Modeling Spatio-Temporal Variability in Human-Robot Interaction with Probabilistic Movement Primitives

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***Abstract*— The task of physically assisting humans requires from robots the ability to adapt in many different ways: to changes in space of the human movement, to changes in the speed of the human, to changes in the environment, etc. This paper presents recent research on teaching robots how to interact with humans and to adapt to different circumstances. The approach presented here is based on Imitation Learning and Probabilistic Movement Representations. In particular, this paper explains the concept of a *Mixture of Interaction Primitives* to learn interactions from multiple unlabeled demonstrations and to deal with nonlinear correlations between the interacting partners. Furthermore, a method to compute reactions to human movements executed at different speeds is presented. A number of experiments with a lightweight robotic arm illustrate applications of the presented methods.**

I. Introduction

Assistive robots can be of great benefit to society, helping to increase the quality of life of people with disabilities and reducing workers' physical strain in the industry, for example. However, humans may need assistance in a practically unlimited number of scenarios. Therefore, preprogramming a robot with a fixed set of rules to deal with every possibility is very hard, if not impossible.

On the other hand, humans can usually adapt much better to new situations than robots can. Therefore, a promising idea is to provide robots with algorithms that allow them to learn from human demonstrations how to behave in new scenarios. Based on this idea, the concept of Interaction Primitive (IP) has been proposed to program a robot for physical collaboration and assistive tasks [1], [2]. IPs are movement primitives that capture the correlation between the movements of two agents—usually a human and a robot. Then, by observing one of the agents, say the human, it is possible to infer the controls for the robot such that collaboration can be achieved.

A main limitation of IPs is the assumption that the movements of the human and the movements of the robot assistant are linearly correlated. This assumption is reflected in the underlying Gaussian distribution that is used to model the demonstrations. This assumption does not hold for tasks consisting of several interaction patterns, such as the box assembly task illustrated in Fig. 1. Besides, even within a single interaction pattern, the correlation between the two agents may be nonlinear, for example, if the movements of the human are measured in the Cartesian space, while the movements of the robot are measured in joint space. In this case, the correlation between the interacting agents can be only locally treated as linear.

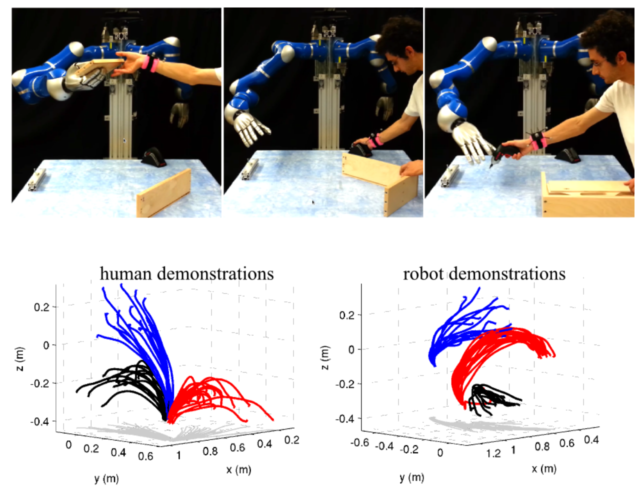

Fig. 1. Box assembly task consisting of three interaction patterns, where each can be represented as an Interaction Primitive. In this work, we want to learn multiple interaction patterns from an unlabeled data set of interaction trajectories. **Blue lines:** plate handover. **Black lines:** holding tool. **Red lines:** screw handover.

Manually labeling each subtask (e.g. "plate handover", "screw handover", "holding screw driver") is a way to model interactions with multiple subtasks and alleviate the nonlinearity of the training data. Ideally, however, robots should be able to identify different subtasks by themselves. Moreover, it may not be clear to a human how to separate a number of demonstrated interactions in different, linearly correlated groups. Thus, a method to learn multiple interaction patterns from unlabeled demonstrations is necessary.

This paper briefly presents the method originally proposed in [3], which uses Gaussian Mixture Models (GMMs) to create a Mixture of Interaction Probabilistic Movement Primitives.

