Towards Associative Skill Memories

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***Abstract*—Movement primitives as basis of movement planning and control have become a popular topic in recent years. The key idea of movement primitives is that a rather small set of stereotypical movements should suffice to create a large set of complex manipulation skills. An interesting side effect of stereotypical movement is that it also creates stereotypical sensory events, e.g., in terms of kinesthetic variables, haptic variables, or, if processed appropriately, visual variables. Thus, a movement primitive executed towards a particular object in the environment will associate a large number of sensory variables that are typical for this manipulation skill. These association can be used to increase robustness towards perturbations, and they also allow failure detection and switching towards other behaviors. We call such movement primitives augmented with sensory associations *Associative Skill Memories* (ASM). This paper addresses how ASMs can be acquired by imitation learning and how they can create robust manipulation skill by determining subsequent ASMs *online* to achieve a particular manipulation goal. Evaluation for grasping and manipulation with a Barrett WAM/Hand illustrate our approach.**

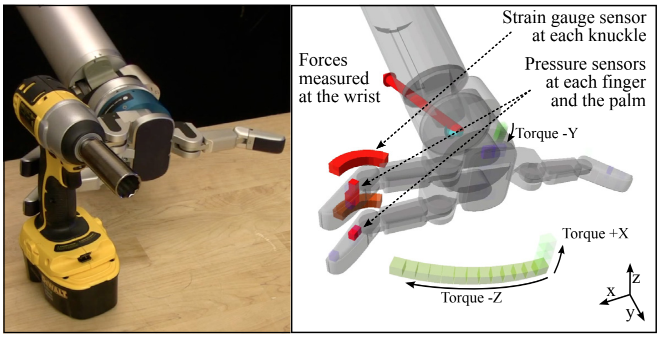


Fig. 1: Barrett WAM and Barrett hand reaching for a drill (left) and corresponding visualization of measured sensor information (right). Forces and torques at the wrist are visualized with the red arrow (forces) and half circles in front of the hand and around the wrist (torques). Torques in the knuckles of the fingers are visualized with half circles. Pressure values at the palm and each finger tip are visualized with cube markers, red cube markers indicate active cells.

I. INTRODUCTION AND RELATED WORK

Robots will only become useful in human environments if they are able to autonomously operate in unstructured environments and physically interact with the environment robustly despite uncertainties due to dynamics in the environment and/or inaccurate sensing. Uncertainty in the sensory-motor system gives rise, for example, to significant errors in the endeffector pose, errors in perceived object locations, and noise and hysteresis in force/torque/touch measurements.

One way to address uncertainty is by means of hardware designs, e.g., compliant hands [1] that passively adapt their shape to the shape of objects. While such passive adaptation creates robustness in some applications, it also entails a loss of accurate control in other scenarios. Other more sophisticated hardware designs have been proposed [2], however, so far, it is unclear how to leverage all the provided functionality.

On the algorithmic side, many of the existing approaches try to minimize uncertainty by heavily relying on well calibrated systems [3],[4]. These approaches to robotic grasping typically involve 1) computer vision methods to estimate the object pose, 2) methods to compute a goal grasp configuration, 3) motion planning algorithms to generate a collision free trajectory from the current configuration to this goal configuration, and 4) controllers that track this trajectory. These four steps form a pipeline which has successfully been applied to tabletop grasping scenarios. The objects to be grasped are usually chosen and placed such that the uncertainty in the task is manageable.

Uncertainty in the sensory-motor system often times leads to imprecise reaching and grasping behavior. Premature, delayed, or offset contacts with the object to be grasped can be the result causing the hand to miss the object or to flip it over. Robustness against those inaccuracies is usually dealt with closing perception-action loops in terms of visual servoing [5] or contact-reactive grasping [6]. Similarly, work has been done to address uncertainty by optimally choosing the next best view [7] or by interacting with the scene to explore the object [8]. Nonetheless, today's robots are still far away from being as dexterous as humans [9]. Even grasping geometrically simple objects in slightly uncertain environments or performing simple manipulation tasks still imposes a major engineering effort [10], [11].

In this paper, we propose an approach that generates motion in the context of grasping and manipulation using knowledge from previous similar task executions. An essential prerequisite that allows the system to relate the current task execution to previous ones is that task executions are performed in a similar fashion, i.e., that particular situations always afford the same movements. We will call these movements *stereotypical movements*. Additionally, we assume that due to the stereotypical movement execution, similar tasks result in similar sensor experiences. For example, opening a door will always result in similar tactile feedback at the finger tips, similar force measurements at the knuckles of the finger, and similar force/torque measurements at the wrist. These sensor experiences resemble the *nominal* behavior and are stored together with the corresponding executed movement. We call this an *Associative Skill Memory* (ASM).

