1 Humans use minimum cost movements in a whole-body 2 task

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7 **Abstract**

8 Humans have elegant bodies that allow gymnastics, piano playing, and
9 tool use, but understanding how they do this in detail is difficult because
10 their musculoskeletal systems are extraordinarily complicated. Nonetheless,
11 common movements like walking and reaching can be stereotypical, and a
12 very large number of studies have shown their movement cost a major factor.
13 In contrast, one might think that general movements are very individuated
14 and intractable, but a recent study has shown that in an arbitrary set of
15 whole-body movements used to trace large-scale closed curves, near-identical
16 posture sequences were chosen across different subjects, both in the average
17 trajectories of the body's limbs and in the variance within trajectories. The
18 commonalities in that result motivate explanations for its generality. One
19 possibility could be that humans also choose trajectories that are economical
20 in energetic cost. To test this hypothesis, we situate the tracing data within
21 a fifty degree of freedom dynamic model of the human skeleton that allows
22 the computation of movement cost. Comparing the model movement cost

23 data from nominal tracings against various perturbed tracings shows that
24 the latter are more energetically expensive, inferring that the original traces
25 were chosen on the basis of minimum cost.

26 **Keywords:** Posture analysis, whole body movement, virtual tracing,
27 kinematic representation, movement variation costs

28 1. Introduction

29 A general principle of human movement is that our nervous system should
 30 exhibit trajectories that are economical in energetic cost [1, 2]. It has been
 31 established for decades and has been well studied in simple movements. In lo-
 32 comotion, there are a number of experiments showing that humans’ walking
 33 speed [3], step frequency/length [4, 5, 6, 7, 8, 9, 10], step width [11, 12] are
 34 all corIn particularrelated with the minimum metabolic cost, In particular,
 35 energetic cost exhibits a U-shaped dependence on step frequency while walk-
 36 ing at a constant speed [13, 8], and the minimum of the U-shape is consistent
 37 with the self-selected or preferred walking frequency. Furthermore, new ev-
 38 idence [14, 15, 16] shows the system can adapt preferred gaits to minimize
 39 energetic cost in response to varying loads.

40 Although the principle that humans’ self-selected trajectories or posture
 41 sequences are economical in energetic cost has been commonly shown in
 42 the studies of simple single-behavior motions such as walking, running, and
 43 reaching, whether the principle is true for large-scale complex movements still
 44 needs to be tested. Thus, we conducted a complex whole-body virtual tracing
 45 experiment [17] that aimed to learn the principles behind *large-scale arbitrary*
 46 movements, particularly regarding variations between different subjects. We
 47 eschewed common movements such as reaching and walking [18, 19, 13] and
 48 also studies of small-scale grasping movements [20, 21].

49 In our study, a full-body virtual-reality tracing task elicited a series of
 50 human movement sequences [17]. At each trial, subjects freely chose their

51 initial postures and were given no instructions on how to comport themselves
 52 during the tracing process. Participants were tracing three-dimensional space
 53 curves at their preferred posture sequences and their postures were continu-
 54 ously recorded using a motion-capture system. Specialized aggregation meth-
 55 ods were developed for data analysis that extracted similarities of posture
 56 sequences in the face of kinematic variations. The exciting and unsuspected
 57 result was that both the movement’s posture sequences and kinematic vari-
 58 ations showed striking commonalities across subjects. The obvious inference
 59 from the observed similarities of movements across different subjects is that
 60 there must be some general principle for humans’ motion commonalities.
 61 This regularity of movements across different subjects implies energetic cost
 62 should be similar. Moreover, these observations arise from the generally
 63 argued principle that the self-selected trajectories should be economical in
 64 energetic cost. This argument is reinforced with by progress in the sparse
 65 coding of temporal sequences [22, 23] that strongly suggest that trajectories
 66 are remembered to obviate the difficulties of computing them online. In ad-
 67 dition, if movements are to be stored, the less expensive ones are likely to be
 68 preferred[24].

