Journal of Neuroscience Methods 214 (2013) 15–20

Contents lists available at SciVerse ScienceDirect

Journal of Neuroscience Methods

journal homepage: www.elsevier.com/locate/jneumeth

Computational Neuroscience
Short communication

Compensation for the intrinsic dynamics of the InMotion2 robot

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ARTICLE INFO

Article history:
Received 7 August 2012
Received in revised form 3 January 2013
Accepted 6 January 2013

Keywords:
Robotics
Motor adaptation
Impedance
Upper extremity
Robot-mediated rehabilitation
Upper limb rehabilitation

ABSTRACT

The InMotion2 and other similarly designed robots, are commonly used for rehabilitation of neurological injuries and motor adaptation studies. These robots are used to simulate haptic environments; however, anisotropy in end-point impedance due to the intrinsic robot dynamics can compromise these experiments. The goal was to decrease the magnitude and anisotropy of the robot impedance using a dynamic compensation algorithm that reduces the forces normally felt by the user during rapid movements. We tested this algorithm with two different methods for real-time calculation of derivatives, a novel quadratic fit method (CQF) and the commonly used backward derivative method (CBD). Six subjects performed a series of point-to-point movements under three conditions (no compensation, CQF, CBD), in different directions at peak speeds of 50, 100 and 150 cm/s. Without compensation, tangential peak-to-peak forces were as large as 69 N in certain directions at the 150 cm/s speed. Both CQF and CBD significantly reduced tangential forces in all directions and speeds. CQF outperformed CBD in the directions with highest intrinsic impedance, reducing tangential forces by 64% in these directions. Compensation also significantly reduced forces normal to the movement direction, with CQF again outperforming CBD in several cases. Anisotropy was assessed by the range of tangential peak-to-peak forces across movement directions. In the no compensation condition, anisotropy was as high as 52.7 N at the 150 cm/s speed, but an average anisotropy reduction of 74% was achieved with CQF. The CQF method can significantly reduce impedance and anisotropy in this class of robot.

1. Introduction

The InMotion2 (Interactive Motion Technologies Inc., Watertown, MA, USA) is the commercial version of the MIT-MANUS arm robot for rehabilitation following neurological injuries (Krebs et al., 1998; Lo et al., 2010). The InMotion2 is a 2-DOF robot that assists planar pointing movements of the shoulder and elbow (Fig. 1). A key feature is low intrinsic end-point impedance, made possible by direct drive DC motors at the base of the device that drive a linkage mechanism that can apply force at the end effector in any direction within the horizontal plane. For rehabilitation, active control is impedance based, whereby the robot minimally interferes with normal movement and applies assistance only when needed to complete tasks. The InMotion2 can also be used to quantify motor impairments in patient populations (Bosecker et al., 2010; Finley et al., 2009).

However, these applications are hindered by the fact that even low-impedance robots can alter the neural control strategies employed during natural movements outside of the robot. Campolo and colleagues showed that in a wrist pointing task, subjects solve the redundancy problem by using intrinsic or "neural" constraints that restrict wrist rotations to subject-specific 2D surfaces within the wrist's 3D configuration space (Campolo et al., 2009). When a hand performs the same task attached to a low-impedance robot, the 2D surfaces are perturbed by the non-zero impedance of the robot, leading to surfaces that were remarkably consistent from trial to trial and between subjects. Importantly, if the robot impedance is reduced with a force control algorithm, subject-specific 2D surfaces reappeared (Tagliamonte et al., 2011). In terms of rehabilitation, the robot impedance results in an artificial haptic environment during robotic training, which may inhibit recovery of efficient movement strategies and limit performance gains outside of the robot.

The InMotion2 and other similarly designed robots are also extensively used in motor adaptation studies whereby the robot applies novel force fields to the arm, and over repeated movement

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http://dx.doi.org/10.1016/j.jneumeth.2013.01.001

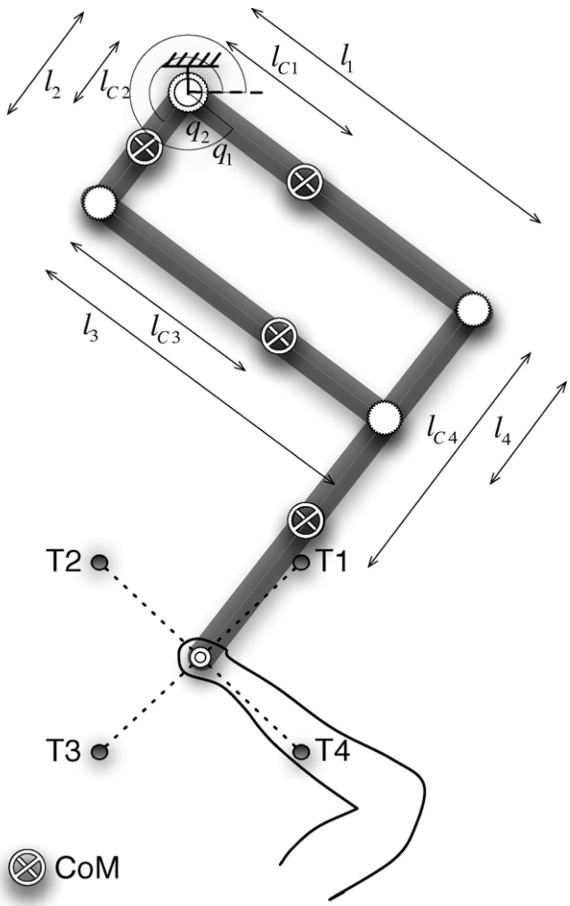

Fig. 1. Top-down drawing of InMotion2 robot with locations of targets. The mass (kg), moment of inertia (kg m^2), proximal link to center of mass distance (m), and length (m) of links 1–4 are: $m_1 = 1.3936$, $m_2 = 0.8143$, $m_3 = 0.7138$, $m_4 = 1.5394$; $I_1 = 0.03346$, $I_2 = 0.00465$, $I_3 = 0.01777$, $I_4 = 0.05770$; $l_{c1} = 0.1021$, $l_{c2} = 0.0728$, $l_{c3} = 0.2032$, $l_{c4} = 0.2461$; $l_1 = 0.4063$, $l_2 = 0.1523$, $l_3 = 0.4064$, $l_4 = 0.1524$.