In subsequent task executions (of the same task), these associations of sensory traces enable our system to predict future sensor measurements. Especially when dealing with uncertainty, it is crucial to be able to continuously monitor task progress and potentially adapt the system's behavior online to correct for unexpected events. Interesting information can be obtained by computing the *difference* between the expected and measured sensor information. Deviations of the measured sensor information from the expected/predicted sensor information indicates an unusual event. Accumulated statistics from past (successful) trials over time can be used to automatically determine reasonable confidence intervals [12]. Predicted sensor information can further be used to adapt the movement plan online in order to match the previously accumulated sensor traces whenever the measured sensor feedback deviates from the expected [13]. This approach does not require the user to manually specify thresholds for particular force sensors measurements that indicate contact [14],[15]. Instead, it allows for continuous adaptation of the movement plan.

This paper will develop our first steps towards ASMs in the context of imitation learning for grasping and manipulation. It extends our previous work on stereotypical movements [12], [13] to determining appropriate manipulation sequences *online* to achieve robust manipulation skills. For this purpose, we will first stress the importance of stereotypical movements in Sec. II and define more concretely the concept of ASMs. We will evaluate our approach in a robot manipulation task with a Barrett arm/hand robot.

II. STEREOTYPICAL MOVEMENTS AND ASSOCIATIVE SKILL MEMORY

Associating experienced sensor information with corresponding robot action facilitates the generation of a memory-based predictive model for subsequent similar situations. These sensory experiences resemble the expected *nominal* sensation during the movement, including confidence intervals from multiple skill executions. Deviations from the nominal behavior can be detected with statistical hypothesis testing [12]. Furthermore, provided knowledge about appropriate Jacobians associated with the location of the sensors, movement plans can be adapted online to react to unforeseen perturbations [13]. However, associating sensor information with a set of similar movement trajectories becomes challenging when employing commonly used stochastic motion planning algorithms. For example, for two very similar grasp scenarios these algorithms may return two rather different approach trajectories, resulting in two rather different sensor experiences. Thus, transferring knowledge from previous trials may become impossible. Additionally, improving task performance over time and designing online adaptation algorithms become similarly challenging simply because the relation to previously successful trials is missing.

In contrast, learning a set of *stereotypical movements* that are applicable to particular grasping and manipulation tasks provides the basis to accumulate sensations of previous trials. Associating experienced sensor traces with stereotypical movements allows for building up a predictive model that

