
Flavio T.P. Oliveira, Digby Elliott, and David Goodman

Anecdotal and scientific evidence suggest humans tend to undershoot targets in rapid movements. We investigated whether this undershoot bias derives from energy minimization mechanisms. Participants performed 200 trials of two tasks: (1) a simple slider push to a target, and (2) a modified version of (1), designed so overshooting was less energy consuming than undershooting. Results support that the undershoot bias found in (1), as well as the overshoot bias found in (2), results from an energy minimization mechanism. Energy minimization might be inherent to biological systems. Movement biases were undesirable for maximal performance. Nonetheless, participants presented biases despite financial incentives to perform maximally. Participants did, however, appear sensitive to systematic errors produced by the attraction to less energy costly responses. We suggest that the motor system is constrained such that maximal performance trades off with energetic optimality although humans are able to learn and compensate for the energy minimization biases.

Key Words: undershoot bias, aiming, goal-directed movement, implement throw

“Skill consists in the ability to bring about some end result with maximum certainty and minimum outlay of energy, or time, or of time and energy.”

(Guthrie, 1952, p.136; emphasis added)

Guthrie’s seminal definition of skill has probably been the most widely used in the field of motor behavior. Others have also referred to minimal energy expenditure as an important aspect of skilled behavior (Robb, 1972; Singer, 1968) suggesting that there is more to skill than just attaining specified goals. This, however, has not been reflected in the majority of research on human motor control, which has

Oliveira and Goodman are with the School of Kinesiology, Simon Fraser University, Burnaby, BC, V5A 1S6, Canada. Elliott is with the Dept of Kinesiology, McMaster University, Hamilton, ON, L8S 4K1, Canada.
tended to focus on either speed of response or accuracy demands of the task. From a dynamical systems perspective (Kelso, 1995), biological systems are inherently subjected to the self-organizing principles that optimize the cost function of motor actions. Recent studies suggest that humans are sensitive to the stochastic properties of their perceptual and motor systems (Engelbrecht, Berthier, & O’Sullivan, 2003; Todorov & Jordan, 2002) and generate adaptive behavior accordingly. Humans appear to search for and use near optimal solutions to motor problems in terms of their cost function.

In the absence of feedback-based regulation, motor control researchers have demonstrated that the variability of movement endpoints scale linearly with the average velocity of the associated aiming movements (Schmidt, Zelaznik, Hawkins, Frank, & Quinn, 1979). This has been extensively researched in the case of goal-directed manual aiming tasks (Elliott, Helsen, & Chua, 2001). Anecdotally, the same finding with respect to variability appears to be the case for aiming tasks involving an implement, where the final position is determined by the instantaneous velocity (magnitude and direction) at time of release (Elliott & Leonard, 1986).

Meyer, Abrams, Kornblum, Wright, and Smith (1988) have suggested that speed–accuracy relations in goal-directed manual-aiming (e.g., Fitts, 1954) result from the performer striking a compromise between greater noise/endpoint variability associated with a rapid aiming movement, and the time-consuming nature of corrective submovements that are necessary when the initial movement trajectory takes the limb outside acceptable target boundaries. Meyer et al.’s optimized submovement model predicts that, over a series of aiming movements, noise in the neuromotor system will result in a distribution of movement endpoints centered at the middle of the target. Only movements at either tail of this distribution will require time-consuming corrective submovements. For implement-aiming tasks, however, corrective submovements are not possible subsequent to release and thus the distribution of endpoints depends on the total impulse of pushing force at the time of release.

For manual aiming movements, a distribution of primary movement endpoints centered on the middle of the target makes sense when one considers corrections from a strictly probabilistic point of view. This is because a distribution centered at the middle of the target minimizes the need for a corrective submovement regardless of the accuracy demands of the movement. This “central-tendency” principle of the optimized submovement model is not, however, consistent with a large body of both manual aiming and eye movement data that indicate primary movement endpoints are more likely to fall short of the target than beyond it (see Elliott et al., 2001; Engelbrecht et al., 2003, for recent reviews) creating an undershoot bias. As Elliott, Hansen, Mendoza, and Tremblay (2004) have suggested, this is because, under normal circumstances, there is a greater cost associated with a target overshoot than a target undershoot. This extra overshoot cost occurs because of two primary factors: (a) the limb must travel a greater distance to the target, hence greater work requirements, and (b) the inertia of the limb at the point of reversal must be overcome. In the case of an undershoot, the limb already has a positive velocity in the direction of the movement when the corrective submovement begins (Elliott, Binsted, & Heath, 1999). Thus target overshooting is normally more costly, both
in terms of time and energy, than target undershooting. Moreover, the increased energetic costs attributed to (a) above might also be applied to implement-aiming tasks. The performer, even if unconsciously, takes both the stochastic properties of neuromotor noise and the relative costs associated with undershooting and overshooting the target into consideration when preparing either a manual aiming or implement aiming movement.

