Comparison of Adaptive Force Control Methods for Robots

I. Raz, J. Dayan and S. Strassberg

Abstract
Several different proposed methods of adaptive force control for robots interacting with an unknown environment are compared quantitatively by simulation. The problem addressed is a robot who is in point contact with a smooth surface whose stiffness is unknown. Criteria and cost functions weighing these criteria were formulated. Three robot models were selected and used in the simulations: a simple 1-DOF single rigid link manipulator, a simple planar 2-DOF robot and a 4-DOF MITSUBISHI RV-M2 industrial robot. For all three models various force trajectories were implied to establish whether one method is superior in its performance over the other methods. The adaptive methods were also compared to a simple PD force controller without adaptation.

Key Words
Adaptive robot force control, hybrid control, Impedance control.

Nomenclature
q - joint position
q̇ - joint velocity
q̈ - joint acceleration
M(q) - robot's inertial matrix in joint space
C(q, q̇) - robot's coriolis matrix in joint space
G(q) - robot's gravitational vector in joint space
τ - joint torque vector
J - robot's Jacobian
x - tool tip position in cartesian space
ẋ - tool tip velocity in cartesian space
ẍ - tool tip acceleration in cartesian space
M(x)(q) - robot's inertial matrix in cartesian space
C(x)(q, q̇) - robot's coriolis matrix in cartesian space
G(x)(q) - robot's gravitational vector in cartesian space
F - Cartesian engine forces vector
F̂ - tool tip force normal to the surface
F̂_d - tool tip desired force normal to the surface
e_F - force error
e_Ḟ - derivative of force error
1. Introduction
Industrial robots are required to perform different tasks such as grinding, polishing, buffing, scraping, deburring, twisting and assembly. These tasks include interaction of the robot with the environment which exerts forces on the environment. For a successful completion of the robot's task, force measurements and force control are required. Since the parameters of the environment are not known, adaptive algorithms are used to compensate the unknown parameters and to successfully complete the robot's task.

This work addresses the problem of a robot which is in point contact with an environment with unknown parameters. The control target is that the robot's end effector performs stable tracking of a force trajectory normal to the environment, while moving in tangential directions on the environment.

A comparison is made between different adaptive force control algorithms, which were recently proposed in literature. The robot's dynamic model and the location of the environment are precisely known. The robot starts its movement when the end effector is at rest in contact with the environment. The unknown parameter is the stiffness of the environment (surface).

The adaptive force control algorithms presented in this work are divided into two categories: hybrid control and impedance control. Most adaptive algorithms presented in this work perform force control while estimating the environment's (surface's) stiffness, while some adaptive algorithms perform force control without the need to estimate the environment's (surface's) stiffness.

The adaptive algorithms are investigated for tracking different force trajectories. The optimal control gains of each algorithm are established by applying cost criteria with weight functions to the control results.

The adaptive force control algorithms are simulated on three robotic systems: one dimension robot arm (one degree of freedom), a simple two link planar robot (two degrees of freedom) [18] and a MITSUBISHI RV-M2 industrial robot (four degrees of freedom) [17].
2. Robot and Environment Model

The robot is in point contact with a stiff environment (fig. 1) which is modeled as a spring with a large stiffness $k_e$ (which is unknown). Since the environment is a smooth surface, the robot exerts forces only in the normal direction to the surface.

![Figure 1. Robot and environment model](image)

The stiffness $k_e$ is the interaction stiffness which includes the stiffness of the plane and the stiffness of the force sensor. The starting point of the robot's interaction with the environment is at $x_e$ (which is known).

Due to the robot's contact with the environment the exerted force is:

$$F_e = \begin{cases} k_e (x - x_e) & x \geq x_e \\ 0 & x < x_e \end{cases}$$  \hspace{1cm} (1)

In order to achieve the desired force the robot must satisfy in the force direction:

$$x_d(t) = x_e + \frac{F_d(t)}{k_e}$$  \hspace{1cm} (2)

The robot's dynamic equation in joint space is:

$$M(q) \ddot{q} + C(q, \dot{q}) + G(q) = \tau + J^T F_e$$ \hspace{1cm} (3)

Since the exerted force is only in the normal direction, it is more convenient to apply cartesian coordinates for the robot. We shall address the normal direction as the x-axis direction. The robot's dynamic equation in cartesian coordinates is:

$$M_x(q) \ddot{q}_x + C_x(q, \dot{q}_x) + G_x(q) = F_x + F_e$$ \hspace{1cm} (4)

The following relations exist between (3) and (4):

$$\tau = J^T F$$ \hspace{1cm} (5)

$$M_x = (J^T)^{-1} M J^{-1}$$ \hspace{1cm} (6)

$$C_x = (J^T)^{-1} C - M_x \ddot{\theta} J^{-1}$$ \hspace{1cm} (7)

$$G_x = (J^T)^{-1} G$$ \hspace{1cm} (8)