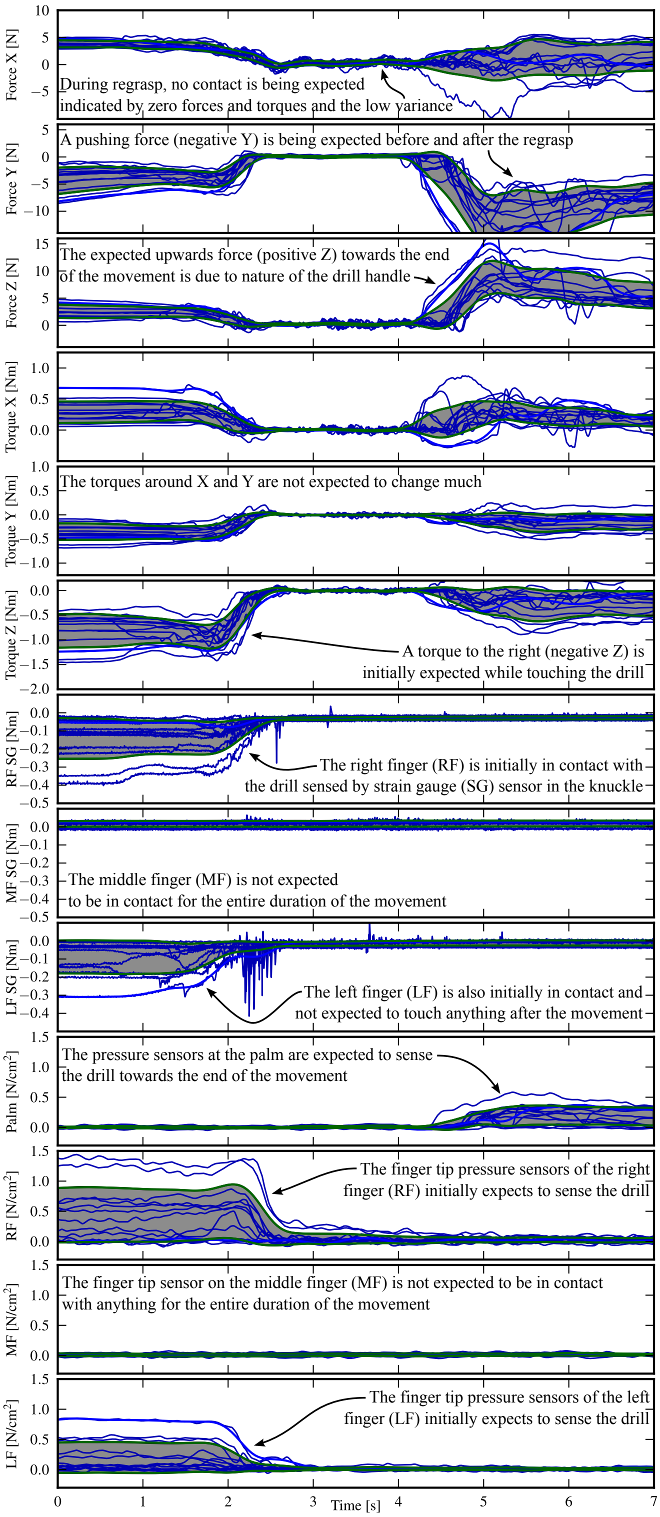


Fig. 2: Recorded sensor values (blue) after touching the drill with the two fingers (see Fig. 1). The executed movement re-aligns the palm of the hand with the drill similar to the correcting movement after step 2 shown in Fig. 7. Mean μ and 1-standard deviations σ (green) resemble the nominal sensor experiences for this stereotypical movement. Even though the start and end of the movement as well as the drill position has been changed slightly, the experienced sensor data shows strong correlations across trials. Our approach servos these sensor traces to create even stronger correlations to previous trials (see Sec. III-B) and exploits these to determine manipulation sequences online (see Sec. V).

can be used in future trials. The concept of stereotypical movements is key to facilitate the design of a system that can improve over time simply because new trials can be related to previous trials, and are thus predictable. The recorded and accumulated sensor information (see Fig. 2) while performing stereotypical movements is referred to as *associative memory*. Over time, each stereotypical movement is paired with a growing set of previous sensor experiences.

The concept of stereotypical movements is inspired by the repetitive nature of day to day manipulation movements such as for example reaching for and turning a door knob. This particular task is naturally decomposed into a sequence of movements: reaching for the door knob, aligning the fingers with it, turning it until its limit, and pulling it to open the door. Humans seem to perform this task (especially when visual feedback is missing) by continuously predicting sensor feedback and constantly confirming these predictions [16],[17]. Our framework is developed to mimic this behavior.

In this paper we propose to use the accumulated sensor information to choose and trigger subsequent movements. Our idea is that a particular movement primitive is only applicable if the associated sensor information corresponds sufficiently with the currently sensed sensor information of the robot. In the door knob task from above, such an approach would, for example, prevent a robot from starting to turn the knob unless the fingers have properly established contact with it (e.g. sensed by finger tip pressure sensors). If this sensory event is missing, a different movement might be chosen and triggered, such as a re-grasp movement.

The example task considered in this paper is to reach for a drill on a table and turn it on. Perceptual uncertainties are simulated and the drill position is varied. A series of grasping and re-grasping (correction) movements are being encoded into Dynamic Movement Primitives (DMPs) and provided to the system. Along with the movement plan, each DMP encodes the expected sensor traces as well. The sensor information are recorded from repeatedly executing each DMP under slightly varying conditions (i.e. slightly different object positions). From these multiple trials, mean μ and standard deviation σ are computed and used as the *nominal* behavior that is to be expected if this particular movement primitive is being executed. The movement plan is adapted online [13] to servo around these expected sensor values further ensuring that similar task execution result in similar sensory experiences.

The combination of reactive behaviors with stereotypical movements can create a rich set of possible motions that account for external perturbations and perception uncertainty to generate truly robust behaviors.

III. MOVEMENT GENERATION

For coding stereotypical movement, we use the Dynamic Movement Primitives (DMPs) approach [18], with the particular variant described in [19]. In brief, a discrete movement is generated by integrating the following equations of motion:

$$\tau\dot{v} = K(g-x) - D\,v - K(g-x_0)s + Kf(s) \quad (1)$$
$$\tau\dot{x} = v \ ,$$
$$f(s) = \frac{\sum_i \psi_i(s)\,\theta_i\,s}{\sum_i \psi_i(s)} \ , \quad (2)$$
$$\tau\,\dot{s} = -\alpha\,s \ , \quad (3)$$

where x and v are position and velocity of the system, x_0 and g are the start and goal position, τ is a temporal scaling factor, K is a spring constant, and D a damping term. The nonlinear function f defines the shape of the movement, where $\psi_i(s) = \exp(-h_i(s-c_i)^2)$ are Gaussian basis functions, with center c_i and width h_i, and θ_i are adjustable parameters. The phase variable s, which monotonically changes from 1 towards 0 during a movement, generates an implicit timing signal. Multiple DOFs are realized by maintaining a separate set of Eqs. (1) as well as separate forcing terms Eqs. (2) for each DOF and synchronize them via one phase signal Eq. (3).