There are, however, situations in which energy minimization becomes undesirable. Nelson (1983) suggested that there is at least some accommodation to physical economy that is not designed to fulfill the primary objective of tasks. The adaptations occurring during the process of motor learning are constrained by the demands arising from the necessity of minimizing energy on one hand and on the other by the demands arising from constraints imposed by the organism, the task, and the environment (Sparrow & Newell, 1998). For tasks in which the objective is to have high-level performance, the inherent features of the human motor system might be forcing adaptations that are counterproductive. Oliveira and Goodman (2004) proposed that the adaptations leading up to the minimization of attention and effort that occur through the process of learning are detrimental to exceptional levels of motor performance. The idea is that when high levels of performance are intended, regardless of the cost associated with the adaptations needed to produce them, the inherent tendency of biological systems to minimize energy expenditure becomes maladaptive. Consistent with this notion is Nelson’s idea that movement control should not be optimal in any single criterion, but rather represent a reasonable trade-off between competing costs, while meeting the requirements and objectives of the task.

Todorov and Jordan’s (2002) optimal feedback control theory develops this notion further by postulating that optimal motor control follows a “minimum intervention” principle. According to these authors, variability and redundancy is allowed in task-irrelevant dimensions and corrections to movement trajectories only occur when they interfere with the goals of task performance. In a simulation of an interceptive task, in which different parameters were varied, it was predicted that increasing effort penalty as a task-relevant constraint would create a similar bias to that seen in the case of the goal-directed manual aiming tasks (Todorov & Jordan). In the case of ballistic implement aiming, movement bias is presumably undesirable because task constraints do not include minimizing movement time and minimization of effort and energy are secondary to accuracy. Nevertheless, according to our predictions, the inherent properties of the human motor system would overrule the extrinsic task-related constraints and goals creating a movement bias even when it is undesirable.

In this experiment, we used a simple one-dimensional implement-aiming task to determine whether movement bias would be present in a task in which movement accuracy was of primary concern. Furthermore, we were interested in determining if we could influence the distribution of movement endpoints by creating a situation in which there would be less energy expenditure or cost associated with a target overshoot than a target undershoot. Based on the idea that inherent minimization processes would override the extrinsic task-relevant constraints, we hypothesized that there would be an undershoot bias in the situation in which overshooting is
more costly and an overshoot bias in the situation in which undershooting is more energy costly.

Materials and Methods

Participants

Twelve right-handed members of the university community (8 males, 4 females, mean age = 24.9 years, SD = 2.5 years) participated in the study. All participants were experiment naïve and provided informed consent consistent with procedures approved by the university ethics committee. Participants were compensated financially for their participation, with an additional bonus based on performance.

Apparatus and Tasks

The apparatus consisted of a track based on a stainless steel tube (length: 2 m, diameter: 3 cm) mounted horizontally on a table at approximately chest height. A low-friction Teflon puck (10-cm diameter by 5 cm thick) had its center bored out such that it could slide along the track. A pointer was attached to the slider, which indicated initial and final position along a ruler placed in parallel with the track. Participants performed 200 trials of each of two tasks. For the second task, the slider device was modified to provide an assistive force by attaching a surgical rubber tube from the puck to the far end of the track. The length of the tube was such that it was in the slack position at the 60-cm mark, and stretched at the start (0 cm) position. On release from the start position it had a propulsive force towards the target.

Task 1 — Unassisted. Participants sat alongside the table with their sagittal plane parallel to the slide device. Their left shoulder was positioned directly in front of the start position (0-cm mark) and their right shoulder closer to the end position. Participants were instructed to propel the slider along the track with their nondominant hand (to increase difficulty of task), in one continuous movement, releasing it before the 40-cm mark. A red line, located at 110 cm from the initial position and 70 cm from the maximum release point, identified the target location. Participants had no vision of the measuring ruler and were not given augmented feedback, being limited to visual feedback from the final position of the slider relative to the target location. The goal of the task was to have the slider stop at or as close as possible to the target location set. In this task, movement was based primarily on concentric contractions of arm, elbow, and wrist flexors.