The methods proposed in [1], [2] and [3] rely on time-alignment techniques to learn interaction models and to

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compute reactions to human movements. Those techniques, however, do not allow for online conditioning on human movements executed at different speeds, because full trajectories are needed to perform the time-alignment. For this reason, in the cited works, the conditioning was usually done in the end of the human movement. In this paper, a method is presented that allows for online conditioning on the human movements, for example on the beginning of movements, allowing for responsive robot reactions according to different human speeds.

The remainder of this paper is organized as follows: Section II presents related work. In Section III, Probabilistic Movement Primitives (ProMPs) and Interaction ProMPs are briefly introduced, followed by the Mixture of Interaction ProMPs technique based on Gaussian Mixture Models (GMMs). Section IV presents a method to compute online the reaction of the robot to human movements executed at different speeds. Section V evaluates the Mixture of Interaction ProMPs technique first on a toy problem that is useful to clarify the characteristics of the method and then on a practical application of a collaborative toolbox assembly. Then, an experiment is described, in which the robot receives a cup from a human who hands it over at different speeds. Section VI presents conclusions and ideas for future work.

II. Related Work

Physical human-robot interaction poses the problem of both action recognition and movement control. Interaction dynamics need to be specified in a way that allows for robust reproduction of the collaborative task under different external disturbances, and a common approach is based on direct force sensing or force emulation [4], [5], [6].

Our method does not use nor emulate force signals, but instead learns the correlation between the trajectories of two agents. Correlating trajectories not only simplifies the problem in terms of hardware and planning/control but also allows us to correlate multi-agent movements that do not generate force during the interaction, for example, the simple gesture of asking and receiving an object.

Graphical models have also been used to describe interaction dynamics. In the computer vision community, HMMs have been widely adopted to model interaction dynamics from input video streams [7], [8]. As a result, graphical models have also gained considerable attention in the field of human-robot interaction [9], [10], [11], [12], [13].

While very successful for classifying actions, graphical models, however, may not be the best option when it comes to generating motions. In [14], for example, the use of a HMM with discrete states, although very successful in action classification, introduces artifacts into the motion generation part that hinders motion generalization. Therefore, a clear problem in physical human-robot interaction is that while graphical models may be suitable in the action recognition domain, motion generation at the continuous level must also be taken into account. Llorens et al. [15] present a hybrid design for a robot to be used on the shoulder. In their work, Petri Nets accounts for discrete control transitions while, at the motion level, Partial Least Squares Regression has been used to find the best action of the robot at future time steps.

Perhaps the principal distinction of our method is the use of Interaction Primitives (IPs), introduced in [1], initially based on Dynamical Movement Primitives [16] and later extended to Probabilistic Movement Primitives [17] with action recognition in [2]. As shown in [2], Interaction Primitives can be used to not only recognize the action of an agent, but also to coordinate the actions of a collaborator at the movement level; thus overcoming in a single framework both layers of discrete action recognition and continuous movement control. Differently from [2], where different interaction patterns must be hand-labeled, [3] proposes the unsupervised learning of a Mixture of Interaction Primitives. This paper presents a slightly shortened explanation of the method proposed in [3] and, in addition, a method to compute online the reaction of the robot to human movements executed at different speeds.

III. Mixture of Interaction Primitives

In this section, we will briefly discuss the Interaction Primitive framework based on Probabilistic Movement Primitives [2], [17]. Then we will present the concept of a Mixture of Interaction Primitives, which is based on Gaussian Mixture Models.

A. Probabilistic Movement Primitives

A Probabilistic Movement Primitive (ProMP) [17] is a movement representation based on a distribution over trajectories. The probabilistic formulation of a movement primitive allows operations from probability theory to seamlessly combine primitives, specify via points, and correlate joints via conditioning. Given a number of demonstrations, ProMPs are designed to capture the variance of the positions q and velocities $\dot{q}$ as well as the covariance between different joints.

For simplicity, let us first consider only the positions q for one degree of freedom (DOF). The position q_t at time step t can be approximated by a linear combination of basis functions,

$$q_t = \boldsymbol{\psi}_t^T \boldsymbol{w} + \epsilon, \tag{1}$$

where ϵ is Gaussian noise. The vector $\boldsymbol{\psi}_t$ contains the N basis functions ψ_i, $i \in \{1,\ 2,\ 3, ...,\ N\}$, evaluated at time step t, where we will use standard normalized Gaussian basis functions. The number N of basis functions is defined by the user. In our experiments involving the box assembly task, for example, 30 basis functions were enough to achieve good approximations of the demonstrated trajectories.