1) Learning from observed behavior: To encode a recorded trajectory $x(t)$ into a DMP, the parameters θ_i in Eq. (2) are adapted such that the nonlinear function forces the transformation system to follow this recorded trajectory. For this adaptation, the following four steps are carried out: first, using the recorded trajectory $x(t)$, the derivatives $v(t)$ and $\dot{v}(t)$ are computed for each time step $t = 0, ..., T$. Second, the canonical system Eq. (3) is integrated and $s(t)$ evaluated. Third, using these arrays, $f_{\text{target}}(s)$ is computed based on Eq. (1), where x_0 and g are set to $x(0)$ and $x(T)$, respectively. Finally, finding the parameters θ_i that minimize the error criterion $J = \sum_s (f_{\text{target}} - f(s))^2$ is a linear regression problem, which can be solved efficiently.

2) Movement generation using DMPs: The transformation system of Eq. (1) is at equilibrium when the current position x is equal the goal position g and $\dot{v} = s = 0$. To trigger a movement and obtain a desired plan $(x_{\text{desired}}, v_{\text{desired}}, \dot{v}_{\text{desired}})$ the system needs to be setup such that the condition for the unique equilibrium point $((x, v, s) = (g, 0, 0))$ is no longer satisfied. Therefore, the start position is set to the current position ($x_0 \leftarrow x$), the goal position is set to the desired goal ($g \leftarrow g_{desired} \neq x$) and the canonical system is reset by setting $s \leftarrow 1$. The desired attractor landscape is obtained through plugging the learned set of parameters $\boldsymbol{\theta}$ into the nonlinear function f and the desired movement duration is adjusted using τ. The desired movement plan is obtained by integrating the canonical system, i.e. evaluating $s(t)$, computing the nonlinear forcing term $f(s)$ and integrating the transformation system.

A. DMPs for quaternion control

As introduced in [13], a specialized (4-dimensional) transformation system is used to represent orientations using quaternions. This quaternion integration rule guarantees the generation of normalized unit quaternions. Furthermore, it ensures that the generated quaternion orientations and corresponding angular velocities and accelerations are differential compatible. Moreover, this new integration rule facilitates a

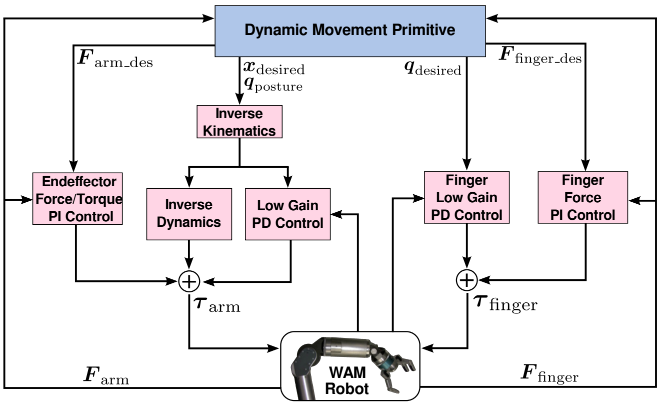


Fig. 3: Diagram of the proposed control architecture: Desired positions and orientation generated by the DMP are tracked using a velocity-based operational space controller together with an inverse dynamics law and feedback error compensation in joint space (see [20] for more details). Tracking of desired arm contact forces is achieved by closing a PI control loop on the force/torque sensor located at the wrist. The fingers are controlled with a position PD controller and a force PI controller using the strain gauge sensors located at the knuckles. The DMP also encodes the expected wrist forces and torques as well as the expected finger torques. These are used as set points of the corresponding force controllers. The DMP feedback adapts the movement trajectories online to remain close to the expected forces and torques.

tight integration of the dynamical system into control loops, as described in the following subsection. Please refer to [13] for more details.

B. Online trajectory generation using sensory feedback

The general feedback function is given by

$$\boldsymbol{\zeta} = \mathbf{K}_1 \mathbf{J}_{sensor}^T \mathbf{K}_2 (\mathbf{F} - \mathbf{F}_{des}) \ , \tag{4}$$

where $\mathbf{J}_{sensor}$ is the Jacobian of the task controlled by the movement primitives with respect to the sensors, $\mathbf{F}$ are the generalized forces read from the sensors and $\mathbf{F}_{des}$ are the corresponding desired forces, that have been acquired in previous task executions (for example mean μ in Fig. 2). $\mathbf{K}_1$ and $\mathbf{K}_2$ are, potentially time-varying, positive definite gain matrices. The feedback is added to the transformation system in Eq. (1) as follows

$$\begin{aligned} \tau \dot{v} &= K(g-x) - D\,v - K(g-x_0)s + K f(s) + \zeta \\ \tau \dot{x} &= v \ . \end{aligned} \tag{5}$$

Similarly feedback is added to the specialized transformation system that encodes the desired orientation. Torque feedback is facilitated by our quaternion integration rule because it uses angular accelerations.