Task 2 — Assisted. Similarly to Task 1, participants sat facing the apparatus and used the same procedures in terms of hand used, release point, target location, feedback provided, and the need to perform the “propulsive movement” in one continuous action. In this task, however, participants had to apply force against the assistive action of the rubber tube and release the slider rather than provide a “push.” It is important to note that if participants were to just release the slider without first slowing it down by applying force in the direction opposite to the
movement, the slider would greatly overshoot the target. In contrast to the first task, the greater the force applied (eccentric primarily via arm extensors) the greater the undershoot. Thus it was more energy efficient to overshoot the target rather than to undershoot it.

**Payoff Schedule**

To provide additional incentive for accurate performance, participants were paid relative to how well they performed on each of the tasks. Before starting the trials they were told that they would receive money according to the following schedule of payment: trials ending within 8 cm of the target location received 1 cent, within 5 cm received 2 cents, within 3 cm received 3 cents, and within 1 cm received 5 cents.

**Design**

The order in which the tasks were performed was counterbalanced across participants, such that half the participants performed Task 1 first while the other half performed Task 2 first. Participants performed 200 trials of each task divided into eight blocks of 25 trials. After each block, participants were given a chance to rest. The duration of the rest periods was self-determined, but did not exceed 3 min.

**Dependent Measures**

To measure directional bias we used constant error (CE) as a magnitude-sensitive measure and we computed a weighted overshoot-to-undershoot difference (WOUD) as a magnitude-insensitive measure. Variable error (VE) was used as a measure of consistency. CE and VE were measured in millimeters and the weighted undershoot to overshoot difference was defined as

\[
WOUD = \frac{O - U}{T}
\]

where \(O\) is the number of trials with errors greater than 0, \(U\) is the number of trials with errors smaller than 0, and \(T\) is the total number of trials. Trials that had an absolute error of less than 1 mm were considered to have zero error for analytical purposes, thus \(T\) is not necessarily equal to \(O + U\) because some trials were considered neither overshoots (\(O\)) nor undershoots (\(U\)). Trials that had an absolute error of over 500 mm were discarded from the CE and VE analysis but were used for the weighted overshoot to undershoot difference analysis as the magnitude of the error was not of concern for this measure.

**Analysis**

To test for differences in task and across blocks during the testing session, 2 (task) \(\times\) 8 (block) repeated-measures analyses of variance (ANOVAs) were used for each dependent measure. Alpha was set at .05 and whenever the assumption of sphericity was violated, the Greenhouse-Geisser correction of degrees of freedom was applied (see Schutz & Gessaroli, 1987).
Results

Directional Bias
The results showed significant task main effects and significant task by block interactions for both CE and the weighted overshoot to undershoot difference (see Table 1 for the corresponding statistics). As predicted, participants performed significantly different in the assisted and unassisted tasks, undershooting the target in the unassisted condition (CE: \(M = -10.3\) mm; WOUD: \(M = -0.09\)) and overshooting the target in the assisted condition (CE: \(M = 12.3\) mm; WOUD: \(M = 0.05\)). Given the expected task by block interaction, the improvements over blocks were interpreted in light of this significant effect for both CE and WOUD. The interaction shows that performance tended to move toward a CE (Figure 1A) and a WOUD (Figure 1B) of 0 across blocks.

<table>
<thead>
<tr>
<th>Factor</th>
<th>CE</th>
<th></th>
<th>WOUD</th>
<th></th>
<th>VE</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Task</td>
<td>1, 11</td>
<td>12.77**</td>
<td>1, 11</td>
<td>7.59*</td>
<td>1, 11</td>
<td>23.69**</td>
</tr>
<tr>
<td>Block</td>
<td>7, 77</td>
<td>0.79</td>
<td>7, 77</td>
<td>1.61</td>
<td>2.59, 28.53^{a,b}</td>
<td>14.01**</td>
</tr>
<tr>
<td>Task (\times) Block</td>
<td>1.97, 21.71^{a}</td>
<td>7.85**</td>
<td>7, 77</td>
<td>6.17**</td>
<td>3.21, 35.28^{c}</td>
<td>2.69^{d}</td>
</tr>
</tbody>
</table>

Note. \(^{a}p = .28. \(^{b}p = .37. \(^{c}p = .46. \(^{d}p = .058. \(^{e}df\) corrected with the Greenhouse-Geisser procedure.
\(^{*}p < .05. \(^{**}p < .01.\)

Consistency
The variable error analysis showed significant task and block main effects, as well as a task by block interaction, \(F(7, 77) = 2.69, p = .015.\) The interaction was not significant, however, with the Greenhouse-Geisser correction (see Table 1 for a complete list of \(F\) values).

