Abstract—Modelling of contact-rich tasks is challenging and cannot be entirely solved using classical control approaches due to the difficulty of constructing an analytic description of the contact dynamics. Additionally, in a manipulation task like food-cutting, purely learning-based methods such as Reinforcement Learning, require either a vast amount of data that is expensive to collect on a real robot, or a highly realistic simulation environment, which is currently not available. This paper presents a data-driven control approach that employs a recurrent neural network to model the dynamics for a Model Predictive Controller. We extend on previous work that was limited to torque-controlled robots by incorporating Force/Torque sensor measurements and formulate the control problem so that it can be applied to the more common velocity controlled robots. We evaluate the performance on objects used for training, as well as on unknown objects, by means of the cutting rates achieved and demonstrate that the method can efficiently treat different cases with only one dynamic model. Finally we investigate the behavior of the system during force-critical instances of cutting and illustrate its adaptive behavior in difficult cases.

I. INTRODUCTION

During the execution of a contact-rich manipulation tasks, the dynamics of the contact can display a great degree of variation due to nature of the object. However, humans are able to gracefully manipulate different objects and tools by adjusting the exerted force according to their sensory feedback. In general, objects can exhibit inter-class differences (different classes of objects need to be treated differently), as well as intra-class ones (not all objects in the same class have the same characteristics, like size or stiffness) which makes these tasks difficult to simulate. In order to deal with these differences in robotic manipulation, classical force control approaches require explicit tuning that depends on the instance of contact. On the other hand, an approach exclusively based on learning requires a vast amount of data [1] that may be considerably expensive to acquire in a real setting.

An alternative control scheme that does not require fine tuning between executions is Model Predictive Control (MPC) [2]. Controllers of that type are able to optimize the control inputs by considering the long-term performance based on an accurate model of system dynamics. However, for tasks exhibiting a large degree of variety in the dynamics, providing such a detailed analytic model can be challenging or even practically unattainable.

Instead, we integrate MPC in a data-driven approach as seen in Fig.1 that employs deep learning and recurrent neural networks to act as the basis for the controller. As a result, we obtain a method that leverages the modeling capabilities of deep learning and combines them with the cutting instant-independent control of MPC. In contrast to open-loop policies, where the complete control sequence depends only on the initial state, receding horizon control schemes, such as MPC, implement a feedback policy with the control action depending on the measured state at every timestep. This way, potential model/plant mismatches or disturbances can be accounted for at the next sampling instant, preventing the system from exhibiting unstable behaviour. Additionally, the model and the controller itself are not coupled since MPC does not require training, so if a different behaviour needs to be encouraged, the user can simply change the cost function parameters to accommodate it.

We chose to examine the potential of the data-driven MPC approach in the context of robotic food-cutting as its intrinsic dynamics provide an excellent test-bed and additionally, this particular application has not been revisited after the seminal work of Lenz et al. [3] to the authors’ knowledge. This is possibly due to the difficulty of the task itself, as well as the difficulty of adjusting and re-implementing a method for different robotic settings, especially when the robots involved display incomparable technical aspects such as payloads or torque limits. It should be noted that most robots used in similar research topics are torque-commanded and inherently...
compliant, unlike the majority of widely-used robots that are either position, or velocity controlled. This adds another level of complexity as the state variables cannot include joint torques and the control laws need to be resolved either through position or velocity. With that in mind, we are taking advantage of Force/Torque sensors to implement a reactive controller that will help encode the desired behavior while also allowing for a task-space control scheme.

The motivation behind this work is to find a balance between classical control approaches that require tuning and an analytic description of the task and purely learning approaches that require a vast amount of data, as simulating this task is not feasible. In this article, we reformulate the work in [19] for velocity controlled manipulators which possess force sensing. We illustrate the effectiveness of our method in learning the dynamics of the manipulation task in a series of experiments and additionally demonstrate its generalization to unknown objects. Finally, we further evaluate its adaptation ability in difficult, force-critical cases.

