Learning Dynamics Models of Contacts from Tactile Sensors

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***Abstract*— Classical methods to estimate the dynamics of a robot in presence of external contacts rely on joint-torque sensing, estimation of the contact position and accurate system identification. While the contact position can be estimated by whole body tactile sensors, this approach requires a kinematic spatial calibration, which is prone to errors. As an alternative to classical model-based approaches we propose a data-driven mixture-of-experts learning approach using Gaussian processes. This model predicts joint torques directly from raw data of tactile and force/torque sensors. We show that the learned model accurately predicts the joint torques resulting from contact forces, is robust to changes in the environment and outperforms existing dynamic models that use of force/torque sensor data.**

I. Introduction

A key challenge for torque-controlled humanoid robots is to accurately estimate their dynamics in presence of contacts, e.g., during manipulation in clutter [11], whole-body movements [12] or ground contacts in locomotion [1]. Analytic dynamics models suffer from inaccurate parameter estimation, unmodeled dynamics (e.g., friction, couplings, elasticities) and noisy sensor measurements. With contacts the problem is even more challenging due to discontinuities and additional non-linearities, which are difficult to model or estimate. Moreover, if contact locations are not fixed a priori or known with sufficient precision, small errors in the localization of the external force can substantially deteriorate the inverse dynamics computation [7]. With inaccurate dynamics models, many control strategies like inverse dynamics control [8], computed torque control [17] or model predictive control [13] that rely on accurate dynamic models produce suboptimal policies. We present the newest developments on this topic stemming from [2]. In contrast to classical techniques based on the identification of dynamics parameters [19], [15], [18], we use a fully data-driven machine learning approach based on non-parametric models, where both the rigid body dynamics and the effect of external forces on the robot structure are learned directly from data collected on the real robot. This model makes use of the raw sensor data and does not require a kinematic/dynamics calibration [19], [15], [18] nor a spatially calibrated model of the skin [6].

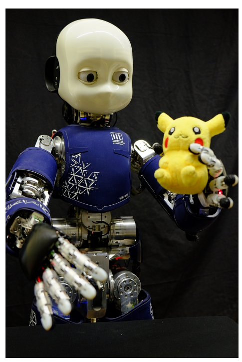

Fig. 1: The humanoid robot *iCub* used in the experiments.

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II. Problem Formulation

The inverse dynamics of a robot in presence of a set of contacts with the environment $\mathcal{C} = \{c_1 \dots c_n\}$ is defined as

$$\boldsymbol{\tau} = \underbrace{\boldsymbol{M}(\boldsymbol{q})\,\ddot{\boldsymbol{q}} + \boldsymbol{h}(\boldsymbol{q}, \dot{\boldsymbol{q}})}_{\boldsymbol{\tau}_{\text{RBD}}} + \epsilon(\boldsymbol{q}, \dot{\boldsymbol{q}}, \ddot{\boldsymbol{q}}) + \sum_{c_i \in \mathcal{C}} \boldsymbol{J}_{c_i}^{\top}(\boldsymbol{q})\,\boldsymbol{\gamma}_i\,, \quad (1)$$

where $\boldsymbol{q}$, $\dot{\boldsymbol{q}}$ and $\ddot{\boldsymbol{q}}$ are the joint positions, velocities and accelerations, respectively, $\boldsymbol{M}(\boldsymbol{q})$ is the inertia matrix and $\boldsymbol{h}(\boldsymbol{q}, \dot{\boldsymbol{q}})$ is the matrix combining the contributions from Coriolis and centripetal, friction (viscous and static) and gravity forces. The term $\epsilon(\boldsymbol{q}, \dot{\boldsymbol{q}}, \ddot{\boldsymbol{q}})$ captures the errors of the model, such as unmodeled dynamics (e.g., elasticities and Stribeck friction), inaccuracies in the dynamic parameters (e.g., masses, inertia), vibrations, couplings, and sensor noise. The last term $\sum_{c_i \in \mathcal{C}} \boldsymbol{J}_{c_i}^{\top}(\boldsymbol{q})\,\boldsymbol{\gamma}_i$ accounts for the additive effect of the external wrenches $\boldsymbol{\gamma}_i$ applied at contact location c_i, and $\boldsymbol{J}_{c_i}(\boldsymbol{q})$ is the contact Jacobian.

Classical approaches for computing $\boldsymbol{\tau}$ or $\boldsymbol{\tau}_{\text{RBD}}$ rely on the dynamics model with known or identified kinematics and dynamics parameters. The torques $\boldsymbol{\tau}_{\text{RBD}} = \boldsymbol{M}(\boldsymbol{q})\,\ddot{\boldsymbol{q}} + \boldsymbol{h}(\boldsymbol{q}, \dot{\boldsymbol{q}})$ can be computed analytically through the rigid body dynamics model of the robot, a standard parametric description of the robot [9]. The term $\epsilon(\boldsymbol{q}, \dot{\boldsymbol{q}}, \ddot{\boldsymbol{q}})$ is often neglected, or implicitly taken into account by considering a perturbation in the dynamics parameters of $\boldsymbol{\tau}_{\text{RBD}}$.