The results show that participants had larger VE in the assisted task \((M = 110.8\) mm) than in the unassisted task \((M = 77.7\) mm). The reason for this could be that the assisted condition presented a more challenging task for the participants, as well as being more dependent on the stochastic nature of the mechanics of the apparatus. Nonetheless, there was a significant reduction over blocks in VE in both the assisted and unassisted tasks as can be seen in Figure 1C. The trend for a task by block interaction effect suggests, however, that participants differentially improved in each of the tasks. Separate repeated measures ANOVAs revealed significant linear, \(F(1, 11) = 25.30, p < .001,\) and quadratic, \(F(1, 11) = 22.15, p < .005,\) trends for the unassisted task, whereas the assisted task only showed a significant linear trend, \(F(1, 11) = 15.40, p < .005.\) It appears that participants stabilized the improvement in consistency earlier in the unassisted condition with large VE decrements on the
Figure 1 — (A) Constant error, (B) weighted overshoot to undershoot difference (WOUĐ), and (C) variable error. Each plot represents the assisted (filled squares, solid line) and the unassisted (open squares, dashed line) tasks for each block of 25 trials, averaged across participants. In (A) and (B) negative numbers represent undershoot biases and positive numbers represent overshoot biases. Bars denote standard error.
first three blocks and then little change after that. On the other hand, the assisted task, in which participants were less consistent throughout, seemed to show more continuous improvements across the eight blocks of trials.

**Trial-by-Trial Error-Correction Strategy**

Trial-by-trial correction strategies were analyzed to investigate whether participants used different error correction strategies after different types of errors (undershoots and overshoots), different tasks (assisted and unassisted) and early and late during the testing session. Each trial was classified as being either an errorless trial (absolute error < 1 mm), an undershoot (error ≤ −1 mm) or an overshoot (error ≥ 1 mm). Constant error, variable error, and the weighted overshoot to undershoot difference were then computed for trials immediately succeeding undershoots (U + 1) and overshoots (O + 1) and averaged into two blocks. The first block included the trials that succeeded the first 20 undershoots and first 20 overshoots of each participant. The second block included the trials that succeeded the last 20 undershoots and last 20 overshoots of each participant. To analyze the data, separate 2 (task) × 2 (block) × 2 (error type) repeated-measures ANOVAs were used for each of the dependent variables. The results (see Table 2) showed significant task main effects in all dependent measures, significant error type main effects for CE and WOUD, and a significant block main effect for VE. Significant task by block interactions for CE and WOUD were also found, as well as task by error type and the triple (task by error type by block) interaction for VE.

These results show that participants used different error correction strategies depending on whether they had undershot or overshot the target immediately before (averaged over all other conditions). Participants overshot the target (CE: \( M = 9.4 \) mm; WOUD: \( M = .03 \)) after undershoots and undershot the target (CE: \( M = −8.7 \) mm; WOUD: \( M = −.09 \)) after overshoots. Scheffé’s post hoc procedures on the significant task by block interaction (\( p < .05 \)) showed that participants used

| Table 2 ANOVA Results (F Values) for the Trial-by-Trial Correction Strategies for Constant Error (CE), Weighted Overshoot-to-Undershoot Difference (WOUD), and Variable Error (VE) |
|-----------------|----------------|----------------|
| Factor          | CE             | WOUD           | VE             |
| Task            | 11.47**        | 6.42’           | 30.51**        |
| Error type      | 9.69’          | 8.61’           | 0.24           |
| Block           | 0.02           | 0.00            | 20.71**        |
| Task × error type | 2.73           | 0.11            | 5.06’          |
| Task × block    | 10.43**        | 11.89**         | 1.26           |
| Error type × block | 0.28           | 2.62            | 0.00           |
| Task × error type × block | 0.16           | 0.15            | 6.28’          |