II. RELATED WORK

A. Classic Control

Traditionally, robotic manipulation has been mainly treated through force control [4]–[6]. Despite their robustness and good performance in simple, well-defined tasks, force controllers lack the ability to discern long-term interactions. In a complicated task that displays a lot of variations in the contact dynamics, that translates to tedious tuning in order to make them effective [7]. Adaptive control [8], [9] offers a mechanism for adjusting such parameters online and can account for some degree of parametric uncertainty in the system. However, it requires much simpler models and even then, results in a greedy policy as opposed to the, locally, optimal ones we are discussing. Parallel and hybrid position/force approaches [10], [11] provide efficient formulations for a plethora of tasks but are still only applicable to simpler interaction models where the geometries can be accurately defined by hand-picking the corresponding position/force controlled axes through the selection matrices. Finally, optimal control approaches such as LQR [12] and its variants, although capable of adapting to the observed dynamics, tend to require linear or linearized models and quadratic costs that inevitably hinder the complexity they can handle.

B. Data-Driven Control

In an attempt to overcome the difficulties of classical control, several categories of data-driven approaches have emerged in manipulation. Some of them, employ human demonstrations in order to learn the force profiles needed to successfully complete complex tasks with impressive results [13]–[18]. However, in our scenario, recording a demonstration by leading the robot through the motion, would prove problematic since it would be impossible to distinguish the wrench applied by the human from the one applied by the object without having to resort in external tracking solutions as the one in [19]. Considerable progress has been made by the reinforcement learning community [1], [20] but a large body of these methods is model-free which is forbidding due to sample complexity. On the other hand, model-based methods [21]–[24] require less samples but employ simpler approximators such as Gaussian processes and linear representations, which are not appropriate for highly non-linear dynamics. In addition, reinforcement learning requires either online exploration, which would be dangerous in this setting, or training in simulation, which is not realistic as it is infeasible to accurately model the dynamics during cutting. Similar to our work, several researchers have used neural networks to learn the dynamics model for an MPC. In [25], [26] however, real world trials are required to improve the RL policy. Differently from our focus, these works are not trying to learn a policy for a task with large variation in dynamics. Lastly, in [27], [28] the authors are combining deep networks and MPC in a manner akin to ours but in the distinct fields of self-tuning optical systems and robot-assisted dressing which do not contain complex contact dynamics.

The goal in this work is to create a data-driven control approach that allows for online adaptation of the system’s behavior in a setting with complex dynamics, such as food-cutting. To this aim, we learn the physical dynamics through a recurrent deep network that allows for online adaptation of the system’s dynamics, while performing online calculations for a Model Predictive Controller. Fig. 1 presents schematically the control process during data collection (Fig. 1a) and online deployment (Fig. 1b).

III. PROBLEM FORMULATION

Consider a robotic manipulator equipped with force sensing. Let \( p(t) \in \mathbb{R}^3 \) denote the translation part of the end-effector pose in the world frame and \( F^e(t) \in \mathbb{R}^3 \) the sensor’s force measurements at time \( t \). Let further \( p_d(t), \dot{p}_d(t) \) denote a desired position, velocity of a trajectory and \( F^r(t), F_d(t) \) the reference and desired contact force. If the goal is to follow a predefined trajectory in a compliant manner, we can employ the inverse damping control law:

\[
 u = K_a (F^e(t) - F^r(t))
\]  

(1)

We can then define the desired compliant behavior as:

\[
 F^r(t) = F_d - K_a^{-1} (\dot{p}_d(t) - K_p \varepsilon_p(t))
\]  

(2)

where \( K_p, K_a \in \mathbb{R}^{3 \times 3} \) are the stiffness and compliance gain matrices and \( \varepsilon_p(t) = p(t) - p_d(t) \) is the position error.
Substituting (2) in (1) results in the desired dynamic behavior:
\[
\dot{p}_t(t) + K_p e_p(t) = K_a e_f(t) \tag{3}
\]
where \(\dot{p}_t(t) = \dot{p}(t) - \dot{p}_d(t)\), \(e_f(t) = F^s(t) - F_d(t) \in \mathbb{R}^3\) are the velocity and force errors respectively.