The weight vector $\boldsymbol{w}$ is a compact representation of a trajectory. Having recorded a number of trajectories of q, we can infer a probability distribution over the weights $\boldsymbol{w}$. In the original ProMP formulation [17], $p(\boldsymbol{w})$ is a single Gaussian distribution. While a single $\boldsymbol{w}$ represents a single trajectory $q_{1:T}$, we can obtain a distribution $p(q_{1:T})$ over trajectories by integrating $\boldsymbol{w}$ out,

$$p(q_{1:T}) = \int p(q_{1:T}|\boldsymbol{w})p(\boldsymbol{w})\mathrm{d}\boldsymbol{w}, \tag{2}$$

where T represents here the number of time steps of each trajectory after time-alignment.

If $p(\boldsymbol{w})$ is a Gaussian, $p(q_{1:T})$ is also Gaussian. The distribution $p(q_{1:T})$ is called a Probabilistic Movement Primitive (ProMP).

B. Interaction ProMP

An Interaction ProMP builds upon the ProMP formulation, with the fundamental difference that we will use a distribution over the trajectories of all agents involved in the interaction. Hence, $\boldsymbol{q}$ is multidimensional and contains the positions in joint angles or Cartesian coordinates of all agents. In this paper, we are interested in the interaction between two agents, here defined as the observed agent (human) and the controlled agent (robot). Thus, the vector $\boldsymbol{q}$ is now given as $\boldsymbol{q} = [(\boldsymbol{q}^o)^T,\ (\boldsymbol{q}^c)^T]^T$, where $(\cdot)^o$ and $(\cdot)^c$ refer to the observed and controlled agent, respectively.

Let us suppose we have observed a sequence of positions $\boldsymbol{q}_t^o$ at m specific time steps t, $m \leq T$. We will denote this sequence by D. Given those observations, we want to infer the most likely remaining trajectory of both the human and the robot.

Defining $\bar{\boldsymbol{w}} = [\boldsymbol{w}_o^T,\ \boldsymbol{w}_c^T]^T$ as an augmented vector that contains the weights of the human and of the robot for one demonstration, the conditional probability over trajectories $\boldsymbol{q}_{1:T}$ given the observations D of the human can be computed by using

$$p(\boldsymbol{q}_{1:T}|D) = \int p(\boldsymbol{q}_{1:T}|\bar{\boldsymbol{w}})p(\bar{\boldsymbol{w}}|D)\mathrm{d}\bar{\boldsymbol{w}}, \tag{3}$$

which can be solved in closed form, assuming $p(\bar{\boldsymbol{w}})$ is a Gaussian.

C. Mixture of Interaction ProMPs

The goal of the Mixture of Interaction ProMPs method is to learn several interaction patterns given the weight vectors that parameterize our unlabeled training trajectories. For this purpose, we learn a GMM in the weight space, using the Expectation-Maximization algorithm (EM) [18].

Assume a training set with n vectors $\bar{\boldsymbol{w}}$ representing the concatenated vectors of human-robot weights as defined in section III-B. In order to implement EM for a GMM with a number K of Gaussian mixture components, we need to implement the Expectation step and the Maximization step and iterate over those steps until convergence of the probability distribution over the weights, $p(\bar{\boldsymbol{w}}; \alpha_{1:K}, \boldsymbol{\mu}_{1:K}, \boldsymbol{\Sigma}_{1:K})$, where $\alpha_{1:K} = \{\alpha_1, \alpha_2, \cdots, \alpha_K\}$, $\boldsymbol{\mu}_{1:K} = \{\boldsymbol{\mu}_1, \boldsymbol{\mu}_2, \cdots, \boldsymbol{\mu}_K\}$ and $\boldsymbol{\Sigma}_{1:K} = \{\boldsymbol{\Sigma}_1, \boldsymbol{\Sigma}_2, \cdots, \boldsymbol{\Sigma}_K\}$. Here, $\alpha_k = p(k)$, $\boldsymbol{\mu}_k$ and $\boldsymbol{\Sigma}_k$ are the prior probability, the mean and the covariance matrix of mixture component k, respectively. We initialize the parameters $\alpha_{1:K}$, $\boldsymbol{\mu}_{1:K}$ and $\boldsymbol{\Sigma}_{1:K}$ using k-means clustering before starting the Expectation-Maximization loop. The number K of Gaussian mixture components is found by leave-one-out cross-validation.

