Environmental Force Estimation for a Robotic Hand: Compliant Contact Detection

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Abstract—This paper presents a model based compensation method to enable environmental force estimation for a robotic hand with no tactile or force sensors. To this end, we utilize multi-joint robot dynamics and disturbance observer based friction identification methods based to account for forces that arise due to Coriolis, gravity, friction and viscous friction. With the effective compensation of these forces, disturbance observer units, implemented for each joint, allow us to estimate environmental interaction forces. To validate the effectiveness of the force estimation with our method, experiments were conducted on an anthropomorphic robot with no haptic sensing capability. The results of these experiments showed that the force estimation was in good agreement with the actual sensor measurements. To further elaborate the effectiveness of the method, compliant contact detection task was implemented on the robot. The result of this experiment indicated that environmental force estimation performance was enough to facilitate the task, and as such our method may eliminate the need for expensive force sensors at the finger tips or the joints for dexterous manipulation.

I. INTRODUCTION

Due to their unique multi-fingered anatomy and biomechanical properties, primate hands allow complex and dexterous behaviors. It is argued that the mechanical dexterity introduced by homo sapiens’ hands played a critical role in evolving a superior brain [1]. Support to this comes from the fact that Central Nervous System (CNS) in primates has direct cortical projections for the control of finger muscles to enable hand dexterity as in precision grips and in-hand manipulation [2]. Motor synergy appears to be one of the key mechanisms of CNS in generating dexterous hand function [3]. With this inspiration, robotic hands are sometimes designed synergistically and/or controlled via synergies imposed over finger joints. For instance, Ajoudani et al. utilized tele-impedance control in simplifying hand complexity into distinct motor patterns [4]. Gabiccini et al. proposed a framework that incorporates the structural properties of a hand in quasi-static setting, so that it could be driven via synergistic actions [5]. Catalano et al. made use of adaptive synergies to demonstrate various grasping behavior on the UNIPI-hand [6].

In robotics, dexterous manipulation is sought, besides synergies, through learning-by-demonstration [7] and reinforcement learning (see [8], [9]) which have proven to be powerful techniques for generating complex robotic hand skills. Imitation learning has become a mainstream technique for tasks involving position control. As an early example, Oztop et al. demonstrated synthesis of ball swapping task using human-in-the-loop robot skill generation [10] [11]. The current challenge appears to be the application of imitation learning to tasks that require force control policies. An example work towards this direction has been given by Peternel et al. in which an anthropomorphic robot arm was thought to learn to adjust its compliance as to cooperate with a human partner to cut a beam of wood using a two-person saw [12]. Another example is given by Li et al. where object-level impedance from human demonstration could be learned [13].

In general for grasping, statistical learning appears to be effective [14] [15], and the contribution of tactile input seems important once the object is in contact with the hand. It is known that infants initially rely on tactile sensation rather than vision to learn how to grasp: the initial reaching attempts initiated -but not guided- by vision are shaped into grasping skills via tactile exploration and tactile feedback [16]. Therefore, contact force information is a crucial phenomenon in dexterous robotic hand control.

As outlined, tactile and force sensors can be seen as prerequisites for a dexterous robotic hand system [17]. However, precise tactile/force sensing - especially in three axes - comes with a significant cost and calibration becomes a necessity. Furthermore, the overall hand/finger hardware design process becomes more complex to accommodate the sensors and the electric wiring in the hand/finger mechanism. While such sensors introduce the difficulties listed above, contact force information is vital and cannot be overlooked when dexterous manipulation is needed. With this in mind, we aimed at utilizing disturbance observer (DoB) technique, which is extensively used in industrial automation for robust control [18], [19], so that we can infer environmental forces acting on the robot fingers.

In general, a DoB can estimate the overall disturbance acting on the system due to robot dynamics (i.e. inertial forces, Coriolis effect, and gravity), friction, and external forces. In [20], Ugurlu et al. hypothesized that if the robot dynamics and frictional loads are sufficiently compensated, DoBs would solely output environmental interaction forces thereby eliminating the need for special sensing hardware. Sharing the common objective, this paper presents a framework to estimate contact force information, in an attempt.
to eliminate the need for tactile/force sensing hardware for reduced complexity in dexterous robotic manipulators, e.g. a multi-fingered anthropomorphic robot hand. The framework incorporates model based compensation loops to account for disturbances based on robot dynamics and joint friction.

The remainder of the paper is organized as follows. The compensation scheme is explained in section II, together with the force estimation method. Target tasks and related compensation scheme is explained in section II, together with the force estimation method. Target tasks and related experiment results are disclosed in section III. The paper is concluded in section IV.

II. COMPENSATION SCHEMES

The general compensation scheme is given in Fig 1. It includes dynamics (Coriolis&centrifugal, gravity) and friction compensation loops.