The variations in the contact properties during a cutting task make it impossible to globally define a fixed trajectory \(p_d, \dot{p}_d\) or even a desired force \(F_d\). For instance, for objects of different size, different types of motion are required to ensure that the knife will make contact. Moreover, a quick motion with large velocity that is appropriate for less stiff objects, will not be obtainable for stiffer ones. Nonetheless, we can produce the desired behavior by determining a reference force \(F^r\) for the axes that are involved in the cutting motion in (3). Since the geometry and the dynamics of the contact are unknown, we model them as a discrete-time dynamics function \(\hat{p}_{t+1} = f(p_t, F^r_t, F^s_t)\) and determine an optimal reference force such that it minimizes a cost \(C(p_t, F^r_t)\) over a time horizon \(T\), by solving the optimization problem:
\[
F^{rs} = \arg\min_{F^r} \sum_{k=1}^{T} C(p_{t+k}, F^r_{t+k}) \tag{4}
\]
We parametrize the dynamics function \(f(p_t, F^s_t, F^r_t)\) as a deep recurrent network that receives the current positions, measured and reference forces, and outputs the estimated future positions. We define the model’s state as the augmented state vector \(x_t = \{p_t, F^r_t\}\) and denote \(u_t = F^r_t\) for brevity, resulting in the formulation:
\[
\hat{p}_{t+1} = f(x_t, u_t) \tag{5}
\]
Incorporating the force measurements in the augmented state vector and defining the transition function is such a way, allows this method to be used with velocity-controlled robots. However, if a torque interface is available, substituting \(F^r\) with the current wrench provided by the robot’s joints and \(F^s\) for the future control input, will result in the formulation in (3).

We simplify the problem by not considering the full pose of the end-effector as the state of the MPC but rather, only the translational components of the motion, namely \(Y\) and \(Z\) as seen in Fig. 2. Since we do not require any trajectories for these axes and \(F^{rs}\) acts as \(F_d\), their respective \(K_p\) gains are set to zero. Accordingly, the rest of the axes are stabilized through a set-point stiffness control law by setting \(\ddot{x}_d\) and the corresponding compliance gains to zero.

### IV. Method

In this section we describe the architecture of the network implementing (3) and the training procedure in sec. IV-A. In sec. IV-B, we explain the data collection process and in sec. IV-C, the preprocessing we applied. Finally, in sec. IV-D, we present the procedure for the online deployment of the method.

#### A. Network Architecture and Training

The network architecture is depicted in Fig. 4 and consists of 6 fully connected (FC) layers and 2 recurrent layers with 30 units each (RNN\(_{\text{latent}}\)). Initially, the system state is processed by 2 fully connected layers that are structured as an Encoder (FC\(_{\text{en}}\)) and provide the latent representation of the dynamics. In cases of systems with contacts, positions and forces carry redundant information that might compromise the network’s performance. By embedding them to their lower-dimensional latent representation, the most salient features of the data are kept, thus allowing learning to be more effective. As we are aiming to reconstruct a dynamics function, we employ a recurrent layer for the latent representation before the output layer. Accordingly, the immediate dependencies on the current state and control input are treated by FC\(_{\text{state}}\), FC\(_{\text{input}}\) and concatenated at the output layer.

Since we are using relative positions, the sign indicates the direction of the motion and depending on the material at hand or the tool used, the forward and backward motions might not have the same dynamics, e.g. using a serrated knife results in completely different force profiles for the two motions. To facilitate learning and ensure that negative values are represented properly, the non-linearities of the network are hyperbolic tangents that do not threshold at zero.

