Hit and Run and Stuff

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Abstract

The brain must select its control strategies among an infinite set of possibilties, thereby solving an optimization problem. While this set is infinite and lies in high dimensions, it is bounded by kinematic, neuromuscular, and anatomical constraints, within which the brain must select optimal solutions. We use data from a human index finger with 7 muscles, 4DOF, and 4 output dimensions. For a given force vector at the endpoint, the feasible activation space is a 3D convex polytope, embedded in the 7D unit cube. It is known that explicitly computing the volume of this polytope can become too computationally complex in many instances. We generated random points in the feasible activation space using the Hit-and-Run method, which converged to the uniform distribution. After generating enough points, we computed the distribution of activation across each muscle, shedding light onto the shape of these solution spaces- rather than simply exploring their bounding boxes. We also visualize the change in these activation distributions in a march toward maximal feasible force production in a givne direction. Although this paper presents a 7 dimensional case of the index finger, our methods extend to systems with up to at least 40 muscles. We challenge the community to map the shapes distributions of each variable in the solution space, thereby providing important contextual information into optimization of motor cortical function in future research.

1 Author Summary

2 Introduction

3 Results

4 Discussion

5 Materials

5.1 Hit-and-Run

The Hit-and-Run algorithm used for sampling in a convex body K, was introduced by Smith in 1984 [6]. The mixing time is known to be $\mathcal{O}^*(n^2R^2/r^2)$, where R and r are the radii of the inscribed and cicumscribed ball of K respectively [1, 4]. In the case of the muscles of a limb, we are interested in the polygon P that is given by the set of all possible activations $\mathbf{a} \in \mathbb{R}^n$ that satisfy

$$\mathbf{f} = A\mathbf{a}, \mathbf{a} \in [0,1]^n,$$

where $\mathbf{f} \in \mathbb{R}^m$ is a fixed force vector and $A = J^{-T}RF_m \in \mathbb{R}^{m \times n}$. P is bounded by the unit n-cube since all variables a_i, $i \in [n]$ are bounded by 0 and 1 from below, above respectively.

Consider the following 1×3 example.

$$\begin{aligned} 1 &= \frac{10}{3}a_1 - \frac{53}{15}a_2 + 2a_3 \\ & a_1, a_2, a_3 \in [0,1], \end{aligned}$$

the set of feasible activations is given by the shaded set in Figure 1.

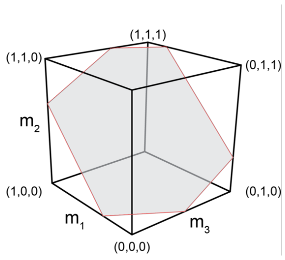

Figure 1: Feasible Activation

The Hit-and-Run walk on P is defined as follows (it works analogously for any convex body).

1. Find a given starting point $\mathbf{p}$ of P (Figure 2) .

2. Generate a random direction through $\mathbf{p}$ (uniformly at random over all directions) (Figure 3).

3. Choose the next point of the sampling algorithm uniformly at random from the segment of the line in P (Figure 4).

4. Repeat from (b) the above steps with the new point as the starting point (Figure 5).

The implementation of this algorithm is straight forward except for the choice of the random direction. How do we sample uniformly at random (u.a.r.) from all directions in P? Suppose that $\mathbf{q}$ is a direction in P and $p \in P$. Then by definition of P, $\mathbf{q}$ must satisfy $\mathbf{f} = A(\mathbf{p} + \mathbf{q})$. Since $\mathbf{p} \in P$, we know that $\mathbf{f} = A\mathbf{p}$ and therefore

$$\mathbf{f} = A(\mathbf{p} + \mathbf{q}) = \mathbf{f} + A\mathbf{q}$$

and hence

$$A\mathbf{q} = 0.$$

We therefore need to choose directions uniformly at random from all directions in the vectorspace

$$V = \{\mathbf{q} \in \mathbb{R}^n | A\mathbf{q} = 0\}.$$

As shown by Marsaglia this can be done as follows [5].