69 For the energetic cost computation, we took advantage of a forty-eight
 70 degrees of freedom dynamic computational model capable of simulating, an-
 71 alyzing, and synthesizing humanoid movements [25]. The model consists of
 72 twenty-one body components connected by twenty joints and incorporates
 73 several novel features. One innovation is that the joint connections are not

74 treated as perfectly rigid constraints but rather as very stiff springs that hold
75 body parts together like tendons and muscles. The model allows computing
76 instantaneous power from the product of net joint torque and joint angular
77 velocity. The work performed at each joint was determined by numerically
78 integrating the instantaneous powers over the entire tracing task. In this
79 way, the energetic cost of human motions can be computed given motion
80 capture data.

81 To test this hypothesis that the minimum energetic cost principle is still
82 held in large-scale complex movements the costs of different subjects' curve
83 traces were computed and compared to the costs of tracing movements un-
84 der two different kinds of perturbations. In one, the tracing trajectories were
85 slightly perturbed by shifting positions of a particular body part of the dy-
86 namic model a small amount for the duration of the trace. In the other, the
87 original tracing path was displaced in certain small increments prior to the
88 trace. The result of both of these kinds of perturbations was that their means
89 of the energetic cost were higher than those of the original curve. In other
90 words, the energetic cost exhibits a classical U-shape with respect to the dif-
91 ferent posture sequences, with the minimum of the U-shape curve consistent
92 with the cost of the original posture traces, which our subjects self-selected.
93 These results strongly suggest that that movement is selected on the basis of
94 predicted minimum cost.

95 2. Background

96 In the past, a common way to address the minimum energetic cost prin-
 97 ciple was to conduct experiments comparing walking and running with many
 98 other strange and unpractised gaits [26, 27]. Nowadays, there are three
 99 commonly used methods to study energy optimization.

100 The most straightforward and frequently used method is to measure the
 101 metabolic cost, e.g., subjects breath through a mouthpiece to measure oxygen
 102 consumption rates (VO_2). For example, subjects were required to walk under
 103 different circumstances, and the results showed that the metabolic cost was
 104 minimum while subjects walked at the condition which was "comfortable" for
 105 them [3, 4, 5, 6, 14, 15, 16]. The advantage of this method is that movements
 106 can be related directly to energetic cost, but the measuring apparatus is
 107 typically very constraining.

108 A common way to measure muscle co-activation and stiffness is to use
 109 Electromyography (EMG). Huang et. al. huang2012reduction showed that
 110 that subjects' metabolic cost is reduced during the learning process of arm
 111 reaching tasks, and their muscle activities and co-activation would parallel
 112 changes in metabolic power. However EMG measures just a correlate that
 113 needs additional modeling to turn it into a energetic cost.

114 A third energetic cost method, dynamic modelling, is to build a closed
 115 form analytical mechanics-based model and determine if the predicted min-
 116 imum mechanical cost correlates with people's kinematic preferences. For
 117 example, [7, 8, 9, 11] use an inverted pendulum model to predict the op-

118 timal step length and compare it with the subjects' real step length while
119 walking.

120 All these methods pose obstacles for our calculation of the energetic cost
121 of whole-body tracing movements collected from the VR experiment [17].
122 These methods are time-consuming, and the required configuration restricts
123 the variety of experiments. For example, the VO2 process does not work
124 for our virtual-reality tracing tasks as subjects need to wear the VR hel-
125 met on their head, leaving little space for a mouthpiece. Besides, the EMG
126 method measures muscle co-contraction, which is correlated with energetic
127 cost, rather than calculating the cost. Another possible way is to build
128 a humanoid dynamic model. The method is the best way to imitate hu-
129 man movements, and it is widely used in biomedical engineering due to its
130 compliance with real-world physical rules. However, it has several critical
131 limitations as well: 1) it is too difficult to model and control a complex
132 system, such as a whole human body. 2) it is challenging to represent "kine-
133 matic loops", such as postures that need both feet are on the ground. 3) for
134 large systems, the equations of motion in nested, rotating reference frames
135 become very complex, making them more challenging to approximate well.
136 Due to the complexity and disadvantages of dynamic modeling method for
137 large complex systems, most of studies took advantages of two-dimensional
138 models to study human part-body motions in the sagittal plane.