The final network is trained to predict a sequence of \(H_b = T_{\text{horizon}}/M\) time-blocks into the future by iteratively using its previous predicted outputs as the new position inputs. During training, the corresponding force input blocks are the forces of the respective future blocks and during online deployment the actual force measurements. The MPC cost can then be calculated as:
\[
C = C(p_b, u_b) + \sum_{i=1}^{H_b} C(\hat{p}_{b+i}, u_{b+i}) \tag{6}
\]
In order to avoid issues with error accumulation in long-term predictions, we utilize the three-stage training approach that proved to be superior to random initialization in [3]. Before switching to next-state predictions, the FC\(_{\text{en}}\) layer is first initialized by training it as an AutoEncoder [29]. During this stage, only the current and previous states are considered and the goal is to make sure the latent representation has captured the dynamics of the task before it is asked to predict the future positions. Next, the rest of the network, excluding the RNN layers, is trained for a single-step prediction into the future and finally, the weights of that model are loaded to the full network that is providing the positions for the next \(H_b\) blocks. The lack of a torque interface does not allow us to record control forces during data collection. However, for training purposes we can use the sensor forces as \(u_b\), in order to enable the network to directly encapsulate the effect of measured forces on the next states, instead of solely relying on their latent representation.

#### B. Dataset Collection

In order to collect data, we employed the controller described in (3) as seen in Fig. 1a. For every trial, a 5th
Fig. 3: Training set

The prescribed motion consists of a periodic triangular trajectory for the sawing axis and a steady descent for the cutting one. The sawing range was kept constant for every trial but we changed the number of repetitions for thicker objects to ensure a complete cut. Our complete training set includes 71 datasets of cutting trials for 9 different cases of object types as seen in Fig.3. During data collection, we used clamps to stabilize the objects on the table. Although our robot is bi-manual, immobilizing the object with a set-point stiffness controller on the second arm would make that arm part of the dynamical system through the restoring forces it exerts. This would introduce additional dynamics due to the relative motion between the object and the knife, which can either enable or impede the cutting itself.

C. Data preprocessing

Before feeding the data to the network, we applied the same preprocessing suggested by [3], namely, instead of considering single points in time, we built non-overlapping blocks consisting of \( M \) timesteps of positions and forces. Every block \( b \) then, corresponds to the sampling interval \([bM, (b+1)M - 1]\) leading to \( x_b \in \mathbb{R}^{M \times 6} \) and \( u_b, \hat{p}_b \in \mathbb{R}^{M \times 3} \). The position part of \( x_b \) is expressed relatively to the previous block’s last position. In that way, a relative displacement over time is acquired which serves as a generalized velocity. This intuitively agrees with our goal of learning interaction control as a mapping between velocities and forces by drawing a parallel to the system’s mechanical impedance. Although we could have used measured Cartesian velocities immediately, in a real robotic setting it is not advisable as the measurements are usually very noisy and not easy to acquire. Finally, both relative positions and forces in every block are normalized by removing the mean and scaled to unit variance to make sure the network weighs them equally. The normalization is performed through a scaler, fitted to the training data during training/validation in order to avoid any information leaking, and to the whole of our dataset during online deployment.

D. Online Model Predictive Control

During online deployment, we follow the process shown in Fig.4. In that setting, we first allow a small motion driven by the controller that was used for data collection in order to make contact with the object and initialize the system.

Solving (4) for non-linear systems is not trivial even in the case of quadratic costs as the time the optimizer requires to converge might be forbidding for real-time control of fast processes. Instead, we employ a random shooting method [25], [28], [31] that samples \( K \) possible control inputs from a normal distribution as the feasible forces and demonstrate that it can achieve effective cutting rates for different object classes. When the state space increases, shooting methods might be slower than the optimization approach but in our case, this method is preferable as it is much simpler and allows us to implicitly set input constraints by sampling from specific distributions.

