{ff}$ in CMP-based symmetric compliant controller is composed of three components:

$$\boldsymbol{\tau}_{ff} = \begin{bmatrix} \boldsymbol{\tau}_{ff,1} \\ \boldsymbol{\tau}_{ff,2} \end{bmatrix} = \boldsymbol{\tau}_{\text{rec}} + \boldsymbol{\tau}_{\text{biman}} - \boldsymbol{\tau}_{\text{vft}}. \tag{6}$$

The pre-recorded or learned task torque $\boldsymbol{\tau}_{\text{rec}}$ ensures trajectory tracking. It is the direct output of the CMP. However, the reference joint trajectories are calculated from the task-space trajectories using the kinematics of the bimanual configuration. Inverse kinematics solution needs to match the posture of the robot during the demonstration.

In eg.6 the bimanual symmetric controller $\boldsymbol{\tau}_{\text{biman}}$ maintains the bimanual task. It is given with:

$$\boldsymbol{\tau}_{\text{biman}} = \mathbf{J}^T \left(\mathbf{K}_{\text{task}} \left(\mathbf{x}_d - \mathbf{x} \right) + \mathbf{D}_{\text{task}} (\dot{\mathbf{x}}_d - \dot{\mathbf{x}}) \right). \tag{7}$$

where $\mathbf{K}_{\text{task}}$ and $\mathbf{D}_{\text{task}}$ are 12×12 diagonal gain matrices for stiffness and damping, respectively (6 DOF for the absolute ($\mathbf{K}_{\text{abs}}$ and $\mathbf{K}_{\text{rel}}$) and 6 for the relative task ($\mathbf{D}_{\text{abs}}$ and $\mathbf{D}_{\text{rel}}$)), $\mathbf{J}$ is a Jacobian matrix, and $\mathbf{x}_d$ are $\mathbf{x}$ desired and actual position of the common coordinate frame in the task space. A low value on the diagonal of $\mathbf{K}_{\text{task}}$ will result in compliant behavior for that DOF, which also means that trajectory tracking in that DOF results in high errors. The controller increases joint torques based on the error in task space. Since the gains are decoupled for separate DOFs, in the case of low gains for the absolute DOFs, $\mathbf{K}_{\text{abs}} << \mathbf{K}_{\text{rel}}$, the robot will be compliant in absolute space, but stiff in relative space. However, it will also not be able to track the desired trajectories in the absolute space. As described in Section II-A, trajectory tracking is ensured through the torque part of CMPs. To ensure that (7) does not act against (2), we set low values for $\mathbf{K}_q$.

The virtual force translation $\boldsymbol{\tau}_{\text{vft}}$ reduces the necessary feedback reaction of (7) and thus increases compliance of the bimanual system. It is given with:

$$\boldsymbol{\tau}_{\text{vft}} = \begin{bmatrix} \mathbf{J}_1^T \left(\mathbf{J}_2^\dagger \right)^T \Delta\boldsymbol{\tau}_2 \\ \mathbf{J}_2^T \left(\mathbf{J}_1^\dagger \right)^T \Delta\boldsymbol{\tau}_1 \end{bmatrix}. \tag{8}$$

where $\mathbf{J}_1$ and $\mathbf{J}_2$ are Jacobian matrices of left and right robot arm, while $\Delta\boldsymbol{\tau}_2$ and $\Delta\boldsymbol{\tau}_1$ are the deviations between measured and desired joint torques for right and left robot arm.

C. Experimental results of the bimanual CMP controller

In Fig. 2 we can see the behavior of the underlying bimanual CMP control approach given with eq. (2) and (6), that is compliant in the absolute task, but maintains low errors in the relative task despite the high forces.

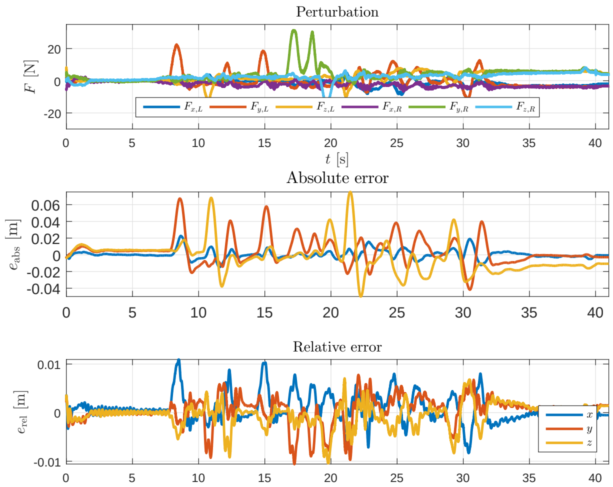

Fig. 2. Absolute error (top), relative error (middle) and end-effector perturbation (calculated from measured joint torques) when using the complete controller, given by eq. (2) and (6).