139 There are some methods of building a dynamic 2D bipedal robot by
140 modeling the whole-body with a skeleton of rigid segments connected with

141 joints. However, those methods over-simplify human bodies so that they can
 142 only study simple single-behavior human movements. The simplest bipedal
 143 robot uses three links to represent the torso and two legs in the sagittal
 144 plane [28, 29]. Five-link biped robots extend the model using two links
 145 to represent each leg [30, 31, 32, 33], while seven-link biped robots further
 146 extend it by adding feet to it [34, 35]. Furthermore, those methods have
 147 many assumptions while studying human locomotion. For example, most
 148 researchers assume that when the swing leg contacts with the ground, an
 149 instantaneous exchange of the biped support legs takes place. In this way, the
 150 biped locomotion with single foot support can be considered as a successive
 151 open loop of kinematic chain from the support point to the free ends, as
 152 robot manipulators. Recently, 3D modeling of closed-form modeling of biped
 153 robots [36, 37] has been developed. However, they are still not sophisticated
 154 enough compared with a real human body.

155 In the face of these complex challenges, a major alternate modeling route
 156 is to forego the neural level of detail as well as one that features muscles
 157 and model more abstract versions of the human system that still use multi-
 158 ple degrees of freedom but summarize muscle effects through joint torques.
 159 The computation of the dynamics of such multi-jointed systems recently has
 160 also experienced significant advances. The foremost of these, use a kine-
 161 matic plan to integrate the dynamic equations directly. Several different

open source dynamic libraries exist, such as MuJoCo¹ [38], Bullet², Havok³, Open Dynamic Engine(ODE)⁴, and PhysX⁵, but an evaluation by [39] found them roughly comparable in capability, and only MuJoCo has been applied to human modeling.

Our 48 degree of freedoms human dynamic model (HDM)⁶ [25] also based on a direct integration method. It was built on top of ODE which is the most commonly used dynamic library in robotic research area. The model has a singular focus on human movement modeling and uses a unique approach to integrating the dynamic equations. A direct dynamics integration method to extracts torques from human subjects in real-time [40, 41, 42] using a unifying spring constraint formalism.

These torques have two components. The major component is the one determined by the open-loop integration of Newton’s equations. These must be supplemented by a closed-loop set of “residual torques” to achieve accurate balance. This organization models the similar dichotomy in the human system.

At each frame, instantaneous power was computed from the product of the net joint torque and joint angular velocity. The work performed at each joint was determined by numerically integrating the instantaneous powers

¹MuJoCo <http://www.mujoco.org/>

²Bullet <https://pybullet.org/>

³Havok <https://www.havok.com/>

⁴OpenDE: <http://www.ode.org/>

⁵PhysX: <https://developer.nvidia.com/gameworks-physx-overview>

⁶The HDM model: https://github.com/EmbodiedCognition/HDM_UI

181 over the entire tracing task. In this way, given motion capture data, we can
 182 compute the mechanical cost without building a humanoid biped robot with
 183 motion equations. An extensive validation of this dynamic model appears
 184 in [25]. Note that it is common to use mechanical measures of work to indicate
 185 the metabolic energy consumption [43]. The “energetic cost” mentioned in
 186 the following sections means the mechanical cost.

187 While doing the virtual tracing experiment, subjects freely chose their
 188 starting posture and were given no instructions on how to perform them-
 189 selves. Therefore, participants were tracing curves at their preferred posture
 190 sequences. In other words, they traced curves under the conditions which
 191 were “comfortable” for them. According to the previous experiments [3, 4,
 192 5, 6, 14, 15, 16], we can expect that the energetic costs of movements with
 193 those trajectories should be a minimum or at least locally minimum. To
 194 support our conclusion, the cost of original virtual tracing movements and
 195 perturbed movements were computed and compared using the human dy-
 196 namic model. As expected, the energetic cost always exhibits a U-shape
 197 while tracing using different postures sequences, with the minimum of the
 198 U-shape curve consistent with the original posture traces, which our subjects
 199 self-selected. In this way, we are able to demonstrate the energetic cost of
 200 original trajectories is a local minimum. The focus of the method section
 201 describes experimental protocol in more detail.