*Note. F(1, 11) for all factors; *\( p < .05 \); **\( p < .01 \).*
different strategies in the trials following the first 20 errors (averaged over type of error) in each of the tasks. Participants overshot the target in the assisted task (CE: \( M = 34.1 \) mm; WOUD: \( M = .18 \)) and undershot the target in the unassisted task (CE: \( M = -34.7 \) mm; WOUD: \( M = -.25 \)). As can be seen in Figures 2A and 2B, despite the fact that it would be intuitively expected that participants would reverse the direction of their errors undershooting after overshoots and overshooting after undershoots, it seems that early in the testing session (black columns), the bias created by the task that participants were performing was stronger than the tendency to compensate for the error committed in the previous trial. The directional bias observed in each task was therefore in the same direction, regardless of the type of error that preceded the trials (note that all black columns on top plots represent positive numbers—i.e., overshoots—and all black columns on bottom plots represent negative numbers—i.e., undershoots). This changed late in the session however. After the last 20 errors, participants compensated their previous error by, on average, reversing its polarity.

We used Scheffé’s post hoc procedures to break down the differences in the task by error interaction, as well as the triple interaction shown for VE. The results (see Figure 2C) showed \( (p < .05) \) that when averaged over blocks, participants presented larger VE in the O+1 trials \( (M = 83.8 \) mm, represented by the columns on right side of the left plot) than in the U+1 \( (M = 76.4 \) mm, represented by the columns on the left side of the left plot) trials of the assisted task. They also presented larger VE in the U+1 trials \( (M = 62.1 \) mm, represented by the columns on the left side of the right plot) than in the O+1 trials \( (M = 52.7 \) mm, represented by the columns on the right side of the right plot) of the unassisted task. This seems to be further evidence that the type of error that preceded trials interacted with the type of task that participants performed, influencing the behavior generated in response. The difference in VE between the U+1 and O+1 trials in each task was, however, found only early in the first 20 trials analyzed as shown by the significant difference between U+1 and O+1 trials in both of the tasks (black columns on left plot are significantly different from each other and black columns on the right plot are also significantly different than each other). As participants learned the task, the effect of the type of error that preceded trials disappeared, as shown by the lack of difference between the U+1 and O+1 trials in both tasks (striped columns on left plot are not significantly different from each other and striped columns on right plot are also not significantly different from each other).

**Discussion**

Energetic efficiency and optimization of resources are normally important aspects of motor skills. Nevertheless, some motor tasks require maximal performance regardless of the energy expenditure. Elite athletes, top-level musicians, medical surgeons, indeed almost any individual who aspires to the highest levels of performance in a particular motor skill would likely choose performance increments over energetic and effort optimization if given the option. It might be the case, however, that energy and effort minimizing processes are inherent properties of the human motor system, thus difficult to avoid. Our results support this notion. As hypothesized, participants presented an undershoot bias in the unassisted
Figure 2 — (A) Constant error, (B) weighted overshoot to undershoot difference (WOUD), and (C) variable error for trials U+1 and O+1 under the assisted and unassisted tasks, averaged across participants. Black columns denote blocks of early (first 20 U+1 and O+1) trials, and striped columns denote blocks of late (last 20 U+1 and O+1) trials. Bars denote standard error. Note that in (A) and (B) positive values represent overshots and negative values represent undershoots.
condition and conversely presented an overshoot bias in the assisted condition. This suggests that the undershoot bias, frequently described in the manual aiming literature and anecdotally seen in other motor skills, might be the result of a more general energy minimization bias. This evidence corroborates our prediction that this energy minimization bias is an inherent mechanism that could at times overrule competing extrinsic goal-related constraints.

Based on Todorov and Jordan’s (2002) minimal intervention principle, the fact that movement trajectories were dictated, at least partially, by energy minimizing mechanisms implies that those mechanisms lie in goal-relevant dimensions. This is in spite of the fact that energy minimization was not part of the external goals of the task. Hence, it appears that energy minimization is an inherent property of the human perceptual motor system. Moreover, participants were able to learn and correct the biases resulting from inherent tendencies of their perceptual motor system. This can be seen by the reduction and virtual elimination of the energy minimization biases, which was accompanied by the reduction in VE shown in both the assisted and unassisted tasks late in the testing session of this study. Despite the attraction to less energy costly responses, in this experiment participants seemed to be able to overcome the biases by intentionally imposing external goal-related constraints. Thus, it appears that the inherent search for the easiest and least energy costly solution to motor problems, which is often seen as a beneficial process, could in fact need to be overcome in highly specialized skills.