The mixture model can be formalized as

$$p(\bar{\boldsymbol{w}}) = \sum_{k=1}^{K} p(k)p(\bar{\boldsymbol{w}}|k) = \sum_{k=1}^{K} \alpha_k \mathcal{N}(\bar{\boldsymbol{w}}; \boldsymbol{\mu}_k, \boldsymbol{\Sigma}_k). \tag{4}$$

Expectation step: Compute the *responsibilities* r_{ik}, where r_{ik} is the probability of cluster k given weight vector $\bar{\boldsymbol{w}}_i$,

$$r_{ik} = p(k|\bar{\boldsymbol{w}}_i) = \frac{\mathcal{N}(\bar{\boldsymbol{w}}_i; \boldsymbol{\mu}_k, \boldsymbol{\Sigma}_k)\alpha_k}{\sum_{l=1}^{K} \alpha_l \mathcal{N}(\bar{\boldsymbol{w}}_i; \boldsymbol{\mu}_l, \boldsymbol{\Sigma}_l)}. \tag{5}$$

Maximization step: Update the parameters α_k, $\boldsymbol{\mu}_k$ and $\boldsymbol{\Sigma}_k$ of each cluster k, using

$$n_k = \sum_{i=1}^{n} r_{ik},\ \ \alpha_k = \frac{n_k}{n}, \tag{6}$$

$$\boldsymbol{\mu}_k = \frac{\sum_{i=1}^{n} r_{ik}\bar{\boldsymbol{w}}_i}{n_k}, \tag{7}$$

$$\boldsymbol{\Sigma}_k = \frac{1}{n_k}\left(\sum_{i=1}^{n} r_{ik}(\bar{\boldsymbol{w}}_i - \boldsymbol{\mu}_k)(\bar{\boldsymbol{w}}_i - \boldsymbol{\mu}_k)^T\right). \tag{8}$$

Finally, we want to use our model to infer the trajectories of the controlled agent given observations from the observed agents. We need to find the posterior probability distribution over trajectories $\mathbf{q}_{1:T}$ given the observations D, as in Section III-B.

In order to compute this posterior using our GMM prior, first we find the most probable cluster k^* given the observation D, using the Bayes' theorem. The posterior over the clusters k given the observation D is given by

$$p(k|D) \propto p(D|k)p(k), \tag{9}$$

where

$$p(D|k) = \int p(D|\bar{\boldsymbol{w}})p(\bar{\boldsymbol{w}}|k)\mathrm{d}\bar{\boldsymbol{w}}$$

and

$$p(\bar{\boldsymbol{w}}|k) = \mathcal{N}(\bar{\boldsymbol{w}}; \boldsymbol{\mu}_k, \boldsymbol{\Sigma}_k).$$

Thus the most probable cluster k^* given the observation D is

$$k^* = \arg\max_k p(k|D). \tag{10}$$

The output of the proposed algorithm is

$$p\left(\mathbf{q}_{1:T}|D\right) = \int p\left(\mathbf{q}_{1:T}|\bar{\boldsymbol{w}}\right) p\left(\bar{\boldsymbol{w}}|k^*, D\right) \mathrm{d}\bar{\boldsymbol{w}}, \tag{11}$$

i.e. the posterior probability distribution over trajectories $\mathbf{q}_{1:T}$, conditioning cluster k^* to the observation D.

IV. Reacting to Movements at Different Speeds

Each trajectory can be associated with a phase function $z(t) = \alpha t$, which assumes values between 0 and Z, where Z is a fixed value defined by the user, typically 1 or 100. The higher the value of α, the faster the phase goes from 0 to Z and the faster the movement gets executed.

The phase parameter α_i of a trajectory indexed by i is given by

$$\alpha_i = \frac{Z}{T_i}, \tag{12}$$

where T_i is the duration of the trajectory i. During training, the phase parameter of each demonstrated trajectory is determined by using (12). Then the mean and the standard deviation of this set of values for the phase parameter are computed, defining a Gaussian probability distribution.