1. Find an orthonormal basis $b_1, \ldots, b_r \in \mathbb{R}^n$ of $A\mathbf{q} = 0$.

2. Choose $(\lambda_1, \ldots, \lambda_r) \in \mathcal{N}(0,1)^n$ (from the Gaussian distribution).

3. $\sum_{i=1}^{r} \lambda_i b_i$ is a u.a.r. direction.

A basis of a vectorspace V is a minimal set of vectors that generate V, and it is orthonormal if the vectors are pairwise orthogonal (perpendicular) and have unit length. Using basic linear algebra one can find a basis for $V = \{A\mathbf{q} = 0\}$ and orthogonalize it with the well known Gram-Schmidt method (for details see e.g. [2]). Note that in order to get the desired u.a.r. distribution the basis needs to be orthonormal. For the limb case we can safely assume that the rows of A are linearly independent and hence the number of basis vectors is $n - m$.

5.2 Stopping Time

In this section we discuss the stopping time of the Hit and Run algorithm. How many steps are necessary to reach an approximate uniform distribution? The theoretical bound $\mathcal{O}^*(n^2R^2/r^2)$ given in [4] has a very large hidden coefficient which makes the algorithm almost infeasible in lower dimensions.

These bounds hold for general convex sets. For convex polygons, as in our case, Ge et al. showed experimentally that up to about 40 dimensions, 10 million random points suffice to get a close to uniform discussion [3]. For our case we generate 10 million points and also test whether the mean of each coordinate converges and whether the upper and lower bounds for each coordinate are met. In detail for the mean we see that it converges after ?? steps. For the upper and lower bounds of the activation we can solve two linear program for each coordinate of $\mathbf{a}$ to find the upper and lower bounds of each a_i. We see that those theoretical bounds match the experimentally obtained bounds.

6 Acknowledgments

References

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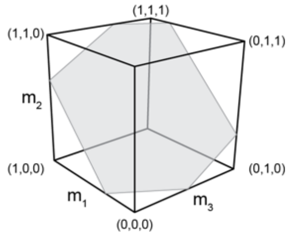

Figure 2: Inner Point

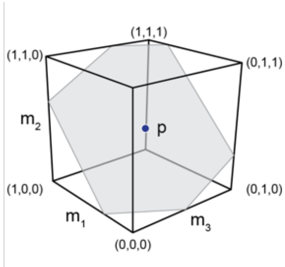

Figure 3: Direction

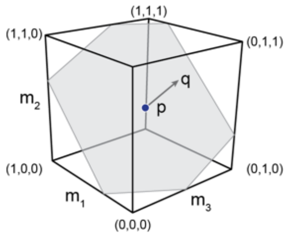

Figure 4: Endpoints

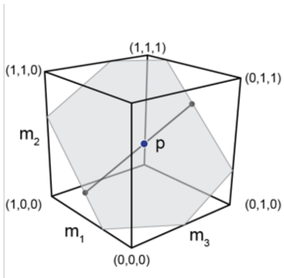

Figure 5: New Point

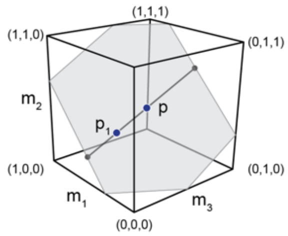

Figure 6: Uniform Distribution

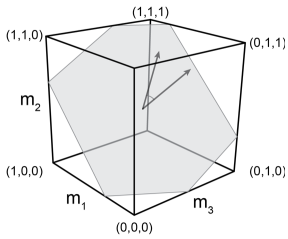

Figure 7: Some Basis

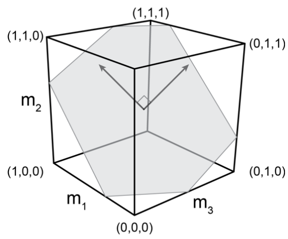

Figure 8: Direction