After the initial motion is executed, for every MPC iteration, a number of feasible actions is generated by sampling from a uniform distribution that limits the amplitude of the generated forces to 8N which was both appropriate for the robot’s limits and for cutting most objects. To make the solution computationally more tractable, every time we generate an action, we assume that it will stay constant during the prediction horizon. The network is queried to predict the next states resulting from these actions, giving us the next Cartesian positions for which the accumulated cost is calculated and the best one is chosen as the next control input. The cost function used comprised two basic terms that encouraged the sawing motion around the center point \( p_{center} \) of the sawing range while moving downwards until the knife reached the table’s height \( p_{table} \), a terminal cost and the norm of the control inputs, namely for every
The cost was given by:

\[
C(p, u) = c_{\text{cut}} \sum_{k=1}^{H_b} (p_k^z - p_{\text{table}})^2 + p_{H_b}^z + c_{\text{saw}} \sum_{k=1}^{H_b} (|p_k^z - p_{\text{center}}|)^2 + c_{u} \sum_{k=1}^{H_b} \|u_k\|^2
\]

where \(c_{\text{cut}}, c_{\text{saw}}\) are positive constants weighting the contribution of the costs associated with cutting and sawing actions respectively to the total cost while \(c_{u}\) is the weighting constant for the control input quadratic term.

V. EVALUATION

In all our experiments, we used a YuMi-IRB 14000 collaborative robot manufactured by ABB with an OptoForce 6axis Force/Torque sensor mounted on its wrist that we controlled at a rate of 10Hz. Since collaborative robots have a low payload (0.5kg) we removed the gripper of the cutting arm and instead attached the knife directly to the arm with a custom-made mount. The controllers for the robot are implemented as ROS control [32] plugins that use the robot’s velocity interface since a torque one is not available. The deep recurrent network modeling the dynamics is implemented in PyTorch [33] and employed in ROS through rospy. More details about the code implementation can be provided upon request.

**A. Cutting Rate**

For the evaluation of the method, we conducted over a hundred experiments where the goal was to completely cut through the object. We deliberately included objects that offered a wide range of interactions during cutting, spanning from homogeneous easy to cut cases (cake, cucumber) that do not offer a lot of resistance and do not display high friction in the lateral axis of motion, to stiff objects with viscus properties (zucchinis, cheese) and finally, to objects displaying high variation in their dynamics and stiffness (bell peppers, red peppers, lemons, unpeeled bananas). All of these types had been encountered in training, but we additionally included the difficult case of an unknown object, i.e. potatoes, to test the generalization ability of the learned dynamics.

As a proof of concept, the performance was evaluated, similarly to [3], in terms of the cutting rate achieved by the proposed method as compared to the ones from the standard trajectory-tracking controller we used for data collection. To make the comparison as fair as possible, we tuned the baseline controller for each class separately by modifying both the stiffness and the trajectory followed to increase the cutting rate as much as possible for every object type. From the experimental results seen in Fig. 5 it is evident that our method outperforms the baseline, except in the case of cheese where the smoother motions produced by the fixed trajectory controller were more effective than their aggressive MPC counterparts to break friction. The difference in rates achieved is more palpable for the red peppers and the potatoes. In the former case, the object at hand is not homogeneous with consistent density so cutting through the skin and moving to the hollow interior immediately alleviates the resistance, thus allowing for an immediate downward motion. Contrary, in the latter case, the MPC could overcome the resistance induced by the knife being fully embedded in the flesh of the potato by switching to more high-frequency sawing motions (Fig. 6a), as opposed to the fixed trajectory controller (Fig. 6b).