Given a set D of observed positions of the human at specific time steps of a movement in execution, the rest of this movement and the reaction of the robot can be computed, as long as this human movement fits into the probability distributions learned in the training phase.

In order to perform this computation, a number of phase parameters α_j are sampled from the Gaussian distribution $\mathcal{N}\left(\alpha; \mu_\alpha, \sigma_\alpha^2\right)$ determined in the training phase. The index j here stands for the index of the sampled phase parameter value. For each α_j, the probability of α_j given observation D is computed[1],

$$p\left(\alpha_j | D\right) \propto p\left(D | \alpha_j\right), \tag{13}$$

where[2]

$$p\left(D | \alpha_j\right) = \int p\left(D | \boldsymbol{w}, \alpha_j\right) p\left(\boldsymbol{w}\right) \mathrm{d}\boldsymbol{w}. \tag{14}$$

Equation 14 can be solved in closed form, as well as the mean trajectory $\boldsymbol{\mu}_{\tau j}$ and the covariance $\boldsymbol{\Sigma}_{\tau j}$ that determine a distribution over trajectories given the phase parameter α_j. The rest of the human movement and the robot reaction can be computed by

$$\boldsymbol{\mu}_\tau = \frac{\sum_j p\left(\alpha_j | D\right) \boldsymbol{\mu}_{\tau j}}{\sum_j p\left(\alpha_j | D\right)}, \tag{15}$$

$$\boldsymbol{\Sigma}_\tau = \frac{\sum_j p\left(\alpha_j | D\right) \left(\boldsymbol{\Sigma}_{\tau j} + \boldsymbol{\mu}_{\tau j} \boldsymbol{\mu}_{\tau j}^T - \boldsymbol{\mu}_\tau \boldsymbol{\mu}_\tau^T\right)}{\sum_j p\left(\alpha_j | D\right)}. \tag{16}$$

This result is thus a weighted average of the predictions with all sampled parameters α_j. By being able to condition on a partial observation of the human movement, while taking into consideration the conditional probability of each sampled phase parameter α_j, this method is able to predict the rest of human movements varying considerably in speed profile and the reaction of the robot, without time-aligning training nor test trajectories.

Predicting the rest of the human movements may be important for example when the robot has to avoid collision with the human or has to intercept his/her trajectory. If the objective of the user is only to compute the reaction of the robot, predicting the rest of the human movements can be left aside, saving computational resources.

V. Experiments

This section presents experimental results in three different scenarios using a 7-DOF KUKA lightweight arm with a 5-finger hand[3].

[1]Note that $p(\alpha_j)$ is not part of the expression, since the phase parameters α_j are being sampled.

[2]Assuming $\boldsymbol{w}$ and α independent variables.

[3]Regarding the control of the robot, the design of a stochastic controller capable of reproducing the distribution of trajectories is also part of ProMPs and the interested reader is referred to [17] for details. Here we use a compliant, human-safe standard inverse-dynamics based feedback controller.

The goal of the first scenario is to expose the issue of the original Interaction Primitives [1], [2] when dealing with trajectories that have a clear multimodal distribution. In the second scenario, we propose a real application of the Mixture of Interaction Primitives where the robot assistant acts as a third hand of a worker assembling a toolbox[4]. Finally, an experiment in which the robot receives a cup from a human demonstrates an application of the proposed method to compute online the reaction of the robot to movements executed at different speeds[5].

A. Nonlinear Correlations between the Human and the Robot on a Single Task

To expose the capability of our method for dealing with multimodal distributions, we propose a toy problem where a human specifies a position on a table and the robot must point at the same position. The robot is not provided any form of exteroceptive sensors; the only way it is capable of generating the appropriate pointing trajectory is by correlating its movement with the trajectories of the human. As shown in Fig. 2, however, we placed a pole in front of the robot such that the robot can only achieve the position specified by the human by moving either to the right or to the left of the pole. This scenario forces the robot to assume quite different configurations, depending on which side of the pole its arm is moving around.