We use a single DMP to encode the desired position and orientation of the endeffector, the arm posture[1], the desired finger joint angles, as well as the expected force and torque trajectories at the wrist and the expected torques at the knuckles of each finger. An overview diagram of our control architecture is shown in Fig. 3.

The proposed form of trajectory generation allows for very robust movements as it adapts its movement plans

[1]The arm posture is encoded to resolve the redundancy in the nullspace of the task similar to the demonstrated movement.

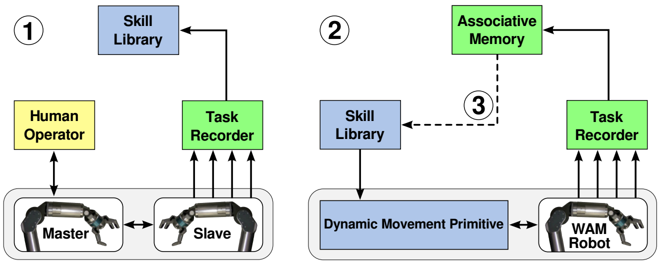


Fig. 4: Diagram of the skill acquiring procedure: (1) First, a human operator demonstrates a set of movement primitives using the master-slave system. Force feedback enables the operator to also teach meaningful force trajectories. The task recorder time aligns all sensor signals and encodes them into DMPs which are stored in the skill library. (2) Second, these DMPs are retrieved and executed on the robot. The task is varied by changing the object position as well as the start/end of each DMP. Again, all available signals are recorded and stored paired with the DMP that has been executed. The mean and standard deviation are computed which represent the nominal sensor expectations for the associated DMP. (3) Finally, the DMPs are updated with the obtained mean trajectories of the recorded forces and torques.

online based on expected force trajectories. In [13] this has been exploited to successfully grasp a flashlight off the table even though the position of the flashlight has been varied significantly. This paper presents an extension to automatically determine the manipulation sequence online based on associative memory. It uses the online movement adaption mechanism [13] to also exploit the fact that servoing around expected forces will ensure that subsequent task executions result in similar sensor experiences. The ability to relate the current sensor experiences to previous executions is key in determining the next movement primitive. Thus, previous work [13] is a crucial prerequisite. Sequences of movement primitives enable our system to deal with even larger uncertainty, such as changing the object pose mid-way.

IV. ACQUIRING MANIPULATION SKILLS

Associative Skill Memories (ASMs) are stereotypical movements (encoded as DMPs) that also maintain a set of associated sensor traces describing the nominal sensor expectations (see Fig. 2). These manipulation skills are acquired in 3 steps (see Fig. 4). First, a particular manipulation movement is demonstrated to the robot (e.g. using a master-slave system, see Sec. VI) while all sensor signals are being recorded. The recorded kinematic variables as well as the measured forces and torques at the wrist and the finger knuckles are encoded into a DMP and stored into the skill library[2]. Second, the DMP is being retrieved and executed on the robot while the manipulation scenario is slightly varied. This allows to capture task specific variations. The mean and the 1-standard deviation for these sensor traces are computed. These sensor statistics reflect the nominal behavior and are subsequently used to predict each sensor signal at each instant of time for the duration of the movement primitive. Finally, the DMP is updated with the mean of previously

[2]Note, encoding expected forces and torques into DMPs avoids discontinuous predictions when transitioning between movement primitives by adapting the initial conditions [19].

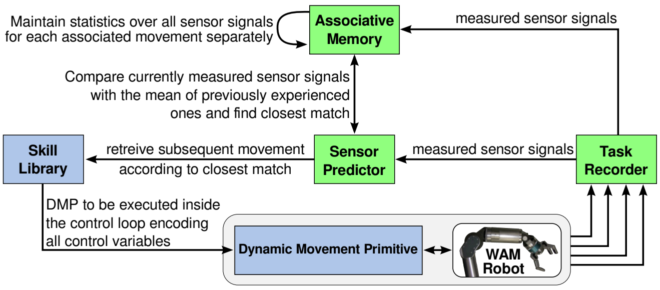


Fig. 5: Diagram of the proposed approach of sequencing ASMs: The sensor predictor constantly compares the currently measured sensor signals with the mean sensor statistics from previous executions of the same stereotypical movement and find the closest match. Towards the end of each movement primitive, the DMP of the associated best match is retrieved from the skill library and send to the real-time robot controller.

recorded forces and torques at the wrist and the finger knuckles.