The system was performing the task-space defined trajectory and the absolute (deviation of a common coordinate frame for both arms in the world coordinate frame) and relative errors (deviation of the tool-center point (TCP) of one arm with respect to the TCP of another arm) are being recorded. The top plot shows the perturbations. We can see that relatively small perturbations result in significant motion of the common coordinate frame, as shown in the middle plot. The bottom plot shows that despite no actual physical coupling through rigidly holding a common object, the relative error between the robots was quite low.

III. GENERALIZATION

In this section is given a description of the generalization of bimanual CMPs using GPR. Since CMPs provide trajectories and torque profiles only for specific solutions, their applicability would remain limited to exactly the same conditions if it were not for generalization. Through generalization, one can make the system applicable to different situations and thus overcome the limitation of confinement to the exact repetitions of pre-learned situations. The task of the system was to bimanually carry an object, by holding it with both hands.

Statistical generalization using GPR can be effectively applied to single-robot tasks. Given a database of CMPs and associated task parameters (e. g., a new CMP is recorded for every new load the robot is carrying), we can then use statistical generalization to calculate CMPs for the loads between the recorded ones. However, the behavior of the robot and the query must transition continuously between the task parameters. We apply this approach for the bimanual tasks and for the generalization of task space trajectory and load imposed to end-effectors. Thus, the goal of the generalization is to learn a model defined as a function:

$$\mathbf{F}_u : c \longmapsto [\mathbf{a}], \tag{9}$$

which uses the database of n learned coupling terms $\mathbf{u}$ to define a new coupling term, defined as the weights $\mathbf{a}$ of RBF terms, adapted to the new query point c. The calculation of the new weights is performed using GPR [19]. The idea behind using GPR to learn the model is to allow as to set a new inputs $\mathbf{c}^*$ for which we can effectively calculate corresponding outputs $\mathbf{a}^*$. The equations explaining the derivation of GPR model are given below.

If $a_k \in \mathbf{a}, k = 1...n$, then training data can be written as $\{a_k, c_k\}_{k=1}^{n}$. If a new set of inputs $\mathbf{c}^*$ is given, Gaussian Process Regression can be applied to compute $\mathbf{a}^*$ as follows:

$$\mathbf{a}^* \;=\; \mathbf{\Sigma}\left(\mathbf{C}^*, \mathbf{C}\right) \cdot \left[\mathbf{\Sigma}\left(\mathbf{C}, \mathbf{C}\right) + \sigma_n^2 \mathbf{I}\right]^{-1} \mathbf{a}. \tag{10}$$

Here $\mathbf{C} = \{c_1, \dots, c_n\}$, $\mathbf{C}^* = \{c_1^*, \dots, c_k^*\}$, σ_n is the noise variance of the output data and

$$\mathbf{\Sigma}(\{c_1, \dots, c_k\}, \{c_1^*, \dots, c_k^*\}) = \\ = \begin{bmatrix} \mathrm{cov}(c_1, c_1^*) & \dots & \mathrm{cov}(c_1, c_k^*) \\ \vdots & \dots & \vdots \\ \mathrm{cov}(c_K, c_1^*) & \dots & \mathrm{cov}(c_k, c_k^*) \end{bmatrix}, \tag{11}$$

$$\mathrm{cov}(c_i, c_j^*) = \sigma_f^2 \exp\left(-\frac{\|c_i - c_j^*\|^2}{2l^2}\right), \tag{12}$$

where σ_f is the signal variance and l the characteristic length-scale, i. e., the change in the input parameters that will cause a significant change of the output value. σ_n, σ_f, and l are hyperparameters that can be determined from the learning data set. One way to calculate σ_n, σ_f, and l is by maximizing the log marginal likelihood

$$\log\left(p(\mathbf{a}|\mathbf{C}, \sigma_l, \sigma_f, l)\right) = -\frac{1}{2}\mathbf{a}^T[\mathbf{\Sigma}(\mathbf{C}, \mathbf{C}) + \sigma_n^2\mathbf{I}]^{-1}\mathbf{a} - \\ \frac{1}{2}\log\left(\det\left[\mathbf{\Sigma}(\mathbf{C}, \mathbf{C}) + \sigma_n^2\mathbf{I}\right]\right) - \frac{n}{2}\log 2\pi. \tag{13}$$

For generalization use case in this paper, the robots were physically coupled through holding a common object (see Fig. 1) and thus no relative error appeared, with low forces acting on the object. For motion in the task space, a half-sinusoidal shape trajectory is chosen. The amplitude of the trajectory is varied in the range from 0.13m to 0.4m with a 0.03m increment. The starting and ending points of the trajectories in task space are set to $\vec{p}_{start} = [0.5,\ -0.2,\ 0.78]^T$ and $\vec{p}_{end} = [0.5,\ 0.2,\ 0.78]^T$ respectively. Fig. 3 shows the trajectories stored in the database for learning the model (blue solid lines) and the shape of trajectories obtained from the model with the input value set between the database values (red dashed lines).