3. Results

Using the kinematic curve tracing data from [17], we fitted the dynamic model to each of the eighteen subjects and then had the models trace the nine curves that are shown in Fig. 1. The energy cost of tracing paths showed marked regularities in the following aspects of the data that was subject to the following analysis summary:

Figure 1: **The nine 3-dimensional paths in the virtual environment that were used in the experiment.** They are ordered by their complexity. For reference, colors denote common segments and points. For the subjects, the paths were all rendered in black, The scale is in meters.

- 208 1. The joints' power allocation while tracing path 1 across different sub-
209 jects showed that although the total costs of the movements varied
210 between subjects, the power use is qualitatively very similar. (See sec-
211 tion 3.1, Figure 2);
- 212 2. The computation of average energy cost while tracing path 1 showed
213 the magnitude of the required residual forces were relatively small. (See
214 section 3.1, Figure 3);
- 215 3. The costs of tracing each path by each subject are very similar and
216 approximately monotonic with the length of paths. (See section 3.2
217 and Figure 4);
- 218 4. Although there are variations in the cost across the repeated traces,
219 the cost of using the perturbed model parameters is significantly higher
220 than the original. (See See section 3.2, Figure 5 Figure 6);
- 221 5. The increment of energy cost while using perturbed model parameters
222 distributes more on the joints' cost than on the residual component.
223 (See section 3.2 and Figure 7);

224 3.1. Detailed Energetic cost analysis of tracing path1

225 **The mean of power across different participants.** As an initial anal-
226 ysis, we established the variations in the energetic costs for tracing path 1
227 exhibited by different subjects. Fig. 2 illustrates the mean and the standard
228 deviation of powers across subjects at each frame. The result reveals that

229 subjects put similar effort at the same points along the path. Thus although
 230 the total cost of the movements may vary between subjects, the power pat-
 231 terns are qualitatively very similar. The VR experiment [17] showed partic-
 232 ipants used similar postures sequences while tracing the same curves from a
 233 kinematic perspective. It is expected that the instantaneous power of joints
 234 at each frame should be similar as well due to the skeleton constraints of
 235 the human body. The similarity of power patterns across different subjects
 236 reinforces this conclusion from a dynamics perspective.

Figure 2: The power of tracing path1 at each frame. Nine subjects traced path1 five times. The plot shows the average joints' power at each frame across subjects. The blue line indicates the mean and the gray shaded area represents the standard deviation of powers. The small standard deviation means that different subjects had similar power patterns while tracing the same curve, which shows that the curve has points of difficulty in tracing shared by the subjects. Path 1 is the most straightforward, but the observation of correlated effort represents patterns in tracing other curves.

237 **Average energy cost of five repetitions.** Although there are qualitative
 238 similarities in the difficult points on the curve, the total costs of the traces
 239 differ across different subjects. This result is expected due to the variety of
 240 subjects' skeletons and weights. Fig. 3 represents the energetic cost per sub-
 241 ject. The total energy of tracing a path1, including the residual components,
 242 is shown in blue, and the residual component is shown separately in orange.
 243 When reporting the energetic costs of the traces, we always use the total cost
 244 shown here in blue.

Figure 3: Energetic costs of tracing path 1 Each subject traced path 1 with five repeats. The horizontal labels indicate the related subjects, e.g., "S1" represents the subject1. The total cost is shown in blue, and the portion of that cost due to residual forces are shown in orange. A low cost in residual torque usually signifies that the dynamic model is a good match for that subject's kinematic data.

245 **Residual forces.** As shown in Fig. 3, the highest cost of the tracing move-
 246 ment is the component owing to the joint torques that are producing the
 247 kinetic trajectories, and the additional cost of the residual from the inverse

dynamic calculation is small. In the human system, this residual is most prominently due to the vestibular system, but just how the vestibular connects to the muscular system is not modeled by the human dynamic model. Instead, we implemented a provisional system of torques referred to as a coordinate system positioned and the center of mass to maintain balance [25].