A. Dynamic Load Compensation

Coriolis&centrifugal and gravity compensation torques are calculated using the dynamics model of the robot and CAD data. Angular velocities for joints, \( \dot{\theta} \), are low-pass filtered to reduce the noise. Inertia term is omitted in equations, as the joint acceleration values were observed to be negligible during the nominal operation.

B. Friction Compensation

With the condition of gravity and Coriolis forces are compensated, friction becomes the only effective disturbance force observed on the system while no external force is applied. Therefore, DoB outputs frictional torque. With this in mind, we implemented ramp inputs with various slope values and observed the frictional torque-angular velocity variations for a single joint is given in Fig. 2(a) [18]. In this figure, red, cyan, green, and blue curves indicate actual frictional torque-angular velocity variations while black lines stand for the fitted model. A similar procedure was carried out for all other joints, thus not plotted.

As may be seen in Fig. 2(a), joint friction can be modeled as a piecewise linear equation, composed of stiction and viscous friction (see the black curve). These two components constitutes an accurate representation of the friction model as Striebeck effect is observed to be negligible in our case.

The model for the \( i^{th} \) joint can be formulated in terms of its angular velocity \( \dot{\theta}_i \) as follows,

\[
T_{fr}(\dot{\theta}_i) = a_1(\lambda_1 + \lambda_2\dot{\theta}_i) - a_2(\lambda_3 - \lambda_4\dot{\theta}_i) \tag{1}
\]

where \( \lambda_1 \) and \( \lambda_3 \) are static friction coefficients for positive and negative direction, and \( \lambda_2 \) and \( \lambda_4 \) are viscous friction coefficients when \( \dot{\theta}_i > 0 \), \( a_1 = 1 \) and \( a_2 = 0 \). Likewise, when \( \dot{\theta}_i < 0 \), \( a_1 = 0 \) and \( a_2 = 1 \). Following the model parameter identification, friction compensation is realized by feeding the actuator with \( T_{fr} \) to account for loads due to joint friction.

C. Compensation Logic

General dynamic model of a torque controlled robot is defined by the following equation,

\[
T_{cmd} = J_r\ddot{\theta} + T_l + T_{fr}(\dot{\theta}), \tag{2}
\]

\[
M(\dot{\theta})\ddot{\theta} + C(\theta, \dot{\theta})\dot{\theta} + G(\theta) = T_{ext} + T_l, \tag{3}
\]

where \( \theta \) is the joint angle vector, \( J_r \) is the rotor inertia, \( T_{cmd} \) is motor command torque vector, \( T_{ext} \) is external force vector, \( T_l \) is the joint torque vector on the links, \( T_{fr} \) is the frictional torque vector, \( M(\dot{\theta}) \), \( C(\theta, \dot{\theta}) \), \( G(\theta) \) are inertia, gravity, and coriolis terms, respectively. Combination of (2) and (3) results as follows.

\[
T_{cmd} = M(\dot{\theta})\ddot{\theta} + C(\theta, \dot{\theta})\dot{\theta} + G(\theta) + T_{fr}(\dot{\theta}) + J_r\dot{\theta} - T_{ext} \tag{4}
\]

Fig. 1. The compensation scheme when the robot is in torque control mode. Inertia terms are omitted as the joint acceleration values were observed to be sufficiently low during the nominal operation.

Fig. 2. a) Frictional torque - angular velocity variations for 4 distinct ramp inputs. The piece-wise fitted friction model is acquired by using these data. b) Having compensated all dynamics and frictional loads, the DoB outputs near zero variation, adequately confirming the accuracy of the proposed compensation scheme. In other words, the robot is approximately free of any dynamics and frictional load.
To eliminate the effects of these dynamic forces acting on the system, overall compensation scheme is designed as shown in Fig. 1 [20]. In this scheme, actuators are supplied with additional torques $T_{fr}$, $T_{gr}$, $T_{ec}$ to respectively compensate for $Fr(\dot{\theta})$, $G(\theta)$, $C(\theta, \dot{\theta})$ in a feedforward manner. Incorporating the compensation terms, $T_{cmd}$ can be rewritten as:

$$T_{cmd} = T_{inp} + T_{fr} + T_{gr} + T_{ec}$$  \hspace{1cm} (5)

In (5), $T_{inp}$ is the task-specific input. Provided the compensation torques sufficiently account for Coriolis, gravity and frictional loads ($T_{ec} + T_{gr} + T_{fr} \cong C(\theta, \dot{\theta})\dot{\theta} + G(\theta) + Fr(\dot{\theta})$), these terms may be canceled out; therefore, the dynamic model of the robot can be expressed as follows.

$$T_{inp} + T_{ext} = J_r \ddot{\theta}$$  \hspace{1cm} (6)

Having compensated torques based on Coriolis effect, gravity and friction terms, we re-ran disturbance estimation to experimentally verify the accuracy of the compensation schemes. To this end, the robot joints are actuated via torque inputs and we observed the DoB outputs for every joint. No external force was implemented. An exemplary data is provided in Fig 2(b). As may be observed, DoB output is simply varied near zero; adequately validating the fact that the robot is free of any dynamics and frictional load. Furthermore, this figure also validates our approach in omitting the inertia terms, as there is almost zero DoB output. Though using DoB for friction identification may be infeasible for more complex joint designs and less accurate under model uncertainties [21], we found it to be accurate where the explicit dynamic model exists.