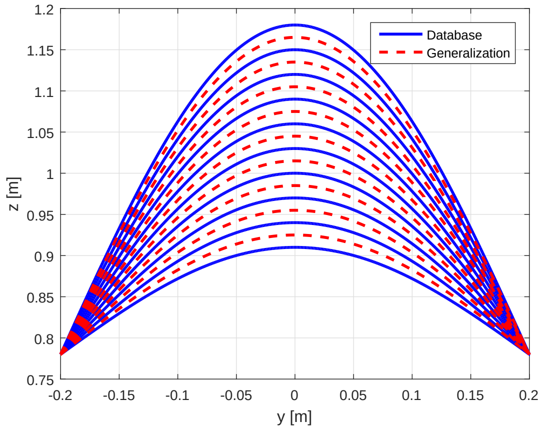

Fig. 3. Bimanual absolute task database trajectories in blue and generalized trajectories in red-dashed.

Also, the object weight varied in the ranged from 0.5kg to 4.5kg at a 0.5kg increment. The query into generalization was thus two-dimensional vector $c = [A\ L]^T$, where A is the amplitude of the half-sinusoidal trajectory and L is the load, i.e. the weight of the object the robot is carrying with two arms.

IV. RESULTS

Experimental setup consisted of two Kuka LWR-4 robots and two BarrettHand BH8-280 hands, as shown in Fig. 1. In this experiments, the rotation of the 3rd axis on both robot arms is locked. Thus the system was not redundant for the task. The system was controlled from MATLAB at the frequency of 500Hz.

Fig. 4 shows an image sequence of still photos during the bimanual task execution with the generalized load of 2.25kg and the amplitude of half-sinusoidal trajectory set at 0.16m. Second image sequence, given in Fig. 5, shows a series of still photos showing the bimanual task execution with the generalized load of 1.25kg and the amplitude of half-sinusoidal trajectory set at the highest value, i.e. 0.4m. During execution of the second task the robot was perturbed through physical interaction with the human. On the sequence of images is visualized that the robot complies to the external force, and after the disturbance is canceled, the robot rejects error in task space and returns to the execution of the requested trajectory.

The results of the generalization are shown in Fig. 6 and Fig. 7. In both figures, light blue stars represent the values

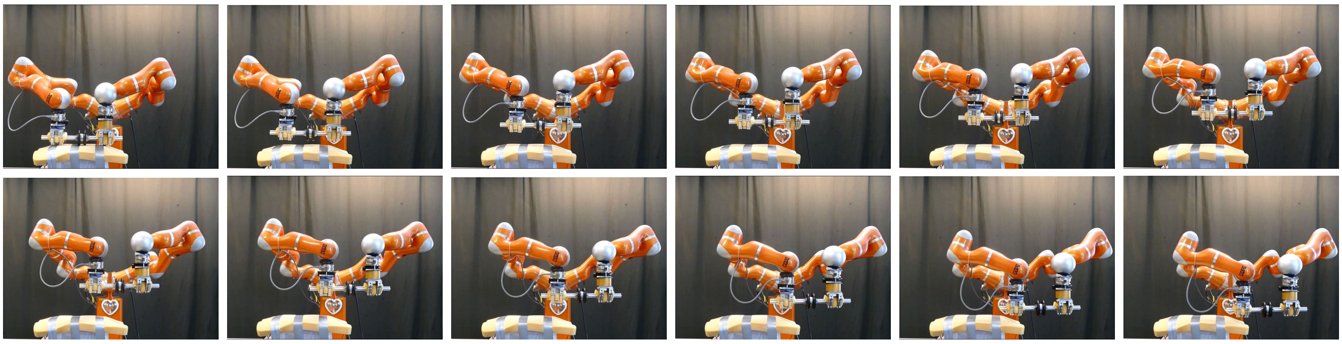

Fig. 4. Image sequence of the bimanual system performing the given task using a generalized model obtained with GPR.