**B. Force-Critical Points**

The ultimate goal in this work is to develop a flexible manipulation scheme that is able to adjust its behavior and
respect its limitations in order to successfully complete the objective. To accomplish this, it is necessary to come up with an evaluation criterion that encompasses both of these aspects and is indicative of the behavior we are seeking. For instance, although the dynamics model’s prediction accuracy is an intuitive measure to this end, a small error is not enough to reflect the network’s ability to discern the dynamic behavior. Even with the normalization of the input vectors, the kinematic features have a much more easily discernible structure when compared to the noisy, instant-dependent forces, which can lead the network to concentrate more on them. This can prove problematic in force-critical cases as simply moving towards the goal when progress is halted by a very stiff material, can potentially lead to failure due to joint torque limits.

Additionally, despite that cutting rate is also an intuitive measure for this task, its applicability and expressiveness are strongly correlated to the robot’s potential at exerting forces and the controller used as baseline. Arguably, it is possible to design control laws that maximize the cutting rate, albeit with tuning between executions, thus confirming our first goal. However, consider the extreme case of a strong industrial manipulator. A far faster cutting rate could be achieved simply by using a position controller since the resistance from the object would never exceed the arm’s potential but in our setting, this is not relevant primarily due to the hardware at hand but mostly as this criterion fails to depict the aforementioned desired behavior.

To this end, we focus at force critical points where the dynamics are imperative and would lead to a failed cut. To evaluate this, we chose to use carrots as they were not encountered during training and their core is almost impossible to cut through with our robotic setting. As seen in Fig. 7 the normal cutting strategy fails the moment the knife hits the thicker center part of the carrot so it retreats until the tip is no longer in contact with that part. The corresponding figures in Fig. 7 show the controller’s outputs and the resulting positions during the same test. From $t = 0$ s until $t = 4.5$ s we observe an intense sawing motion to break the friction which enables the downwards motion until approximately $t = 6$ s where the knife reaches the stiff part, the controller tries to lift it to re-apply pressure while only commanding positive forces on $Y$ that pull the knife away from the force-critical point in order to minimize the cost.

VI. Conclusions and future work

In this article, we presented a data-driven MPC approach for the task of food-cutting. We reformulated an older work by incorporating measurements from a Force/Torque sensor and restated the control problem. Instead of solely considering previously encountered objects during evaluation, we demonstrated that, with the same model, this method can generalize to unseen ones and treat different object types by adjusting its behavior. We investigated the system’s failure modes by introducing an object that warranted an unsuccessful cut and observed the resulting trajectory. Although the outcome is a sensible solution, the direct effect that the learned dynamics model has on this behavior is unclear and
will be further investigated in future work.

Robotic food cutting is however only one example of numerous possible applications for this type of controllers. Integrating a complex, non-linear data-driven model into MPC, can potentially allow for elegant solutions that are able to generalize without the need for fine-tuning. This would add significant flexibility in difficult manipulation scenarios such as ones involving deformable objects where the contact dynamics are also challenging to model.

An interesting addition to our work, would be to incorporate the second arm as an explicit part of the system and explore the dynamics of the coupled motion. By actively controlling the second arm, we can induce more motion when necessary to move the knife faster out of areas with considerable friction in the lateral axis, or stabilize the object better to accelerate the motion.

However, by doing so, the control task becomes even more complicated and the state space will increase accordingly. As a consequence, random shooting will be insufficient and there will be need for a more sophisticated solution such as the one presented in [34], that offers guarantees of global optimality.