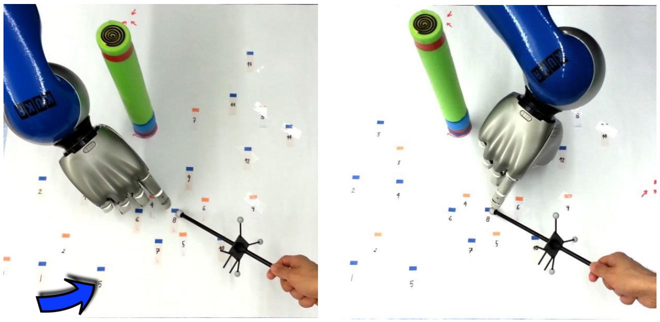
During demonstrations, the robot was moved by kinesthetic teaching to point at the same positions indicated by the human (tracked by motion capture) without touching the pole. For certain positions, as the one indicated by the arrow in Fig. 2(a), only one demonstration was possible. For other positions, both right and left demonstrations could be provided as shown in Fig. 2(a) and 2(b). The demonstrations, totaling 28 pairs of human-robot trajectories, resulted in a multimodal distribution of right and left trajectory patterns moving around the pole.

In this scenario, modeling the whole distribution over the parameters of the trajectories with one single Gaussian (as in the original Interaction Primitive formulation) is not capable of generalizing the movements of the robot to other positions in a way that resembles the training, as the original framework is limited by assuming a single pattern. This limitation is clearly shown in Fig. 3(a), where several trajectories generated by a single cluster GMM (as in the original Interaction Primitive) cross over the middle of the demonstrated trajectories, which, in fact, represents the mean of the single Gaussian distribution.

Fig. 3(b) shows the predictions using the proposed method with a mixture of Gaussians. By modeling the distribution over the parameters of the trajectories using GMMs as described in section III-C, a much better performance could be achieved. The GMM assumption that the parameters are only locally linear correlated seemed to represent the data much more accurately.

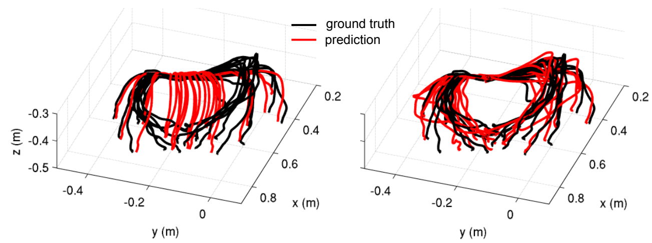
[4]Video available at http://youtu.be/9XwqW_V0bDw

[5]Video available at https://youtu.be/hAJHPep5KuQ



(a) (b)

Fig. 2. Experimental setup of a toy problem used to illustrate the properties of the Mixture of Interaction Primitives. The robot is driven by kinesthetic teaching to point at the positions specified by the human (pointed with the wand). Certain pointed positions can be achieved by either moving the arm to the right (a) or to left (b) of the pole placed on the table. Other positions, such as the one indicated by the arrow, can only be achieved by one interaction pattern.



(a) (b)

Fig. 3. Results of the predictions of the robot trajectories in Cartesian space. Both subplots show the same ground truth trajectories generated by driving the robot in kinesthetic teaching. The predictions are generated by leave-one-out cross-validation on the whole data set comprised of 28 demonstrations. (a) Prediction using the conventional Interaction ProMPs with a single Gaussian. (b) Prediction using the Mixture of Interaction ProMPs.

B. Assembling a Box with a Robot Assistant

In this experiment, we recorded a number of demonstrations of different interaction patterns between a human and the robot cooperating to assemble a box. We used the same robot described in the previous experiment. During demonstrations, the human wore a bracelet with markers whose trajectories in Cartesian coordinates were recorded by motion capture. Similarly to the first scenario, the robot was moved in gravity compensation mode by another human during the training phase and the trajectories of the robot in joint space were recorded.

There are three interaction patterns. Each interaction pattern was demonstrated several times to reveal the variance of the movements. In one of them, the human extends his/her hand to receive a plate. The robot fetches a plate from a stand and gives it to the human. In a second interaction, the human fetches the screwdriver, the robot grasps and gives a screw to the human as a pre-emptive collaborator would do. The third type of interaction consists of giving/receiving a screwdriver. Each interaction of plate handover, screw handover and holding the screwdriver was demonstrated 15, 20, and 13 times, respectively.

