Manipulating a whip: the advantage of primitive actions

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I. INTRODUCTION

Humans are remarkably agile and dexterous, despite their extremely slow neuromuscular system. We propose that this is accomplished by encoding movements based on (at least) three distinct classes of motor primitives — *submovements* and *oscillations* for forward-path control of motion, and *mechanical impedances* for managing physical interaction [1]. Composing movements in terms of parameterized primitive actions may be an essential simplification required for learning, performance, and retention of complex manipulation skills. To test this hypothesis, we studied one of the most complex and exotic tools which humans can manipulate — a whip.

Studying how humans learn to manipulate a complex objects such as a whip promises new insights. In fact, a whip forces us to confront the daunting complexity of tools which humans routinely master. A whip is a flexible object, with non-uniform mechanical properties, that interact with complex compressible fluid dynamics and, in the case of whip-cracking, operate into the supersonic regime [2]. An engineering/physics based model competent to describe the complex whip dynamics requires nonlinear partial differential equations of infinite order. Controlling this extremely high degrees-of-freedom (DOFs) object (in principle an infinite number) with complex dynamics is a challenge, especially when popular optimization-based methods are involved which scale poorly with system dimensions. Dubbed the "curse of dimensionality" by Richard Bellman [3], optimization becomes computationally intractable for even moderately high dimensions (e.g., starting from $\sim$6 to 10 dimensions) and often fails to converge to an optimal solution. However, almost indifferent to this excruciating complexity, humans learn to manipulate a whip, often without any apparent difficulties, with some "whip masters" reaching an impressive level of expertise. This observation suggests that humans employ a fundamentally different approach than optimization based on an engineering-style model. Instead, we speculate that encoding movements in terms of primitive actions may be the key strategy for humans to manipulate complex objects.

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We studied (in simulation, using a software called MuJoCo [4]) whether a distant target could be reached with a whip using a (small) number of motor primitives, whose parameters could be learned through optimization. Regardless of the target location in 3D space, this approach was able to manage the complexity of an extremely high DOF system (54-DOF yielding a 108-dimensional state-space representation), and identified the optimal upper-limb movement that achieved the task. Detailed equations of motion describing the complex whip dynamics were not needed for this approach, thereby dramatically simplifying the complexity of the control task. Simulation results were in good qualitative agreement with experimental observations which suggests that human subjects may use a small number of primitive motions to reach a target with a whip [5]. These results support our hypothesis that composing control using motor primitives may be a key strategy which humans use to enable their remarkable dexterity.

II. METHOD

A. Modeling

The model used for the simulation consisted of two main parts: the upper-limb model (the manipulator) and the whip model (the object being manipulated). The human upper-limb was modeled as a two-bar 4-DOF open-chain linkage — 3-DOF on the shoulder and 1-DOF on the elbow. The continuous dynamics of a whip was modeled as a equivalent "lumped-parameter" model, in which the continuum was approximated and replaced by a finite 50-DOF system composed of three lumped-parameter elements: an (ideal) point-mass, a linear torsional spring and a linear torsional damper. Summarizing, the whole system resulted in a 54-DOF open-chain linkage. The geometrical and inertial parameters of each limb segment were obtained from a computational model by Hatze [6], and the whip parameters were obtained from an experimentally-fitted whip model [7], where the values were measured and experimentally derived from an actual bull whip.

B. Controller

To account for physical interaction between the upper-limb and the whip, the model included a first-order impedance controller:

$$\boldsymbol{\tau} = \boldsymbol{K}(\boldsymbol{\phi} - \boldsymbol{\theta}) + \boldsymbol{B}(\dot{\boldsymbol{\phi}} - \dot{\boldsymbol{\theta}}) + \boldsymbol{\tau}_G \qquad (1)$$

In this equation, $\boldsymbol{K}, \boldsymbol{B} \in \mathbb{R}^{4\times4}$ are constant symmetric joint stiffness and damping matrices, respectively; vector $\boldsymbol{\tau}(t) \in \mathbb{R}^4$ and $\boldsymbol{\tau}_G(t) \in \mathbb{R}^4$ denote net torque input and gravity compensation torque on each joint, respectively; vector $\boldsymbol{\theta}(t) \in \mathbb{R}^4$ denotes the actual joint angle trajectory of the upper-limb defined in relative angle coordinates; $\boldsymbol{\phi}(t) \in \mathbb{R}^4$ represents a motion command from the Central Nervous System (CNS) as a zero-torque trajectory, i.e., neglecting gravitation effects, if the actual joint angle trajectory $\boldsymbol{\theta}$ exactly matches with the zero-torque trajectory $\boldsymbol{\phi}$, no torque will be exerted by the upper-limb model. Gravitational effects were compensated with $\boldsymbol{\tau}_G$, so that the actual upper-limb posture $\boldsymbol{\theta}$ could exactly match the zero-torque posture $\boldsymbol{\phi}$ when the whole model was at rest [8].