REFERENCES

[1] S. Levine, C. Finn, T. Darrell, and P. Abbeel, “End-to-end training of deep visuomotor policies,” J. Mach. Learn. Res., vol. 17, no. 1, pp. 1334–1373, Jan. 2016. [Online]. Available: http://dl.acm.org/citation.cfm?id=2946645.2946684
[2] D. Q. Mayne and H. Michalska, “Receding horizon control of nonlinear systems,” IEEE Transactions on Automatic Control, vol. 35, no. 7, pp. 814–824, July 1990.
[3] I. Lenz, R. A. Kepper, and A. Saxena, “Deepmpc: Learning deep latent features for model predictive control,” in Robotics: Science and Systems, 2015.
[4] N. Hogan, “Impedance control: An approach to manipulation,” in 1984 American Control Conference, June 1984, pp. 304–313.
[5] B. Siciliano and L. Villani, Robot Force Control, 1st ed. Norwell, MA, USA: Kluwer Academic Publishers, 2000.
[6] J. D. Schutter and H. V. Brussel, “Compliant robot motion i. a formalism for specifying compliant motion tasks,” The International Journal of Robotics Research, vol. 7, no. 4, pp. 3–17, 1988. [Online]. Available: https://doi.org/10.1177/027836498800700401
[7] Y. Karayiannidis and Z. Doulgeri, “An adaptive law for slope identification and force position regulation using motion variables,” vol. 2006, 06 2006, pp. 3538 – 3543.
[8] D. Zhang and B. Wei, “A review on model reference adaptive control of robotic manipulators,” Annual Reviews in Control, vol. 43, pp. 188–198, 2017. [Online]. Available: http://www.sciencedirect.com/science/article/pii/S1367588116301110
[9] Y. Karayiannidis, C. Smith, F. E. V. Barrientos, P. Ogren, and D. Kragic, “An adaptive control approach for opening doors and drawers under uncertainties,” IEEE Transactions on Robotics, vol. 32, no. 1, pp. 161–175, Feb 2016.
[10] S. Chiaverini and L. Sciavicco, “The parallel approach to force/position control of robotic manipulators,” IEEE Transactions on Robotics and Automation, vol. 9, no. 4, pp. 361–373, Aug 1993.
[11] M. H. Raibert and J. J. Craig, “Hybrid position/force control of manipulators,” Journal of Dynamic Systems Measurement and Control, vol. 103, 12 1980.
[12] V. Mehrmann, “The autonomous linear quadratic control problem : Theory and numerical solution,” vol. 163, 01 1991.
[13] K. Kronander and A. Billard, “Learning compliant manipulation through kinesthetic and tactile human-robot interaction,” Haptics, IEEE Transactions on, vol. 7, pp. 367–380, 07 2014.
[14] M. Li, H. Yin, K. Tahura, and A. Billard, “Learning object-level impedance control for robot grasping and dexterous manipulation,” in 2014 IEEE International Conference on Robotics and Automation (ICRA), May 2014, pp. 6784–6791.
[15] A. X. Lee, H. Lu, A. Gupta, S. Levine, and P. Abbeel, “Learning force-based manipulation of deformable objects from multiple demonstrations,” in 2015 IEEE International Conference on Robotics and Automation (ICRA), May 2015, pp. 177–184.
[16] S. Manschitz, M. Gienger, J. Kober, and J. Peters, “Mixture of attractors: A novel movement primitive representation for learning motor skills from demonstrations,” IEEE Robotics and Automation Letters, vol. 3, no. 2, pp. 926–933, April 2018.
[17] B. Akgun and A. Thomaz, “Simultaneously learning actions and goals from demonstration,” Auton. Robots, vol. 40, no. 2, pp. 211–227, Feb. 2016. [Online]. Available: https://doi.org/10.1007/s10514-015-9448-x
[18] B. Huang, M. Li, R. L. De Souza, J. J. Bryson, and A. Billard, “A modular approach to learning manipulation strategies from human demonstration,” Autonomous Robots, vol. 40, no. 5, pp. 903–927, Jun 2016. [Online]. Available: https://doi.org/10.1007/s10514-015-9501-9