3. Adaptive Force Control Methods

We compare 6 different adaptive force control methods recently proposed:

1. Roy, Whitcomb [9] (fig. 2)
2. Villani, Natale, Siciliano [10] (fig. 3)
3. Tsapronnis, Aspragathos [11] (fig. 4)
4. Tzafestas, M'sirdi, Manamani [12] (fig. 5)
5. Matko, Kamnik, Bajd [13] (fig. 6)
Methods 1,2,3 are classified as hybrid control while methods 4,5,6 are classified as impedance control. The comparison also included a simple PD force controller (fig. 8). Table-1 summarizes the different signals in the control methods.

<table>
<thead>
<tr>
<th>Algorithm</th>
<th>Type</th>
<th>F_d</th>
<th>K_r</th>
<th>e_F</th>
<th>&amp;_r</th>
</tr>
</thead>
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<tr>
<td>Roy</td>
<td>Hybrid</td>
<td>YES</td>
<td>NO</td>
<td>YES</td>
<td>NO</td>
</tr>
<tr>
<td>Villani</td>
<td>Hybrid</td>
<td>YES</td>
<td>YES</td>
<td>YES</td>
<td>YES</td>
</tr>
<tr>
<td>Tsapronnis</td>
<td>Hybrid</td>
<td>YES</td>
<td>NO</td>
<td>YES</td>
<td>YES</td>
</tr>
<tr>
<td>Tzafestas</td>
<td>Impedance</td>
<td>YES</td>
<td>YES</td>
<td>YES</td>
<td>NO</td>
</tr>
<tr>
<td>Matko</td>
<td>Impedance</td>
<td>YES</td>
<td>NO</td>
<td>NO</td>
<td>YES</td>
</tr>
<tr>
<td>Jung</td>
<td>Impedance</td>
<td>YES</td>
<td>NO</td>
<td>NO</td>
<td>NO</td>
</tr>
<tr>
<td>PD</td>
<td>----</td>
<td>YES</td>
<td>NO</td>
<td>NO</td>
<td>YES</td>
</tr>
</tbody>
</table>

Table 1

4. Comparison of the Adaptive Force Control Methods

4.1 Criteria and Cost Functions

To compare the various methods, a criterion is formulated to quantitatively evaluate the performance of the control method. For each method and each desired force trajectory, the set of optimal control parameters is found and used for the purpose of comparison. The optimized control parameters have the same meaning of proportional and derivative gains in the different methods and are summarized in Table-2. The control parameters are being optimized by the criterion while the update law parameters are constant. The left parameters represent derivative gains and the right parameters represent proportional gains.

<table>
<thead>
<tr>
<th>Algorithm</th>
<th>Type</th>
<th>Control Parameters</th>
<th>Update Law Parameters</th>
<th>Estimate Stiffness?</th>
</tr>
</thead>
<tbody>
<tr>
<td>Roy</td>
<td>Hybrid</td>
<td>K_d, K_F</td>
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<td>YES</td>
</tr>
<tr>
<td>Villani</td>
<td>Hybrid</td>
<td>K_v, \lambda_F</td>
<td>\sigma</td>
<td>YES</td>
</tr>
<tr>
<td>Tsapronnis</td>
<td>Hybrid</td>
<td>Q, A</td>
<td>\gamma</td>
<td>YES</td>
</tr>
<tr>
<td>Tzafestas</td>
<td>Impedance</td>
<td>B_r, K_r</td>
<td>\gamma</td>
<td>YES</td>
</tr>
<tr>
<td>Matko</td>
<td>Impedance</td>
<td>B_r, K_r</td>
<td>a_r, b_r, c_r, \omega</td>
<td>NO</td>
</tr>
<tr>
<td>Jung</td>
<td>Impedance</td>
<td>B_r</td>
<td>\eta</td>
<td>NO</td>
</tr>
<tr>
<td>PD</td>
<td>----</td>
<td>K_d, K_p</td>
<td></td>
<td>NO</td>
</tr>
</tbody>
</table>

Table 2
The criterion is composed of the following factors:

1. The maximal steady state force error relative to the desired force amplitude:
   \[ \text{cost}_1 = \frac{\max |e_F|_{0.8T_{set}}} {\max |F_d|} \]  \hspace{1cm} (9)

2. The settling time it takes the contact force to converge into the 2% range around the desired force:
   \[ \text{cost}_2 = t_1 \quad \text{if} \quad \left\{ \frac{\max |e_F|}{\max |F_d|} \leq 0.02, \quad t_i \leq t \leq T \right\} \]  \hspace{1cm} (10)