The input of the upper-limb controller was the zero-torque trajectory $\boldsymbol{\phi}(t)$, which followed a discrete rest-to-rest minimum-jerk profile in joint coordinates:

$$\boldsymbol{\phi}(t) = \boldsymbol{\phi}_i + (\boldsymbol{\phi}_f - \boldsymbol{\phi}_i) \cdot (10\tau^3 - 15\tau^4 + 6\tau^5) \qquad (2)$$

where $\tau \equiv t/D$ is a normalized time variable defined on the domain [0, 1]; D is the duration of a single upper-limb movement; t is time and subscripts i and f denote the initial and final (zero-torque) postures, respectively. For times greater than the duration D (i.e., $t > D$), the zero-torque trajectory of the upper-limb remained at the final posture $\boldsymbol{\phi}_f$. Summarizing, the zero-torque trajectory $\boldsymbol{\phi}(t)$ was determined by 9 movement parameters: 4 for the initial posture $\boldsymbol{\phi}_i$, 4 for the final posture $\boldsymbol{\phi}_f$, and 1 for the movement duration D.

C. Task Definition and Optimization

The objective of the whip-targeting task was to minimize the distance between the tip of the whip and the target, L, with a single discrete upper-limb movement, i.e., a single set of 9 movement parameters ($\boldsymbol{\phi}_i,\ \boldsymbol{\phi}_f,\ D$). The minimum value of the distance L reached with a single discrete (i.e., rest-to-rest) upper-limb movement, L^*, was the quantitative measure to assess the performance of the whip-targeting task, i.e., the objective was to find the optimal 9 movement parameters which resulted in the minimum L^* value.

Three different target locations were defined for the whip-targeting task. To avoid chaotic behavior due to the whip colliding with a target, all three targets were distanced 0.01m outside a sphere centered at the shoulder joint, of radius R equal to the sum of the lengths of the upper limb segments and the full length of the whip. In a spherical coordinate system (radius-azimuth-elevation), the three targets were located at coordinate $(R,\ 0°,\ 0°)$, $(R,\ 45°,\ 0°)$ and $(R,\ 45°,\ 45°)$, respectively. The DIRECT-L algorithm of the nlopt (nonlinear optimization) Python tool box was used for the optimization [9]. Within the bounding box constraint for the 9 movement parameters [7], [8], the DIRECT-L optimization algorithm conducted 600 iterations.

III. Results, Discussion and Conclusions

Considering the dimensionality of the whole system, this task is by no means trivial — the task was to coordinate a 54-DOF system (108-DOF in state-space representation) to reach a distant target. It was not *a priori* obvious that the optimization would converge, let alone produce a meaningful result. Nonetheless, for all three targets, the DIRECT-L algorithm di converge to an optimal set of 9 movement parameters that yielded the minimum value of distance L^* [7], [8]. Encoding upper-limb movements using the parameters of dynamic primitives dramatically simplified the whip-targeting task and successfully managed the complexity of an extremely high DOF system.

It is worth emphasizing that the upper-limb controller was "ignorant" of the complex whip dynamics — the whip-targeting task was achieved without the need to store or recall any detailed mathematical representation of the object being manipulated. Even though it is straightforward to derive the equations of motion with the Lagrangian dynamics of an open kinematic chain of rigid bodies, the likelihood of a successful optimization based on this detailed mathematical model seems slim indeed. Instead, using dynamic motor primitives completely avoided the need to acquire the detailed mathematical model of the whip, and the acquisition of the motor skill was completely substituted with the optimization of a small set of movement parameters (9 parameters for this case) which minimized the objective value L^*. This approach may be a key simplification required to learn complex motor skills, since only a small set of parameters are acquired and retained regardless of the dimensionality of the object being manipulated. To the extent that dynamic motor primitives offer a simplified solution to complex and flexible object manipulation, this approach may facilitate robotic manipulation of flexible materials, which is presently still a major challenge.

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