3.2. Energy cost analysis of tracing individual paths

Energy cost of tracing nine paths. Although there are similar energetic costs per subject in tracing a same path, this arrangement does not carry over to the comparison between paths, which has larger differences. We hypothesized that the cost should scale as the length of the path, as shown in Fig. 4, which shows the average energetic cost of tracing the nine different paths. The paths differ in tracing cost, but the costs of tracing each path by each subject are very similar and approximately monotonic with the length of the paths.

Given these regularities, the next step was to evaluate the significance of perturbations in the tracing protocol. The hypothesis is that if the tracing postures are chosen to be of minimum energy, changing the configuration away from the original tracing situation should incur a cost, which was what happened.

Model perturbation. The first perturbation test changed in model marker trajectories, called model perturbation. Specifically, the right elbow marker was shifted by a small delta, which produced a new constraint that the model

Figure 4: Cost of tracing nine paths. These results portray the possibility that the costs vary across the best-fit five subjects. The statistics show that each path traced has a unique cost that distinguishes it from the rest.

needed to satisfy while tracing paths. To implement it, the dynamic model had to trace paths using the same posture sequences except for lifting its right elbow. Although kinematics of the body parts except the right elbow remained for the unperturbed trace – only the kinematics of the right elbow changed, the joints’ constraints bias the dynamic model adapt to follow the new perturbed trace.

For each trace, the right elbow marker was raised by 5 cm. The rest of the system adapted the way dictated by the dynamic constraints. Fig. 5 shows the difference in cost of constrained motions and original motions. It is seen that although there are variations in the cost across the repeated

traces, the cost of using the perturbed model is higher than the original. Note that outside of the changes, the rest of the model solves the inverse dynamic model with the unperturbed parameters, and thus the model has substantial degrees of freedom at its proposal. The significant test showed the difference is reliable, with a p-value less than 0.001. Furthermore, it is obvious that the increase of tracing complex paths is larger than that of tracing simple paths.

Figure 5: Energetic cost of tracing with model perturbation Energetic cost of tracing each of the nine paths with perturbations in the right elbow marker. The elbow was moved up 5cm. This shows that for all the paths and the averages across subject tracers, the original path is always the least expensive. Moreover, the differences between the energetic costs of original trajectories and perturbed trajectories are highly significant.

Path perturbation. The second perturbation test made adjustments in the traced path, called path perturbation. Some effects of displacement can be intuited. For example, if a subject has to reach over their head during the

Figure 6: Energetic cost of tracing with path perturbation Each of the nine paths has two perturbations of 5 cm: left in blue, right in green. This main result shows that for both averages across subject traces, the original path is always the least expensive.

289 trace, it can be expected that lowering the traced path would result in cost
 290 savings. For this reason, we chose path perturbations in the horizontal plane.
 291 Two such perturbations were used: a 5-centimeter leftward displacement and
 292 a 5-centimeter rightward displacement. Left and right are referenced to the
 293 coordinate system used for the four points used for all nine curves (See Fig 1).

294 In this way, new constraints were produced as the dynamic model was
 295 required to trace the perturbed paths while the starting tracing positions
 296 were not changed. In contrast to the model perturbation, the model's trace
 297 paths were shifted while the posture sequences remain the same. Again, the
 298 dynamic model took advantage of internal joint constraints to adjust original

299 posture sequences to trace the perturbed paths.

300 Figure 6 shows the difference in average energetic costs for tracing dis-
 301 placed paths and original paths across subjects. The blue dots indicate the
 302 difference between motions of tracing left-shifted paths and motions of trac-
 303 ing the original path while the green dots represent the other case. For most
 304 cases, the original paths are seen to be consistent with the lowest cost. The
 305 path 2 with 5cm leftward displacement costs less than the original path 2.
 306 The reason is that subjects preferred to stand near the left corner which is
 307 the starting tracing point. However, the left part of path 2 is much easier
 308 than its right part (See Fig. 1). Therefore, when shifting the path 2 to left,
 309 subjects became closer to the right part, which led to an easier tracing. In
 310 contrast, subjects had to move their bodies more in order to trace properly
 311 when shifting path 2 to right.