3. The accuracy of the force along the trajectory:
   \[ \text{cost}_3 = \int_0^T |e_F| \, dt \]  \hspace{1cm} (11)

4. The maximal force overshoot relative to the desired force amplitude:
   \[ \text{cost}_4 = \frac{\max |F_o|}{\max |F_d|} \]  \hspace{1cm} (12)

5. The maximal control force (command) to the robot's engines in the force direction:
   \[ \text{cost}_5 = \max |F_{\text{control}}_x| \]  \hspace{1cm} (13)

6. The control force (command) to the robot's engines in the force direction along the force trajectory:
   \[ \text{cost}_6 = \int_0^T |F_{\text{control}}_x| \, dt \]  \hspace{1cm} (14)

7. The energy in the force direction along the force trajectory:
   \[ \text{cost}_7 = \int_0^T |F_{\text{control}}_x \cdot \delta t| \, dt \]  \hspace{1cm} (15)

The overall criterion is:
   \[ \text{COST} = \sum_i w_i \text{cost}_i \]  \hspace{1cm} (16)

4.2 Force Trajectories Tests
To compare the various methods various force trajectories tests are applied. The tests are divided into two groups (A and B). Group A tests features desired force trajectories of step, ramp and sine. Tests A-1, A-2, A-3 are applied to the 1-DOF and the 2-DOF robots which are required to follow the desired force trajectory while maintaining a constant position on the surface:

- \[ F_y(t) = -50 \] TEST A–1
- \[ F_d(t) = \begin{cases} -50t & 0 \leq t \leq 1 \\ -50 & 1 < t \end{cases} \] TEST A–2
- \[ F_d(t) = -(30 + 20 \cos(2\pi t)) \] TEST A–3

- \[ x_o(t) = y_o, \delta \dot{x}_o(t) = 0, \delta \dot{y}_o(t) = 0 \]  
- \[ x_o(t) = z_o, \delta \dot{x}_o(t) = 0, \delta \dot{z}_o(t) = 0 \]  

Test A-4 is applied only to the 2-DOF robot which is required to follow the desired force trajectory while moving in a straight line along the surface:
\[ F_d(t) = -50 \]
\[ x_{\nu y}(t) = y_0 + 0.05t, \omega_{\nu y}(t) = 0.05, \omega_{\nu z}(t) = 0 \quad \text{TEST A - 4} \quad (18) \]
\[ x_{\nu z}(t) = z_0, \omega_{\nu z}(t) = 0, \omega_{\nu x}(t) = 0 \]

Test A-5 is applied only to the Mitsubishi RV-M2 robot which is required to follow the desired force trajectory while moving in an elliptical trajectory along the surface:
\[ F_d(t) = -50 \]
\[ x_{\nu y}(t) = 0.03 \sin(2\pi t) + 0.2663 \quad \text{TEST A - 5} \quad (19) \]
\[ x_{\nu z}(t) = 0.06 \cos(2\pi t) + 0.4013 \]

Group B tests features desired force trajectories of step, ramp and sine while applying:
1. Noise in the force sensor according to:
   \[ F_s(t) = k_s(x - x_s) + 0.5 \cdot \text{rand}(0,1) \]
   \[ (20) \]
2. Step changes in the stiffness of the surface depending on the movement of the robot along the surface.
3. Smooth changes in the stiffness of the surface depending on the movement of the robot along the surface.

### 4.3 Performing Comparison between the Adaptive Methods
First group A tests are applied to establish the optimal control gains of every method for each test and robot model. The optimal control gains are established by minimizing the criterion in section 4.1. Then group B tests are performed using the optimal control gains found. The same criterion in section 4.1 is used to evaluate performance of the control parameters and establish the superior method. The superior method is that which minimizes the criterion. The applied tests are summarized in Table 3.

<table>
<thead>
<tr>
<th>STEP + MOVEMENT</th>
<th>SINUS</th>
<th>RAMP</th>
<th>STEP</th>
<th>TEST</th>
<th>Robot</th>
</tr>
</thead>
<tbody>
<tr>
<td>NO</td>
<td>YES</td>
<td>YES</td>
<td>YES</td>
<td>No Disturbances</td>
<td>1 DOF Robot</td>
</tr>
<tr>
<td>NO</td>
<td>YES</td>
<td>YES</td>
<td>YES</td>
<td>Noisy Force Sensor</td>
<td>1 DOF Robot</td>
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<tr>
<td>YES</td>
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<td>No Disturbances</td>
<td>2 DOF Robot</td>
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<tr>
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<td>YES</td>
<td>YES</td>
<td>Noisy Force Sensor</td>
<td>2 DOF Robot</td>
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<tr>
<td>YES</td>
<td>NO</td>
<td>NO</td>
<td>NO</td>
<td>Stiffness Step Changes</td>
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<td>NO</td>
<td>NO</td>
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<td>Stiffness Smooth Changes</td>
<td>2 DOF Robot</td>
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<tr>
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<td>NO</td>
<td>NO</td>
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<td>Mitsubishi RV-M2</td>
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<td>NO</td>
<td>NO</td>
<td>Noisy Force Sensor</td>
<td>Mitsubishi RV-M2</td>
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<tr>
<td>YES</td>
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<td>NO</td>
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<tr>
<td>YES</td>
<td>NO</td>
<td>NO</td>
<td>NO</td>
<td>Stiffness Smooth Changes</td>
<td>Mitsubishi RV-M2</td>
</tr>
</tbody>
</table>