When contacts are exerted on the robot structure at locations other than the classical end-effectors, it is still possible to compute an inverse dynamics model, but this requires both pervasive joint torque sensing, such as in *Toro* [15], and additional force/torque and tactile sensing, such as in *iCub* [10]. Moreover, it requires the precise knowledge of the contact locations detected by the tactile sensors, which necessitates a spatial calibration of the skin [6]. This procedure is prone to errors, and small errors in the kinematics calibration of the taxels (i.e., the tactile units) can induce non-negligible errors in the estimation of the contact forces [7].

III. Learning Inverse Dynamics with Contacts

When learning inverse dynamics with contacts (1), we assume that the contact-free inverse dynamics can be computed precisely, either from an analytic model or from a learned model [14]. As a result, only the model of the residual term of the external forces $\sum_{c_i \in \mathcal{C}} \boldsymbol{J}_{c_i}^{\top}(\boldsymbol{q})\,\boldsymbol{\gamma}_i$ has

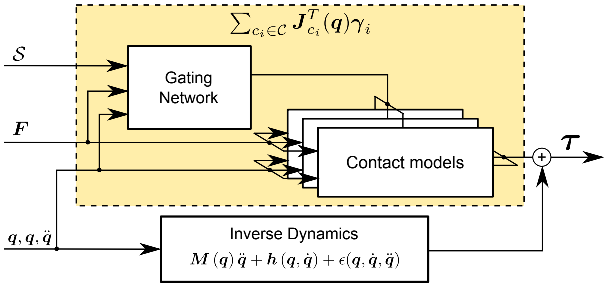

Fig. 2: Our approach extends existing inverse dynamics without contacts by learning many contact models, which serve as correction terms under different contact types. Which contact model to activate is decided by a gating network.

to be separately learned. We consider a robot provided with skin measurements $\boldsymbol{S}$ from the tactile sensors, force measurements $\boldsymbol{F}$ from the force torque sensors (FTS) and the ground truth of the torques $\boldsymbol{\tau}$ from the joint torque sensors (JTS). The problem of learning the external forces can be defined as learning a mixture-of-experts model such that

$$\sum\nolimits_{c_i \in \mathcal{C}} \boldsymbol{J}_{c_i}^{\top}(\boldsymbol{q})\,\gamma_i = \sum\nolimits_{j \in \mathcal{J}} f_j([\boldsymbol{q}, \boldsymbol{F}]) + w\,, \qquad (2)$$

where $\mathcal{J}$ is the set of active contacts and f_j the expert corresponding to each contact. The advantage of this formulation is that the high-dimensional skin input $\boldsymbol{S}$ is not explicitly part of the inputs of the experts. Therefore, each single expert f_j is now sufficiently low-dimensional to be modeled independently and the skin $\boldsymbol{S}$ is used in the gating network to determine which expert is currently active. An illustration of our approach is shown in Fig. 2. As single expert f_j we use Gaussian processes [16], a state-of-the-art regression method often used in robotics to learn dynamics models [5] and for control [4].

IV. Experimental Evaluation

The experiments were conducted on the *iCub*, a humanoid robot with 53 degrees of freedom equipped with four 6-axis force/torque sensors placed proximally in the middle of legs and arms, and an artificial skin consisting of many distributed tactile elements (taxels) mounted on the robot covers [3]. These sensors are used to estimate the joint torques and the external contact forces by the *iDyn* library [10].

We consider a scenario having the *iCub* performing a circular motion with its left arm. We initially performed two experiments with an obstacle either on the left and on the right of the reference trajectory (see Fig. 3). With the data collected in these two contact cases, we trained two independent expert models f_1, f_2, one for each contact. We repeated the experiment, but this time with both left and right contacts and used this last unseen case to validate our models. Fig. 4 shows an example of the prediction and the corresponding activation of the two contact models. During both the right and the left contact, the corresponding experts are activated by the gating network. Therefore, we can successfully combine the contributions of the single contact models learned to generalize to unseen cases with multiple contacts. Moreover, the gating network allows us to combine the experts to generalize to unseen environments, such as in the case of both contacts.

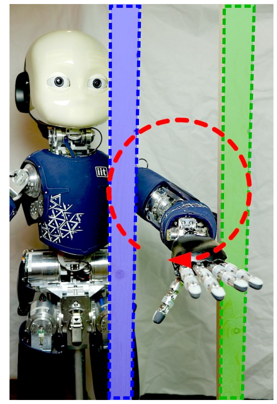

Fig. 3: The robot performs a circle with its left arm. The forearm collides alternatively with the left, the right or both contacts.

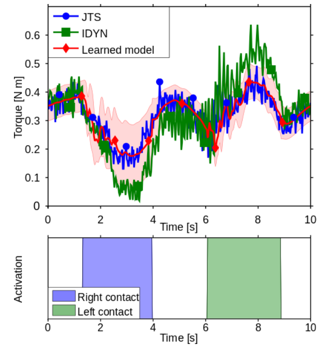

Fig. 4: Prediction of torques with multiple contacts and the corresponding activation of the gating network. Our mixture-of-experts model combines the learned single-contact models into a multiple-contact model.

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