Do Muscle Models Explain How We Reach for Things?

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***Abstract*— Human arm trajectories for simple reaching tasks are highly predictable. These paths generally follow bell shaped speed profiles and depend on the relative configuration between the start and end points. In order to model these trajectories, a popular approach in literature is to consider these as solutions to an optimization problem.**

In this report we investigate the criteria of minimization of rate of change of torque proposed by Uno, et al for determining the optimal trajectory in reaching a point in space. We simulate a simple 3 degree of freedom arm to evaluate our cost function. We obtain an initial trajectory treating the arm as a kinematic chain and then proceed to determine the optimal stimulation trajectory for a muscle tendon model subject to the same cost function.

I. INTRODUCTION

For many day to day mundane activities, we reach out our arms to grab objects. In all these situations, our hands move from a definite start position to an end point. Due to redundancy in our joints, we can choose any trajectory between these end points, where a trajectory is defined both in terms of spatial and temporal context. However, the trajectories we use are highly predictable and repeatable [1].

There are two classical approaches to this problem [2], in terms of trajectory selection as a planning exercise, such as to move the hand in a straight line, or to keep the ratios of the angular velocities of the shoulder and elbow constant. The other approach is to explain these observed trajectories as solutions to optimization problems. In [1], the authors showed that neither of the two proposed planning approaches mentioned matched observations of human subjects performing simple reaching tasks when instructed to not worry too much about the accuracy of their arm movements, whereas approaches based on optimizing criteria have been shown to explain observed trajectories much better.

There are a few major criteria proposed in literature to explain arm trajectories. The first is the minimum jerk hypothesis [3], where the authors propose that we plan arm movements in task space, preferring kinematically smooth trajectories. Essentially, this criteria is given by

$$J = \int_0^T \dddot{x}^T \dddot{x}$$

However this criteria clearly does not take into account dynamics of the arm system; reaching tasks with heavy loads affixed to the hand are predicted to have the same trajectories, which is intuitively not correct. Further, although the criteria did explain the bell shaped velocity profiles observed in human subjects, the paths it chose did not match experimental data by [1]. Based on these shortcomings, Uno, et al [4] proposed the minimum joint torque change criteria to encode the system dynamics within the optimization. This approach demonstrated hand trajectories much closer to observed human trajectories in [1], and is the criteria that we examine in this report. The criterion is given by

$$J = \int_0^T \dot{\tau}^T \dot{\tau}$$

Other criteria include approaches that minimize the travel cost and the metabolic energy cost [2], [5].

This class of problems can be solved in Matlab using Simulink to forward simulate the arm to obtain a numerical solution to these problems, since analytic solutions are often intractable. Thus we intend to investigate the minimum torque change criteria on a simple three degree of freedom arm.

II. MODEL

A. Kinematic Description

The arm is modelled as kinematic links with point masses at the centers of gravity. The upper arm has length of 0.28m and mass 1.9 kg. It's center of mass is at a distance 0.14m from the shoulder joint. The forearm has mass 1.5 kg and length 0.32m. It's center of mass is at 0.16m from the elbow. These dimensions and masses are empirically chosen for simplicity from data on adults given in [6]. The mass of the arm is assumed to be concentrated at the center of gravity for simplicity. There are two degrees of freedom at the shoulder for external and internal rotation and abduction and adduction respectively. The third degree of freedom is at the elbow in the saggital plane. Anatomical restrictions on the ranges of joint angles are taken from [2], The angle of the elbow can vary from $0°$ to $150°$. The angle of the shoulder is taken as zero when the arm points vertically and it's permitted range in the sagittal plane is $-45°$ to $180°$ and in the frontal plane from $0°$ to $120°$. If the joint values exceed these angles at any point in the simulation, then execution of the simulation is terminated.

B. Muscle Model Description

The muscle model used in the analysis is a slightly modified version of that used in [7]. Specifically, the muscle tendon unit does not take into account buffer elasticity and joint oversaturation torques are used to enforce joint limits on both ends of the elbow. Since the actual human arm has a large number of muscles acting on these joints that even span multiple joints, for simplicity we only consider one muscle actuating each degree of freedom. For muscle parameters, we use the biceps long (BICl) and for the exterior rotating upper arm we use the scapular deltoid (DLTs). The values of muscle parameters for these muscles are obtained from [8]

C. Optimization Pipeline

1) Cost Function: The chosen criteria for determining the optimal arm trajectory is the minimum rate of change criterion proposed in [4]. In order to enforce time constraints in reaching the target, we limit the simulation time to 1 second, which is close to the duration that subjects in [1] took in their reaching tasks. Penalty terms are added to ensure that the end effector of the arm reaches the target point with minimal velocity. Thus the cost function has the following form

$$J = \sum_{i=i}^{3} \int_{t_i}^{t_f} \dot{\tau_i}^T \dot{\tau_i} \ + \lambda \left|\left|x_f - x(t_f)\right|\right|_2 + \psi \left|\left|\dot{x}(t_f)\right|\right|_2$$

where $x(t)$ is the end effector position as a function of time, x_f is the final desired location for the end effector, and τ_i is the torque of the i^{th} joint. The values for λ and ψ are determined from progressively increasing from a comparable magnitude of the sum of the change of torques term on the left. In the event that any of the joint limits are reached, the simulation terminates. In this event a much higher cost is returned that drops off with time to completion of trajectory to coax the optimizer to a trajectory that is plausible, i.e.

$$J = \mu \frac{t_f}{t_f - t_{sim}}$$

where μ is an arbitrary large constant, $\mu \gg \lambda$, $t_f = 1s$, the duration of the trajectory, and t_{sim} is the time at which the simulation terminates due to hitting a joint limit.