312 Here again, the overall result is striking. Although there are some over-
 313 laps, the original paths are more economical for almost all curves than the
 314 displacements. The significant test showed the effects of shifting paths is not
 315 very clear but still reliable, with a p-value less than 0.01. The observation
 316 that the averages of all the perturbed costs are larger than the average cost
 317 of their original progenitors strongly suggests that energy cost is the factor
 318 in the choice of tracing postures.

319 **Residual forces.** Given the dynamics dichotomy, a natural question that
 320 arises concerns the magnitude of the extra torques in the perturbation cases.
 321 Are the extra costs carried by the dynamic model or the residual? It can be

Figure 7: Residual torques The average of the means of the cost changes for path 1 with five repeats across five participants.

322 answered by interrogating the simulation, and it turns out that the dynamics
 323 model's contribution is dominating. This is shown in Fig 7.

324 Note that if the constraints on the dynamics were extremely stiff, then
 325 the model would have no course other than tracing an exact copy of the
 326 unperturbed trajectory and let the residual torques contribute the needed
 327 difference. However, the markers on the body for these experiments were
 328 limited to 15~18 of key body segments, leaving the extra degrees of freedom
 329 to be determined by the dynamics. Moreover, the torque computation, to
 330 model the reality of muscles [44], used spring constraints at each joint degree
 331 of freedom. Finally, the right finger was required to contact the displaced
 332 paths, and the remaining features of the movement are the same, leaving the

333 dynamics to fill in the rest.

334 Discussion

335 Given that the cost of the movements is a significant fraction of a human's
 336 caloric budget [45], one might expect that humans would exhibit common
 337 low-cost postures. It turns out to be the case for stereotypical situations
 338 such as reaching or walking on a planar surface, but arbitrary whole-body
 339 movements have been less studied, so the expectations are open. Thus it was
 340 a surprise to measure arbitrary movements in a large-scale tracing task and
 341 find markedly common posture sequences used by all tested subjects [17]. An
 342 obvious possibility for similar posture sequences is energetic cost, especially
 343 since there were no complex constraints in the movements and no constraints
 344 in the time to perform the traces. Our simulation extends the kinematic find-
 345 ing to show that tests of human dynamics provide evidence that movements
 346 are chosen on the basis of energetic economic costs. The cost of tracing
 347 scales monotonically with the length of a traced path as expected, and the
 348 necessary residual forces, as would be expected from the human's vestibular
 349 system and others, were relatively small, given that the subjects had to
 350 choose their movements.

351 The main substantive results are that subjects' traces of each of nine
 352 space paths all have minimal costs with respect to local perturbations. One
 353 manipulation introduced perturbations in their kinematic variables – the sub-
 354 jects traced the path but their model with small displacements in kinematic

355 markers. The other experiment used local horizontal displacements of the
356 paths. Verticals were not used as they can be equivocal. The displacements
357 can interact with the different body heights, e.g., a short subject has to reach
358 an uncomfortable height. However, outside of this caveat, all the data can
359 be interpreted as the tracing posture sequences selected based on energetic
360 cost.

361 The hypothesis that humans use minimum cost movement trajectories
362 is shown by the use of a human dynamic model that leverages a major in-
363 novation in dynamics computation that allows the recovery of torques from
364 kinematic data. The disadvantage of the current method is that we perturbed
365 motions manually, so it is possible that we found only a local minimum in the
366 space of possible movements. However, as tracing a path usually takes more
367 than 1000 frames and at each frame, there are 50 markers representing a pos-
368 ture, the perturbation space is significantly vast. Therefore, our future work
369 is to introduce an algorithm with the capability of seeking potential pertur-
370 bations automatically, such as reinforcement learning, while still reflecting
371 the constraints of possible postures.