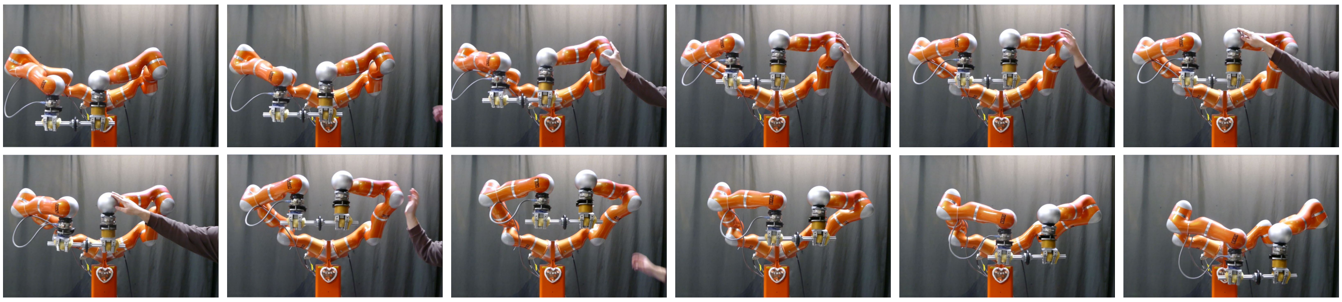

Fig. 5. Image sequence of the bimanual system performing a given task using a generalized model with imposed external disturbance.

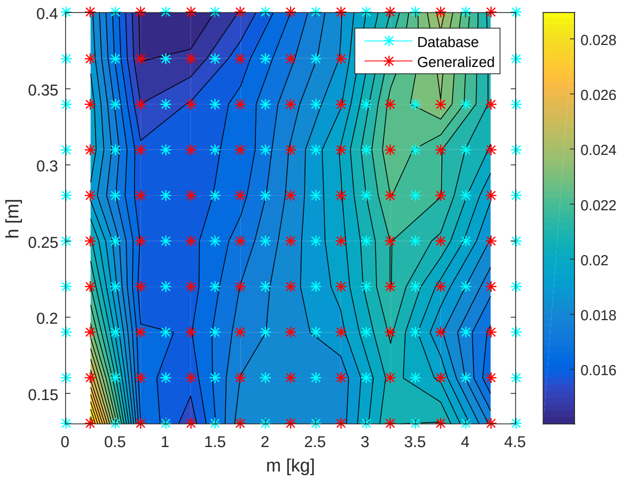

Fig. 6. Sum of the RMS error of the position of the common coordinate frame with respect to the desired trajectory

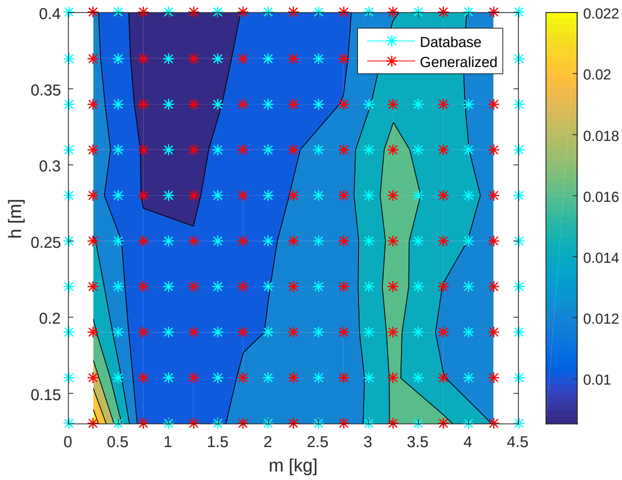

Fig. 7. Mean norm of the position error vector

of the parameters of the task for which the measurements are stored in the database and later used for the learning process. The red stars represent the query point for which the learned CMPs are used from the generalized model and for these CMPS the measurements during the task execution are recorded. Fig. 6 shows the color map of the root mean square (RMS) error of the absolute task, i.e. the sum of the RMS error of all three position components of the common coordinate frame with respect to the desired trajectory for different loads. We can say that the error is small bearing in mind that the system is configured as very compliant in the absolute task, and only in that case, the use of generalization is actually justified. Fig. 7 shows the mean value of the intensity of the error vector. The results shown in this plot, are comparable to the results obtained in [6], with the notice that in this paper the generalization is derived for the task space and in the bimanual configuration.

V. CONCLUSION

In this paper is shown that the generalization was successful for the execution of requested absolute tasks thus allowing application of the bimanual system within the generalization area, and not only for the pre-learned examples. During the execution of the bimanual task, the robots were physically coupled by holding a rigid object. This lead to the low error in the relative task. In this configuration, we showed that the system is compliant to external disturbances while maintaining the execution of bimanual task, and that the controller is general to the absolute task parameters that can change load and shape of the trajectory in task space.

In the experiments is shown that the proposed controller calculates all the control signals in real time, and proves the applicability of the method. For the future work, we will focus on the experiments that asks for dynamic relative task with the robot holding one elastic or multiple rigid objects. Also we will consider designing the hybrid controller that allows the seamless switching between the execution of symmetric and asymmetric bimanual tasks.

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