2) Selecting a solver: The selection of the seed trajectory is done by using a PD controller to actuate the links. Since the optimization cannot be performed on all the elements of the time series, we pick up control points at 75 ms intervals and perform a spline interpolation between these points to obtain the driving trajectory to the simulator. The first attempts at using just this seed trajectory gave results that were too influenced by it. This is a typical problem for nonlinear non convex problems that have multiple local minima. Thus, to better initialize the global optimization process this initial trajectory is perturbed randomly with a Gaussian noise about the initial seed trajectory and then provided to a global black box minimizer.

For the purpose of choosing the best solver, a variety of solvers were used. First, we tried using Matlab's built in fminsearch algorithm that uses a derivative free minimization. However, since this is not a global minimizer, it provided solutions that were very similar to the initial seed trajectory. Then we tried Matlab's simulated annealing optimization, but the optimization crashed due to memory issues after a day. The intermediate solutions were still unsatisfactory. We then tried the multistart minimization but that didn't complete within reasonable time. Finally, we tried a couple of third party black box minimization libraries, namely NOMAD [9] and NL-OPT and we finally settled on the Direct-L algorithm [10] implemented in NL-OPT that seemed to provide the right balance between fast convergence to a minimum and a more global search.

3) Process to determine the optimal stimulation trajectory: After obtaining the optimal kinematic torque trajectory for our cost function, we obtain the optimal stimulation trajectory for individual muscles given that the other joints are being actuated as per the obtained torque. Clearly, since the dynamics of the system change, the torques applied to the other links as per the kinematic optimization are no longer optimum torque trajectories, but they serve as good initialization torques.

Thus, we first attempt to determine the optimal stimulation trajectory for the muscle actuating the elbow while the upper arm is actuated by the optimal torque trajectory determined according to the kinematic structure. After doing the same process for the other joints, we then use these individual stimulation trajectories as seed trajectories to find a final stimulation trajectory for all three joints actuated by the muscle tendon units simultaneously. The step interval for these trajectories is chosen to be 200 ms to model low speed neural feedback.

III. RESULTS

For the kinematic linkage, we obtain a bell shaped velocity profile (Fig.1) for two joints to reach a particular position at [0.5,0,0] that closely matches the bell shaped velocity profiles described to be performed by human test subjects in [1]. The velocity curve of the shoulder joint is not completely bell shaped due to residual effects of the seed trajectory.

For the muscle model, we have an initial setup for stimulation trajectory of the forearm being actuated by our muscle tendon model with the upper arm being actuated by the torques according to the kinematic chain. Over a 6 hour period, we haven't seen an update in the parameter vector, thus indicating that maybe either the model is incorrectly implemented, or that discretizing the trajectory in 200 ms increments is losing descriptive power.

The entire codebase is open source and available at https://github.com/icoderaven/bio-opt

IV. CONCLUSION AND DISCUSSION

In this project we investigate a postulated hypothesis that tries to explain how humans naturally reach for objects when not focussing on being too precise. We obtain results that match those presented by the authors of this hypothesis. The obtained velocity profile of the joints is bell shaped, and qualitatively matches the human subject trajectories reported in [1]. We further outline a process to determine the optimal stimulation trajectory for a muscle tendon modelled version of the arm and present an intermediate result towards the same.

The issue of obtaining a good globally minimized trajectory is a very significant problem in itself. Further, the greater the number of parameters to be optimized, the longer and harder the optimisation becomes. Hence, one way to improve the optimization process is to encode some constraints in the trajectories and parameterizing them to a low dimensional representation. For instance, we can assume that the torque trajectories will be smooth cubic splines and reduce the parameters we are optimizing by a very large factor. However, care needs to be taken not to lose out on the descriptive ability of such a parametric model.

Additionally, there are other criteria that will be interesting to evaluate given this setup, such as minimizing the work done by the muscles. The only difference would be in the one line formulation of the cost function within the code.

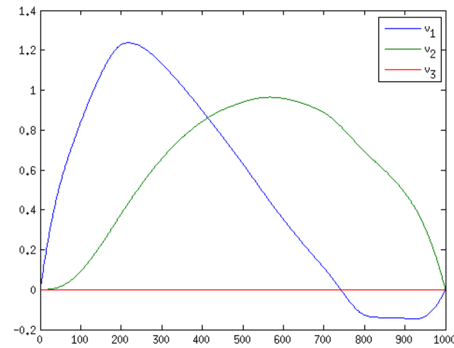

Fig. 1. Velocity profiles for the optimal trajectory obtained while treating the arm as a kinematic chain. The blue curve corresponds to the external rotation of the shoulder joint and the green corresponds to the flexion of the elbow joint. Note the close match of the bell shaped nature of the velocity trajectories.