V. SEQUENCING MANIPULATION MOVEMENTS BASED ON ASSOCIATED SENSOR INFORMATION

After acquiring a set of ASMs our system is able to constantly predict all sensor information and even use it inside the real-time control loop to servo around these predictions. Furthermore, the difference between current measurements and predicted sensor signals allows to constantly confirm successful execution of the task. Failure conditions are immediately detected when the measured signal deviates significantly from the expected behavior [12]. Furthermore, the proposed approach facilitates distinguishing between different kinds of failure conditions, which enables branching into the appropriate recovery action. On the other hand, if the measured signals matches the predictions, the next action in the default sequence is executed. This way of sequencing ASMs ensures successful execution of each movement before proceeding to the next. It subsequently follows that the initial sensor signature for the next ASM matches the currently measured signals (as indicated by the vertical dashed lines in Fig. 8). An overview of the proposed approach is shown in Fig. 5. For the presented experiments switching to subsequent ASMs were triggered only after 90% of the movement has been executed. The closest match between currently measured sensor signals and the initial sensor signatures of all ASMs maintained in the library is computed using Nearest Neighbors with squared euclidean distance metric. This closest match resembles the most appropriate subsequent movement. After a particular ASM was selected a total of 10 times, the corresponding DMP was sent to the controllers immediately (see Fig. 3). Note, the current implementation switches instantly between subsequent DMPs (as described in [19]) which causes the acceleration profiles to be discontinuous. However, transitions that maintain a continuous acceleration profile while switching between DMPs can easily be added, e.g. [21]. For the presented experiments this did not pose a problem because at the time of switching between movements the robot was moving very slowly.

VI. EXPERIMENTAL SETUP

The experimental setup consists of two Barrett WAMs equipped with one Barrett BH280 three finger hand each (see Fig. 6). The sensor suite of the hands include force/torque and accelerometer sensors at the wrist, pressure sensors on each finger tip and the palm, and strain gauge sensors in the knuckles of each finger (see Fig. 1). All the sensors are polled at 300 Hz except the pressure sensors which are polled at 25 Hz.

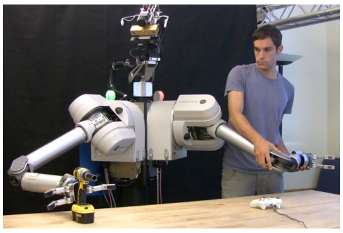
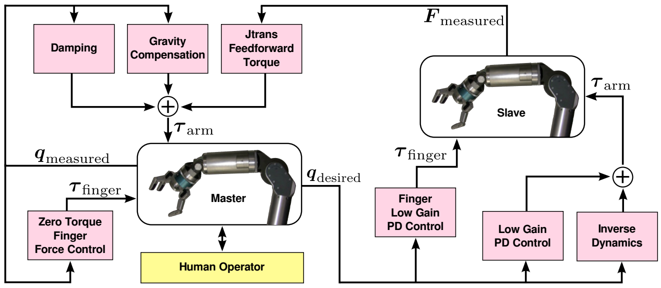


Fig. 6: Dual arm manipulator used as master-slave system to teach manipulation skills (left) and corresponding control diagram (below). Movements of the master arm are mimicked by the slave arm. Force feedback is provided using the f/t sensor at the wrist of the slave arm.



To record movements as well as sensor data from the hand we developed a master-slave system in which one arm is used to teleoperate the other. The master-slave system is realized by setting the measured arm and finger joint angles of the master arm to be the desired arm and finger joint angles of the slave arm. The finger joints on the master arm have been made actively compliant by closing a force control loop on the strain gauges. Furthermore, force feedback is provided to the human operator using the force/torque sensor at the wrist of the slave arm (see Fig. 6). The master-slave system preserves all the sensor information experienced during the demonstration. Using kinesthetic teaching (by moving one of the robot arms directly) would result in significantly disturbed sensor signals.

VII. EXPERIMENTAL RESULTS

The task consisted of turning on a drill standing upright on a table. We taught 5 different reaching movements with the drill placed at 5 different locations to simulate perception uncertainties. The 5 locations are chosen such that initial contact is made with the palm, with the first link of the middle finger, the fingertip of the middle finger (see Fig. 7.2), the first links of the left and right fingers, and the fingertips of the left and right fingers (see Fig. 1). Appropriate regrasp behaviors were demonstrated for 4 of these object positions. Finally, finger closing and triggering behaviors were demonstrated, resulting in a total of 11 ASMs. Each of these movements has only been demonstrated once using the master-slave system. The demonstrated movement primitives have been chosen to facilitate very robust task execution