As described in section III, all training data are fed to the algorithm resulting in 48 human-robot pairs of unlabeled demonstrations. The presented method parameterizes the trajectories and performs clustering in the parameter space in order to encode the mixture of primitives.

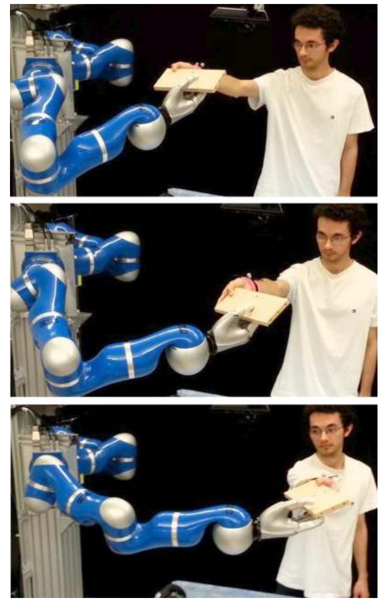


Fig. 4. Handover of a plate. Conditioning on three different positions of the wrist (using motion capture) of a human coworker.

In the inference/execution phase, the algorithm first computes the most probable Interaction Primitive mixture component based on the observation of the position of the wrist of the human by using (10). Using the same observation, we then condition the most probable Interaction Primitive, which allows computing a posterior distribution over trajectories for all seven joints of the robot arm as in (11). Finally, the mean of each joint posterior distribution is fed to a standard inverse dynamics feedback tracking controller.

As an example, Fig. 4 shows the robot executing the plate handover at three different positions based on the location of the wrist marker. Note that the postures of the arm are very different, although they are all captured by the same Interaction Primitive.

C. Reacting to Human Movements Executed at Different Speeds

In this experiment, a human moved at different speeds to hand over a cup to the robot. The reaction of the robot was computed online after observing only the beginning of the human movement. The robot reacted faster or slower, according to the human's speed.

During training, the human moved with different speeds in the direction of the robot but also varying the position at which he handed over the cup, while the robot was moved by kinesthetic teaching to receive the cup at the correct position. The trajectories of the human were about 150 cm long. Each of those trajectories was a sequence of (x, y, z) coordinates of the human's left wrist, which had markers attached to it detectable by a motion capture system.

During test, the human was observed only during the first 50 cm of his trajectory. Then, 15 values for the phase parameter α were sampled from the $p(\alpha)$ learned in the training phase. Subsequently, the rest of the movement of the human and the expected reaction of the robot were computed online using the method presented in Section IV.

The methods proposed in [1], [2] and [3] could not condition online on the beginning of the human's movement, since it is not possible to time-align his trajectory before it has been completed.

VI. Conclusions

In this paper we presented a Mixture of Interaction Primitives where Gaussian Mixture Models are used to model multiple interaction patterns from unlabeled data. In addition, this paper presented a method to compute online the reaction of a robot to human movements executed at different speeds. This method is able to condition on the beginning of the human movement, allowing the robot to start reacting before the human reaches the end of his/her trajectory.

In the future, we intend to use the stochastic feedback controller provided by the original ProMP work in [17]. With this controller, the compliance of the robotic arm increases with the variance of the trajectory.

We are currently considering extensions of our work where the human positions are replaced by other variables of interest. For example, the same framework can be used to correlate joint and end-effector trajectories of the same robot to learn nonlinear forward/inverse kinematic models. Similarly, the Mixture of Interaction Primitives can be used to correlate the interaction between motor commands and joint trajectories to learn inverse dynamics models.

Solutions must still be found for situations such as the human stopping in the middle of his/her movement or changing his/her mind and deciding to perform another movement after having started a different one. The presented framework can compute reactions of the robot to human movements, as long as these movements fit into the probabilistic distributions learned in the training phase, both in terms of space and speed. Therefore, if there were no situations during training phase in which the human stopped in the middle of his/her movement, the reaction of the robot would probably not be a suitable one if the human would act in this way during test phase.

The combination of the framework presented here with sensory feedback to allow the robot for detecting obstacles, objects and perturbations may also be promising.

VII. Acknowledgments

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