Table 3
5. Simulations
5.1 Simulation parameters
For the simulations the environment stiffness was chosen as $k_e = 10^4 \, N/m$.

For the 2-DOF robot the step changes in the stiffness of the surface were according to:

$$ k_e(y) = \begin{cases} 
10000 & y_0 \leq y < y_0 + 0.1 \\
5000 & y_0 + 0.1 \leq y < y_0 + 0.2 \\
13000 & y_0 + 0.2 \leq y 
\end{cases} \quad (21) $$

For the 2-DOF robot the smooth changes in the stiffness of the surface were according to:

$$ k_e(y) = \begin{cases} 
10000 & y_0 \leq y < y_0 + 0.05 \\
10000 - 5000\sin(10\pi(y - 0.05)) & y_0 + 0.05 \leq y < y_0 + 0.1 \\
5000 & y_0 + 0.1 \leq y < y_0 + 0.15 \\
5000 + 8000\sin(10\pi(y - 0.05)) & y_0 + 0.15 \leq y < y_0 + 0.2 \\
13000 & y_0 + 0.2 \leq y 
\end{cases} \quad (22) $$

For the Mitsubishi RV-M2 robot the step changes in the stiffness of the surface were according to:

$$ k_e(y, z) = \begin{cases} 
10000 & 0.2663 < y \\
13000 & 0.2663 \geq y 
\end{cases} \quad (23) $$

For the Mitsubishi RV-M2 robot the smooth changes in the stiffness of the surface were according to:

$$ k_e(y, z) = \begin{cases} 
10000 + 3000\sin\left(\frac{25\pi}{6}(0.4613 - z)\right) & 0.2663 < y \\
13000 - 3000\sin\left(\frac{25\pi}{6}(z - 0.3413)\right) & 0.2663 \geq y 
\end{cases} \quad (24) $$

For the adaptive methods that estimate the stiffness of the plane, the initial guess of the stiffness was chosen as $\hat{k}_e(0) = \frac{5}{6} k_e$.

5.2 Simulation Results
Table 4 summarizes the superior method for each test.

<table>
<thead>
<tr>
<th>STEP + MOVEMENT</th>
<th>SINUS</th>
<th>RAMP</th>
<th>STEP</th>
<th>TEST</th>
<th>Robot</th>
</tr>
</thead>
<tbody>
<tr>
<td>Tzafestas</td>
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<td>1 DOF Robot</td>
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<td>Tzafestas</td>
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<td>Roy</td>
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<td>Roy</td>
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<td>2 DOF Robot</td>
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<tr>
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<td>Roy</td>
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<td>Mitsubishi RV-M2</td>
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<td>Mitsubishi RV-M2</td>
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</tr>
</tbody>
</table>

Table 4
6. Conclusions
The main conclusion which arises from our work (as can be seen in table 4) is that there is no one superior method for all test cases and all robot models. For every test case and robot task one must find the best method to execute the task.
The optimal control gains received for all the adaptive methods (except Tsapronnis) showed high values for the derivative gains and very small values for the proportional gains. This means that the controller's performance in these adaptive methods is established according to the derivative gains. This is because the high stiffness of the environment serves as a high proportional gain, so no extra proportional gain is needed.
The optimal control gains received for each method showed the same or very close values in all the robot models for each force trajectory. This is because the full dynamics of the robot is known, so the controller employs exact inverse dynamics for all robot models leaving only the force and movement equations regardless of the robot model.
The adaptive algorithms almost always are superior to the simple PD force controller, which performs no adaptation.
Figure 2: Model for Roy & Whitcomb

Figure 3: Model for Villani, Natale, Siciliano
Figure 4: Model for Tsapronnis, Aspragathos

Figure 5: Model for Tzafestas, M'sirdi, Manamani
Figure 6: Model for Matko, Kamnik, Bajd

Figure 7: Model for Jung, Hsia
Figure 8: Model for PD force controller
References