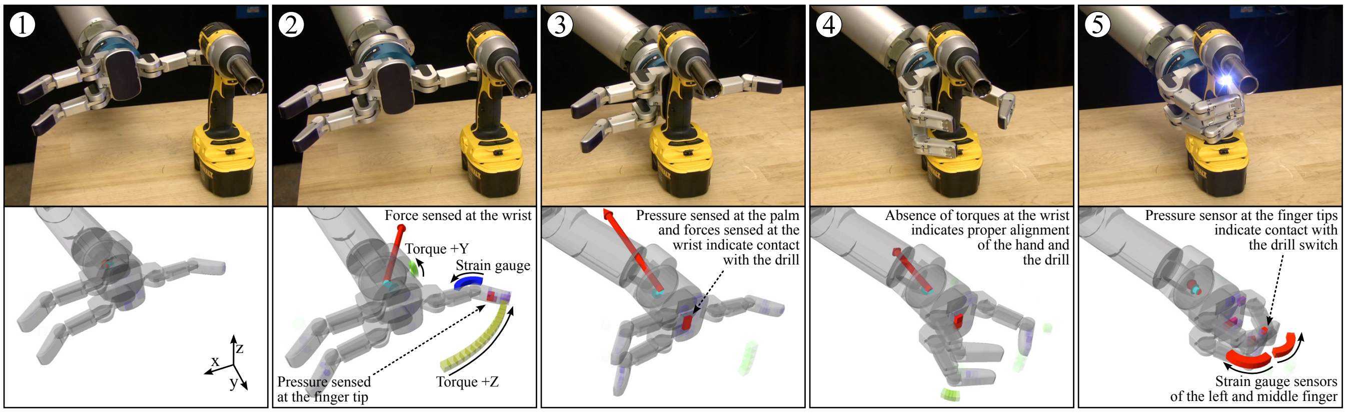


Fig. 7: Sequenced execution of movement primitives leading to successfully turning on the drill even though the drill was misplaced (top row) and visualized sensor data (bottom row). Fig. 8 and Fig. 9 show the corresponding plot of expected and measured sensor traces.

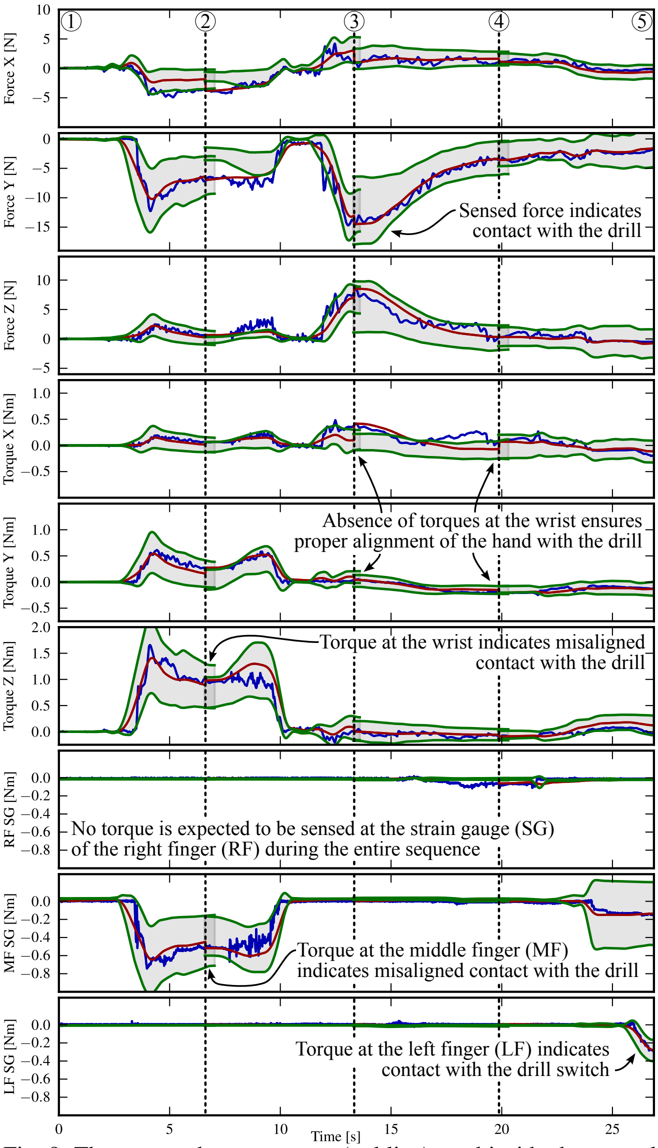


Fig. 8: The expected sensor traces (red line) used inside the control loop (see Fig. 3) are set to the current sensor state (blue line) at the point of switching. The green lines show $\pm$ 1-standard deviation. Dashed vertical lines indicate transitions. The plot shows that our method closely predicts all sensor values while performing the task (see Fig. 7) and correctly chooses subsequent movement primitives.