D. Force Estimation via Disturbance Observer

The simple DoB architecture for a single joint is displayed in Fig. 3 [18]. Motor model, rotor inertia, actual disturbance torque, estimated disturbance torque (DoB output) and command torque input are symbolized with $P(s)$, $J_r$, $T_d$ and $T_i$, respectively. In this scheme, an approximation for the inverse plant model is utilized to estimate the disturbance acting on the joint.

$$T_d^* = gJ_r \dot{s} \theta - \frac{g}{s + g} (T_i + gJ_r \dot{s} \theta)$$  \hspace{1cm} (7)

$$T_d^* = \frac{s^2 J_r \ddot{s} \theta}{s^2 + 1} - \frac{1}{s^2 + 1} T_i$$  \hspace{1cm} (8)

$$T_d^* \cong \left( J_r \ddot{s} \theta - T_i \right) \cong T_d$$  \hspace{1cm} (9)

For a multi-joint robotic system, $T_d^*$ term consist of the resultant disturbance torque that arises due to robot dynamics (inertial, Coriolis, and gravity) friction, environmental interaction. Given the fact that inertial effect is negligible, and Coriolis, gravity and friction terms are compensated, DoB simply outputs the environmental force. At this stage, please note the analogy between the final DoB equation, (9) and our final derivation after the compensation, namely, Eq. (6). Input torque and external force ($T_{inp}$, $T_{ext}$) in Eq. (6) corresponds to $T_i$ and $T_d$ in Eq. (9).

Since the torque that occurs due to environmental interaction, $T_{ext}$, can be obtained via DoBs, finger tip forces ($F_{tip}$) can be calculated via the related Jacobian for each finger.

$$F_{tip} = (J^{-T}) T_{ext}$$  \hspace{1cm} (10)

If the Jacobian matrix, $J$, is not square, Moore-Penrose inverse may be used.

III. TARGET TASKS AND EXPERIMENT RESULTS

A. Hardware Testbed: Gifu Hand-III

The robotic hand used in this study is the Gifu Hand III (Dainichi Co. Ltd., Japan) which consists of a thumb and four fingers (see Fig. 4) with total 16 degrees of freedom. The robot is connected to a Windows machine with several PCI boards, namely, A/D, D/A, Counter and Timer boards. The A/D PCI cards allow the PC to read the motor currents. The Counter PCI cards are used to obtain number of encoder clicks, i.e. joint angle changes. The D/A cards convert the PC’s digital outputs to analog voltages that drive the hand motors. Controller of the robot hand runs at 500 Hz. Dimensions of the hand and a single finger is given in Fig. 4. Fig. 5 displays the actual robot while grasping two distinct objects.

Even though the robot hand is equipped with force sensing resistors, they could not provide reliable sensory information. Therefore, we stripped off force sensing resistors from the hand and investigated an approach to estimate environmental contact force.

B. Contact Force Estimation

While running the proposed contact force estimation method, the fingers pushed a force sensor to see whether
the estimation matches well with actual measurements. Fig. 6 depicts results for index and little fingers, where solid green and purple lines respectively indicate actual (sensor output) and estimated force outputs.

Scrutinizing Fig. 6, one can see that estimation results are in good agreement with actual measurements. The data sets shown in Fig. 6 are strongly correlated. Specifically, the Pearson correlation coefficient for index and little fingers are $r = .940$ and $r = .905$, respectively.

Similar results were acquired for other fingers, therefore, not plotted. Although time responses differ in a sense, it is commended that the estimation algorithm may eliminate the need of tactile sensors. This greatly simplifies the hardware design and potentially contain the costs.

C. Compliant Contact Detection

When performing a grasp in the presence of positioning inaccuracies, acquiring tactile sensing is of importance to detect early and/or unexpected contacts with objects. For instance, Chen et al. utilized integrated joint torque sensors to detect early contacts for a compliant grasp with position uncertainties [22].

To see whether a similar contact detection task is technically possible with no tactile or torque sensors, we designated a task in which the robot hand fingers unexpectedly contacts with a rigid object. To assure compliant contact, the admittance controller in Fig. 7 was implemented. This controller uses a PD controller for the position control loop. On top of this controller, a force control loop is constructed using an admittance control scheme. In this controller, force estimator is used by means of fingertip force measurement.