372 4. Methods

373 4.1. *Virtual tracing experiment*

374 The original kinematic data capture were collected from a virtual whole-
375 body tracing experiment that was to elicit natural movements under common
376 goals [17]. Subjects wore a virtual-reality helmet, Oculus Rift [46], to see a

virtual three dimensional interior room with a dojo backdrop via stereo video. They were required to trace a series of paths positioned at fixed locations in the virtual environment. The movements of their bodies and variables relevant to the tasks were simultaneously recorded using the PhaseSpace motion capture system [47]. The WorldViz Vizard software package [48] both controlled the virtual tracing protocol and the recording of the motion capture data. Fig. 8 shows the virtual environment setup. Fig. 1 shows the nine paths that subjects traced.

Data pos-processing. For some frames the motion capture system is unable to determine the 3-dimensional location of some markers, thus raw motion capture data usually contains some segments of signal loss (dropouts). Dropouts are relatively infrequent in practice but can occur over significant temporal intervals, which makes linear interpolation a poor choice for reconstructing the raw motion capture data. In this experiment, trajectory-based singular value threshold was implemented to reconstruct missing marker data with a minimal impact on its statistical structure. The data for each subject was interpolated using a separate matrix completion model.

In addition to the data interpolation process, if a participant did not trace the path successfully we would consider this tracing invalid and the data unusable. Because if a recording of a tracing trial failed, e.g., too many markers were off during a tracing, it will lead to extremely large joint torques, which is unrealistic.

Figure 8: the virtual environment setup. (a) shows a full view of a path, denoted by a black path, and the starting position, denoted by a large white sphere. The small white sphere on the path at the end of a red segment is the tracing target sphere. (b) depicts the scene when a trial is finished. The green path is the actual tracing trajectory generated by a subject. (c) illustrates a subject in the act of tracing a path in the laboratory's motion capture $2 \times 2 \times 2$ meter volume. and (d) shows the lab coordinate system. The scale on the graph is in meters. The the subject's skeleton and the traced path in the 3D space are plotted. The color dots correspond to a subset of the fifty active-pulse LED markers on the suit and the virtual-reality helmet.

399 **4.2. Human dynamic model**

400 **Model topology.** To compute the energy cost of subjects tracing paths,
401 we used our human dynamic model [25]. By replaying the virtual tracing
402 experiment’s kinematic data, we can compute the joints’ properties, e.g.
403 torques and angles, at frame rates. The human dynamic model is built on
404 top of the ODE physics engine [49]. It consists of a collection of rigid bodies
405 connected by joint. Each joint connects two rigid bodies with anchor points
406 (center of rotation) defined in the reference frame of both bodies. Fig. 9
407 shows the number of body segments and topology of the human dynamic
408 model.

B

Joint	Part 1	Part 2	DOF/joint	Total DOF
Cervical	Head	Neck	3	3
Thoracic	Neck	Upper Torso	3	3
Lumbar	Upper Torso	Lower Torso	3	3
Sacral	Lower Torso	Pelvis	3	3
c.Clavicle	Upper Torso	c.Collar	3	6
c.Shoulder	c.Collar	c.Upper Arm	3	6
c.Elbow	c.Upper Arm	c.Lower Arm	2	4
c.Wrist	c.Lower Arm	c.Hand	2	4
c.Hip	c.Pelvis	c.Upper.Leg	3	6
c.Knee	c.Upper Leg	c.Lower Leg	2	4
c.Ankle	c.Lower Leg	c.Heel	2	4
c.Tarsal	c.Heel	c.Sesamoid	1	2

Figure 9: **The 48 internal DOF Model A.** Four ball-and-socket joints connect five body-segments along the spine from the head to the waist. Ball-and-socket joints are also used at the collar-bone, shoulder, and hip. B. A summary of the joints used in the model. c. = chiral: there are two of each of these joints (left and right). Universal joints are used at the elbows, wrists, knees, and ankles. Hinge joints connect the toes to the heels. All joints limit the range of motion to angles plausible for human movement. Our model assumes that joint DOFs summarize the effects of component muscles.

Fig. 10 shows a user interface that allows the simulation of human movements via a multi-purpose graphical interface for analyzing movement data captured through interaction with the virtual environment. With this tool, it is possible to interactively fit a model to motion capture data, dynamically adjust parameters to test different effects, and visualize the results of kinematic and dynamic analysis, such as the example in Fig 11, which shows a four stages in a tracing sequence made originally by a participant of the virtual tracing experiment and recreated by applying the inverse dynamics method using this tool.