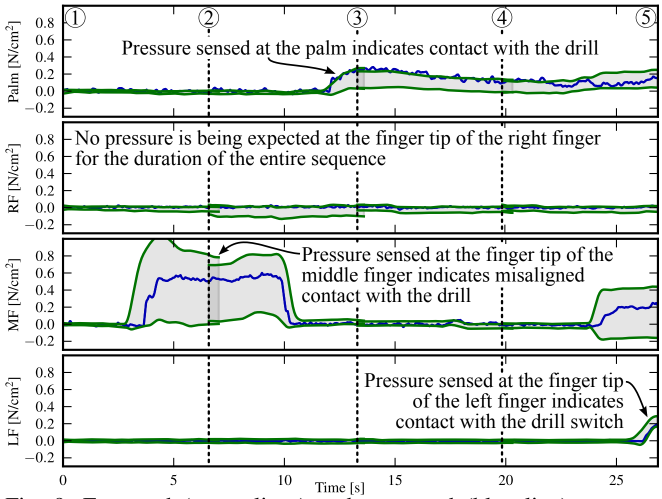


Fig. 9: Expected (green lines) and measured (blue line) pressure sensor signals while performing the task shown in Fig. 7.

by appropriately choosing subsequent primitives online (see Sec. V). During the ASM acquisition procedure (see Sec. IV) the start and goal of each DMP was varied by a few centimeters to explore different parts of the workspace. The Jacobian of the task $\mathbf{J}_{sensor}$ in Eq. (4) simplified to an identity matrix $\mathbf{I} \in \mathbb{R}^{9\times 9}$ given that the DMP has been encoded in the hand frame and the particular location of the sensors. As shown in Fig. 3, the desired position and orientation $\boldsymbol{x}_{\text{desired}}$ has been adapted online based on the difference between the expected forces and torques (red lines in top 6 plots in Fig. 8) and those measured at the wrist (corresponding blue lines). Respectively, the desired finger joint trajectories $\boldsymbol{q}_{\text{desired}}$ have been adapted based on the difference between the expected finger torques (red lines in bottom 3 plots in Fig. 8) and those measured at the finger knuckles (corresponding blue lines). The recorded sensor traces associated with the "regrasp right movement" are shown in Fig. 2. The proposed method was verified for various initial drill positions. Fig. 7 shows one trial in which the drill was misplaced to the left. The corresponding plots for the force/torque sensors at the wrist and the strain gauge sensors at the knuckles are shown in Fig. 8, and plots of the pressure sensors are shown in Fig. 9. Dashed vertical lines in Fig. 8 and Fig. 9 indicate transitions between successive ASMs, and the state of the system at these transition points is depicted in Fig. 7. At time instant (2), torques at the wrist and middle finger, and pressure at the finger tip indicates that the drill is misaligned. Subsequent ASMs are determined online as described in Sec. V, i.e., the past 30 sensor values (corresponding to 0.1 seconds) of all available sensors are compared with all initial sensor signatures of all 11 ASMs maintained in the library. The closest match is selected, in this case the "re-grasp left movement", also facilitating continuous (predicted) sensor signals. Execution of this re-grasp behavior aligns the hand with the drill, which is confirmed by the sensed force at the wrist and pressure at the palm, see instant (3). This allows the system to proceed with the finger closing and triggering behaviors, finally bringing the system to the state at time instant (5) where pressure sensed at the left finger tip indicates contact with the drill switch. Determining subsequent ASMs online facilitates our system to cope with significant object pose uncertainty, even if the drill is being moved mid-way as shown in the video [22]. The red lines in Fig. 8 correspond to the predicted sensor signals that have been used inside the real-time control loop, see Fig. 3. As described in Sec. IV, these sensor signals have been encoded into DMPs. At the point of transition between two subsequent ASMs (dashed lines in Fig. 8) the start of the sensor DMP is set to the current state. The obtained online movement adaptations of the desired endeffector and finger joint trajectories drive the current sensor state to remain close to the predicted values. This significantly contributes to generating stereotypical sensor traces even under uncertainty. That is, even if the drill is misplaced causing for example premature contact, the online adaptation of the desired endeffector pose and finger joint trajectories based on force feedback causes the hand and fingers to give in ensuring that subsequent executions result in similar sensor experiences; a key feature that allows our system to successfully retrieve the most appropriate subsequent ASMs. The task could successfully be completed even if the drill was misplaced manually mid-way through the trial, as shown in the video [22]. We want to stress the generality of the proposed approach. No task specific engineering has been done to achieve these results.

VIII. Conclusion and Future Work

We presented a first step towards Associative Skill Memories (ASMs). We have shown a method to acquire manipulation skills such that we are able to continuously predict all associated sensor signals. These predictions can be used to determine robust sequences of acquired skills online to achieve a complete task. We have demonstrated the feasibility of this approach on a real robot. We want to emphasize that our approach presents a general method to close perception-action loops for manipulation tasks. We are working towards including visual information such as extracted object poses in the presented framework, i.e. following up on previous work [19] and also using visual information within feedback control loops. We are also investigating the use of automated movement segmentation algorithms [23] to allow for more complex imitation learning scenarios.

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