trials, one can study the sensorimotor processes associated with implicit adaptation to the novel environment (Hwang et al., 2006; Huang et al., 2010; Schabowsky et al., 2007, 2008; Scheidt and Stoeckmann, 2007). In these applications, the end point force applied by the robot is often controlled open loop and based solely on the Jacobian that relates end point force to the motor torques. In these cases, low intrinsic impedance is critical to achieve accuracy in the applied forces. However, most studies ignore the magnitude and anisotropy of the intrinsic impedance of the robot. This could be problematic in cases where data from left and right arms are pooled together or compared, and when movements in different directions are compared.

In this study we quantified the intrinsic impedance of the InMotion2, and developed a compensation algorithm to reduce the impedance felt by the subject during use of the robot. The dynamic equations of motion of the robot were derived and a feedforward compensation scheme was implemented whereby the algorithm commands the robot motors to generate torques real-time to compensate for inertial and velocity-dependent forces that would normally be felt by the user during dynamic movements. Successful implementation is heavily dependent on the accuracy of real-time calculation of velocities and accelerations of the robot links. Two methods for digital differentiation of the robot encoders were tested, including a novel method involving use of a least squares polynomial fit of recent data at each time step. Performance of the algorithms were tested by measuring the robot-user interaction forces during fast reaching movements.

2. Materials and methods

2.1. InMotion2 dynamics

The Euler–Lagrange approach was used to derive the inverse dynamics equations for the InMotion2 (Fig. 1).

$$\begin{bmatrix}\tau_1\\ \tau_2\end{bmatrix} = \begin{bmatrix} I_{11} & I_{12}\\ I_{21} & I_{22}\end{bmatrix}\begin{bmatrix}\ddot{q}_1\\ \ddot{q}_2\end{bmatrix} + \begin{bmatrix}(s_1c_2 - c_1s_2)(m_3l_2l_{c3} + m_4l_{c4}l_1)\dot{q}_2\dot{q}_2\\ (c_1s_2 - s_1c_2)(m_3l_2l_{c3} + m_4l_{c4}l_1)\dot{q}_1\dot{q}_1\end{bmatrix},$$

$$\begin{aligned} I_{11} &= m_1l_{c1}^2 + m_3l_{c3}^2 + m_4l_1^2 + I_1 + I_3,\\ I_{22} &= m_2l_{c2}^2 + m_3l_2^2 + m_4l_{c4}^2 + I_2 + I_4,\\ I_{12} &= I_{21} = (s_1s_2 + c_1c_2)(m_3l_2l_{c3} + m_4l_{c4}l_1) \end{aligned} \quad (1)$$

m_i, I_i, l_{ci}, l_i are respectively, the mass, moment of inertia, distance from proximal link to center of mass, and length of link i ($i = 1$–4). These mechanical properties were available from the manufacturer. We also confirmed the mass and center of mass location of each link after disassembling the robot linkage. Moment of inertia can also be estimated using the pendulum method (Dowling et al., 2006). τ_k and q_k are the torques and angular displacements of the two motors ($k = 1$–2). $s_k = \sin(q_k)$ and $c_k = \cos(q_k)$. The subject moves the robot handle and consequently changes the angular displacements, velocities and accelerations of the robot links. At each time step, the motor torques were calculated using Eq. (1) and commanded at the motors to compensate for the dynamics of the robot.

2.2. Software algorithms

Control software for the robot was written in Matlab Real Time Workshop and XPC-Target (Mathworks Inc., Natick, MA, USA). Two approaches for calculating the real-time angular velocities and accelerations were coded. A commonly used backward difference method was implemented. For velocity, the difference between the previous and current angles was divided by the sample period and filtered with a second-order Butterworth filter (cutoff frequency = 31 Hz). The cut-off frequency was empirically chosen by reducing it until chatter during robot operation was not perceptible. A similar procedure on the velocity profile was used to calculate accelerations.

A second approach was developed based on estimating the quadratic curve that best fits the most recent portion of angle data, and calculating the current derivative directly from the quadratic equation. The effects of noise are minimized by the fitting procedure, eliminating the need for any further filtering of the signal. The equations that define the best quadratic curve were derived using standard least squares methods. Briefly, we fit a portion of the angle profile to the following equation:

$$u = a_0 + a_1t + a_2t^2$$

a_0, a_1, and a_2 are the quadratic coefficients, and u is the angle profile. For n time points, the least squares criteria requires minimizing the following quantity:

$$\sum_{i=1}^{n} e_i^2 = \sum_{i=1}^{n}(u_{i,\text{measured}} - u_{i,\text{model}})^2 = \sum_{i=1}^{n}(u_i - a_0 - a_1t_i - a_2t_i{}^2)^2$$