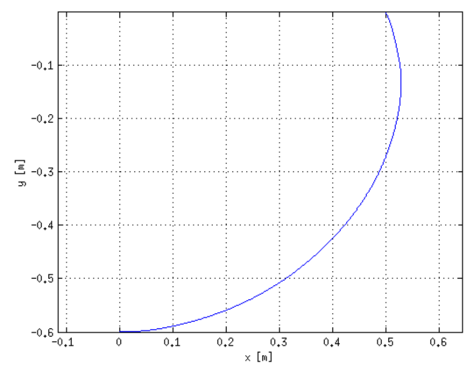

Fig. 2. Profile of the end effector position from start (bottom left, (0,-0.6) to end top right, (0.5,0). Note how the trajectory is strongly convex, as shown in [1]. The primary reason for this is that system tries to minimize gravitational torque acting on it

Finally, to quantitatively evaluate whether this is how we move our arms to reach a target position, we can compare EMG activity with the stimulation trajectory obtained.

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REFERENCES

[1] C. G. Atkeson and J. M. Hollerbach, “Kinematic features of unrestrained vertical arm movements,” *The Journal of Neuroscience*, vol. 5, no. 9, pp. 2318–2330, 1985. 1, 2, 3

[2] R. M. Alexander, “A minimum energy cost hypothesis for human arm trajectories,” *Biological cybernetics*, vol. 76, no. 2, pp. 97–105, 1997. 1, 2

[3] T. Flash and N. Hogan, “The coordination of arm movements: an experimentally confirmed mathematical model,” *The journal of Neuroscience*, vol. 5, no. 7, pp. 1688–1703, 1985. 1

[4] Y. Uno, M. Kawato, and R. Suzuki, “Formation and control of optimal trajectory in human multijoint arm movement,” *Biological cybernetics*, vol. 61, no. 2, pp. 89–101, 1989. 1, 2

[5] D. A. Rosenbaum, L. D. Loukopoulos, R. G. Meulenbroek, J. Vaughan, and S. E. Engelbrecht, “Planning reaches by evaluating stored postures.” *Psychological review*, vol. 102, no. 1, p. 28, 1995. 1

[6] A. David, “Winter. biomechanics and motor control of human movement,” *Wiley,*, vol. 6, p. 1, 1990. 2

[7] H. Geyer and H. Herr, “A muscle-reflex model that encodes principles of legged mechanics produces human walking dynamics and muscle activities,” *Neural Systems and Rehabilitation Engineering, IEEE Transactions on*, vol. 18, no. 3, pp. 263–273, 2010. 2

[8] B. A. Garner and M. G. Pandy, “Musculoskeletal model of the upper limb based on the visible human male dataset,” *Computer methods in biomechanics and biomedical engineering*, vol. 4, no. 2, pp. 93–126, 2001. 2

[9] S. Le Digabel, “Algorithm 909: Nomad: Nonlinear optimization with the mads algorithm,” *ACM Transactions on Mathematical Software (TOMS)*, vol. 37, no. 4, p. 44, 2011. 2

[10] J. M. Gablonsky and C. T. Kelley, “A locally-biased form of the direct algorithm,” *Journal of Global Optimization*, vol. 21, no. 1, pp. 27–37, 2001. 2

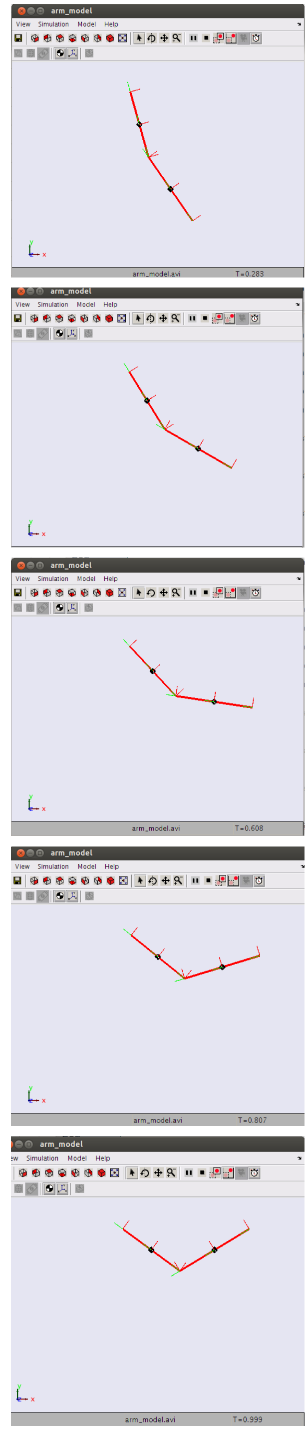

Fig. 3. Sequence of images of the arm for the optimal kinematic trajectory