The force control loop processes the joint torque error. It is then inserted to an admittance block to compute the corresponding joint displacement $\theta_c$. In other words, $\theta_c$ is the joint displacement that corresponds to the force error. When the system experiences force errors due to unexpected contact with the environment, $\theta_c$ updates the position reference $\theta_{ref} := \theta_{ref} - \theta_c$. The sensitivity to force error can be adjusted by the admittance parameters, namely, $k$ and $b$.

In case there is no force error, $\theta_c$ simply becomes zero. Then the system becomes equivalent to a classical PD-based position controlled robot. Note that compensation scheme in Fig. 1 is enabled at all times to refine the controller performance.

In order to validate this approach, experiments were conducted when the proposed admittance control was activated.
Only-PD control experiments are also conducted to provide a frame of reference for our results. Exemplary experiment results can be observed in Fig. 8 and Fig. 9 from index finger middle joint, and little finger base joint. Similar results were acquired from other joints, hence, not included.

Around $t = 0.4$, the robot hand fingers unexpectedly contacted with the object in such a way that the robot hand motion was restrained, i.e., it could not move.

In Fig. 8(a) and Fig. 9(a), dotted blue and solid purple lines indicate reference and actual joint angles when the robot was controlled using the PD controller. As the robot hand motion was restrained after the contact, the actual angles stayed constant, and therefore, could not track the reference signals.

Dotted cyan and solid green lines stand for reference and actual joint angles when the robot was controlled using the proposed admittance controller. In this case, reference angles were updated so as to comply with the force constraints; the joints maintained their positions after the contact.

The current measurements are displayed in Fig. 8(b) and Fig. 9(b). Orange and red signals indicate current sensor readings for the proposed admittance and classical PD controllers, respectively. It should be noted that desired grasp behaviour is achieved by proper admittance parameter selection. While Fig. 8(b) shows a soft and damped touch for an end-joint, a base-joint in Fig. 9(b) has a less sensitive behaviour which overshoots and oscillates before settling. Since the classical PD controller do not incorporate force constraint, the motors consume maximum current in an attempt to pierce through the object to follow the reference signals. As a result, the motor drives halted due to overcurrent protection. Grasp stability can further be improved by tuning admittance parameters.

The proposed controller simultaneously process force and position constraints in a compliant way; thus, the reference signal is automatically updated to cope with unexpected contact with the object. By the virtue of this approach, current consumption was well contained and the robot hand maintained its position. Compared to the case with PD controller, current consumption was decreased 3 to 5 times.

In this task, our force estimation algorithm played a major role as it facilitated the contact force information. As mentioned, main contribution presented in this task is not utilizing an admittance controller, but rather showing that a task such as compliant contact detection or compliant grasping can be realized with the proposed force estimation method removing the need for extra sensors.

IV. CONCLUDING REMARKS

In this paper, a compensation scheme was proposed for a robot hand to account for disturbance torques that arise due to robot dynamics and friction. Implementing the proper identification techniques, friction model was constructed in a way so as to cancel out stiction and viscous friction. The robot dynamics model was utilized to cancel out Coriolis effect and gravity forces. In doing so, the robot hand becomes hypothetically disturbance-free.

Disturbance observers can estimate the resultant disturbance acting on an actuation module. They are used in industrial automation for robust position control. In this work, we combined disturbance observers with the proposed compensation scheme. Through the effective compensation of the robot dynamics and friction loads, disturbance observers only output forces due to environmental interaction. This enabled us to obtain relatively accurate estimations of fingertip forces.

To verify the force estimation method, the fingers were physically interacted with a force sensor. As a result, the force estimation significantly matched with the sensor data; the Pearson correlation coefficient for the estimation and sensor data were calculated as $r = .940$ and $r = .905$ for index and little fingers. Other fingers also performed in a similar manner. Therefore, it is commended that tactile/force sensors may be eliminated from robotic hands for certain tasks. This would allow us to greatly simplify the hardware and contain costs.

Furthermore, force estimation was actively used by means of tactile sensing in a compliant contact detection task. An admittance controller was employed to simultaneously process both position and force constraints. Compared to classical PD control, it allowed the active modifications on the reference angle signal and prevented overcurrents when the robot motion was restrained unexpectedly via an object.

The future work will include compliant grasping of distinct objects on top of the algorithms (compensation scheme, environmental force estimation) presented in this paper. A machine learning algorithm will be employed to optimize active joint admittance to increase the grasp success rate [23].

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Fig. 8. Compliant contact detection experiment results for the index finger, middle joint. a) Joint angle references and measurements. b) Current measurements.

Fig. 9. Compliant contact detection experiment results for the little finger, base joint. a) Joint angle references and measurements. b) Current measurements.

REFERENCES