Residual forces/torques. The energetic costs are derived from the inverse dynamics technique described in [25], which combines measured kinematics and external forces to calculate net joint torques in a rigid body linked segment model. A feature of the dynamic method is that it can reduce potential errors, both in the matches of the motion capture suit and the model. Analogous to the human body's ligament structure to join joints, some leeway is allowed in the model joints in the integration process. Nonetheless, even after these adjustments, some errors remain. In the model, the main source of the residual forces is usually attributable inaccuracies in the matches between the motion capture suit makers and their match with their corresponding points on the model. This is commonly resolved by introducing 'residual forces,' which compensate for this problem [50]. This resolution with a dichotomy of forces is analogous to the human system, which combines feedforward lateral pathway forces with medial pathway feedback forces. Therefore, a low cost

Figure 10: Our analysis tools use the physics engine to compute inverse kinematics and inverse dynamics. They also support various visualizations of relevant data and control for analyzing and producing physically-based movements. The programmed parameters of the model consist of its joints and its 3D marker positions. For example, the right column represents the positions of the markers relative to their corresponding body segments, e.g. the first row shows the information of marker1: 1) "1" represents the marker index, 2) "head" means marker 1 is attaching to the "head" body segment, 3) the remaining three float numbers are marker1's relative position.

in residual forces usually implies that the dynamic model is a good match for that subject's kinematic data.

4.3. Energy cost computation

The centerpiece of the analysis depends critically on the definition of a posture. At each frame, posture is defined as a vector of the joint torques and angles of each of N joints ($N = 22$ in our dynamic human model). The posture p at a frame is a $6n$ -dimensional column vector presenting the joints

Figure 11: **Model capability illustration.** Four points in a tracing sequence reproduced with physics-engine-based inverse dynamics using recorded motion capture data from a human subject.

439 properties of the i th participant, thus

$$\mathbf{p} = [\mathbf{j}_1, \mathbf{j}_2, \dots, \mathbf{j}_N] \quad (1)$$

$$\mathbf{j}_i = (\boldsymbol{\tau}_i, \mathbf{a}_i) \quad (2)$$

440 where $\boldsymbol{\tau}_i = (\tau_{ix}, \tau_{iy}, \tau_{iz})$ and $\mathbf{a}_i = (a_{ix}, a_{iy}, a_{iz})$ represents the torques and
 441 angles of the i th joint at a frame respectively and $i = 1, 2, \dots, N$. For the
 442 joints which have less than three dimensions, e.g. hinge joints, universal
 443 Joints, the values at unused dimension were assigned zero.

444 The power W of i th joint at a frame t is a scale and equals to the inner
 445 product of its torque $\boldsymbol{\tau}_i$ and its angular velocity $\boldsymbol{\omega}_i$, thus

$$\boldsymbol{\omega}_i(t) = \mathbf{a}_i(t) - \mathbf{a}_i(t-1) \quad (3)$$

$$P_i(t) = \boldsymbol{\tau}_i(t) \cdot \boldsymbol{\omega}_i(t) \quad (4)$$

446 Therefore the power of a posture at frame t is presented as:

$$W(t) = \sum_{i=1}^N W_i(t)$$

447 Assuming it takes a participant T frames to trace a path, then the total
 448 energy cost E of the participant tracing a path is:

$$W = \sum_{t=1}^T P(t)$$

449 The energy cost analysis is naturally organized into three separate stages.
 450 Initially, we analyze the subjects energy cost and residual torques of tracing
 451 path1 which is the simplest path. Next, we computed the tracing cost of all
 452 nine paths. To compare the energy cost of tracing a path across subjects, we
 453 computed the average energy cost for all five repeated traces of each subject.
 454 Finally, we measured the tracing cost of perturbed participant's trajectories
 455 and perturbed paths.

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459 Declaration of Interests

460 The authors have no financial or personal relationships with other people
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