[19] T. Tang, H.-C. Lin, and M. Tomizuka, “A learning-based framework for robot peg-hole-insertion,” in ASME 2015 Dynamic Systems and Control Conference, 10 2015, p. V002T27A002.
[20] S. Levine and V. Koltun, “Learning complex neural network policies with trajectory optimization,” vol. 3, 06 2014.
[21] J. Boedecker, J. T. Springenberg, J. Wlting, and M. Riedmiller, “Approximate real-time optimal control based on sparse gaussian process models,” in 2014 IEEE Symposium on Adaptive Dynamic Programming and Reinforcement Learning (ADPRL), Dec 2014, pp. 1–8.
[22] R. Lioutitik, A. Paraschos, J. Peters, and G. Neumann, “Sample-based information-theoretic stochastic optimal control,” in 2014 IEEE International Conference on Robotics and Automation (ICRA), May 2014, pp. 3896–3902.
[23] S. Levine and P. Abbeel, “Learning neural network policies with guided policy search under unknown dynamics,” in Advances in Neural Information Processing Systems 27, Z. Ghahramani, M. Welling, C. Cortes, N. D. Lawrence, and K. Q. Weinberger, Eds. Curran Associates, Inc., 2014, pp. 1071–1079. [Online]. Available: http://papers.nips.cc/paper/5444-learning-network-policies-with-guided-policy-search-under-unknown-dyn
[24] M. Deisenroth and C. Edward Rasmussen, “Pilco: A model-based and data-efficient approach to policy search.” 01 2011, pp. 465–472.
[25] A. Nagabandi, G. Kahn, R. S. Fearing, and S. Levine, “Neural network dynamics for model-based deep reinforcement learning with model-free fine-tuning,” arXiv preprint arXiv:1708.02596, 2017.
[26] G. Williams, N. Wagener, B. Goldfain, P. Drews, J. M. Rehg, B. Boots, and E. A. Theodorou, “Information theoretic MPC for model-based reinforcement learning,” Proceedings - IEEE International Conference on Robotics and Automation, pp. 1714–1721, 2017.
[27] T. Baumeister, S. L. Brunton, and J. N. Kutz, “Deep Learning and Model Predictive Control for Self-Tuning Mode-Locked Lasers,” pp. 1–9, 2017.
[28] D. Erickson, H. M. Clever, G. Turk, C. K. Liu, and C. C. Kemp, “Deep haptic model predictive control for robot-assisted dressing,” arXiv preprint arXiv:1709.09735, 2017.
[29] Y. Bengio, P. Lamblin, D. Popovici, and H. Larochelle, “Greedy layer-wise training of deep networks,” in Advances in Neural Information Processing Systems 19, B. Schölkopf, J. C. Platt, and T. Hoffman, Eds. MIT Press, 2007, pp. 153–160. [Online]. Available: http://papers.nips.cc/paper/3048-greedy-layer-wise-training-of-deep-networks.pdf
[30] C. Oni, Cartesian Impedance Control of Redundant and Flexible-Joint Robots, 1st ed. Springer Publishing Company, Incorporated, 2008.
[31] A. Rao, “A survey of numerical methods for optimal control,” Advances in the Astronautical Sciences, vol. 135, 01 2010.
[32] S. Chitta, E. Marder-Eppstein, W. Meeussen, V. Pradeep, A. Rodriguez Tsooruakkadjan, J. Bohren, D. Coleman, B. Magyar, G. Raiola, M. Lüdtke, and E. Fernández Perdomo, “ros-control: A generic and simple control framework for ros,” The Journal of Open Source Software, 2017. [Online]. Available: http://www.thejoeg.org/joss-papers/joss.00456/v10i115/os.00456.pdf
[33] A. Paszke, S. Gross, S. Chintala, G. Chanan, E. Yang, Z. DeVito, Z. Lin, A. Desmaison, L. Antiga, and A. Lerer, “Automatic differentiation in pytorch,” in NIPS-W, 2017.
[34] Y. Chen, Y. Shi, and B. Zhang, “Optimal Control Via Neural Networks: A Convex Approach,” pp. 1–26, 2018. [Online]. Available: http://arxiv.org/abs/1805.11835