Heath, (2004) in a goal-directed manual aiming study, showed that in the absence of feedback, participants continued to present an undershoot bias even after a considerable number of trials. This could be interpreted as further evidence of an attraction to less energy costly responses. Without information about previous trials, participants were prevented from intentionally imposing the external constraints needed to reduce or eliminate the bias and achieve maximal accuracy.

As Nelson (1983) proposed, coordination might emerge as the result of numerous trade-offs between competing costs. By looking at the trial-by-trial error correction strategies that participants used in our study, two sources that influenced how participants made responses were identified. The first was the type of task that participants were performing. The differing influence of the two tasks on performance could have been caused by the same energy minimization mechanism appearing in different forms (i.e., intrinsic tendency to undershoot in the unassisted task and intrinsic tendency to overshoot in the assisted task). The second influence on participants’ performance was the type of error that preceded a trial. This influence, which is a tendency to (over)compensate for the previous error by shifting the error in the direction of the target, competed with the influence of the different tasks. This was very evident early in the testing session. In the first 20 U+1 and O+1 trials, participants continually undershot the target in the unassisted task and overshot the target in the assisted task, regardless of the type of error that preceded the trials. In two conditions, O+1 in the assisted task and U+1 in the unassisted task, higher competition between the influence of the task and the influence of the type of error preceding trials were expected. In those conditions, the task exerted its influence, biasing performance towards the same direction of the preceding trial and thus in the opposite direction of the bias created...
by the influence of the preceding trial. This competition between the two sources of influence could be the locus of the increased variability in performance shown in those two conditions (see Figure 2C, black columns on the right in the left plot and on the left in the right plot) early during the testing session.

As Engelbrecht et al. (2003) noted, humans appear to be very good at identifying trends over time (even if they are stochastic as in Engelbrecht et al.’s case) and adapt accordingly. In our experiment it was no different. The influence of the task on performance seemingly disappeared late in the testing session, and the influence of the previous error, which was more relevant to the external goal of the task, predominated. This could result from an improvement in the participants’ ability to deal with the different intrinsic biases created by each of the tasks. As a result of presumably identifying the systematic error caused by each of the tasks early in the session, participants were able to make compensations for it late in the session. Consequently, participants presented the expected behavior of correcting errors on a trial-by-trial basis by “moving” the error in the direction opposite to that of the previous trial. This can be seen (in the striped columns) in Figures 2A and 2B, which show that, late in the session, the shape of the CE and WOUD graphs in the assisted (top plots) and unassisted (bottom plots) tasks are similar (positive values for left-striped columns and negative values for right-striped columns). Moreover, it appears that reducing the influence of the tasks on performance virtually eliminated the competition between the two sources of attraction. Figure 2C shows that VE, which was initially higher under the conditions with more competition between the two sources of influence, became no different across the two different types of errors late in the testing session. The mechanism governing those corrections seems to be unconscious as none of the participants reported noticing any performance biases, when questioned immediately after the end of their testing session.

Scott (2002) suggested that the neural circuitry controlling movements is based in part on “evolutionary baggage” and might be optimal only when the entire motor repertoire is considered. This could explain the presence of energy minimization biases. According to Brener and Carnicom (2000), organisms with natural tendencies to minimize energy and effort in foraging had an advantage in natural selection and survived to pass these traits on to their progeny. Moreover, they suggest that selection of energy-efficient behavior, even in situations other than foraging, is a common trait across a variety of species. Evolution could have shaped the nature of the human biological system such that maximal performance is secondary to energetic efficiency. Today’s world, however, provides an abundance of energetic resources and cultural and social aspects have created niches for highly specialized motor behavior. Thus, at least for some skills, it appears that evolutionary mechanisms might be lagging behind the need for expert performance. The result of this hypothetical evolutionary baggage could manifest itself as an inherent tendency to minimize effort (Oliveira & Goodman, 2004) and energy. Others have shown that energy minimization processes appear to require no external feedback to function (Sparrow & Newell, 1998) but might be related to levels of perceived effort (Desmurget, Pellisson, Rossetti, & Prablanc, 1998; O’Dwyer & Neilson, 2000; Sparrow, Hughes, Russell, & Le Rossignol, 1999). Sparrow and colleagues (Lay, Sparrow, Hughes, & O’Dwyer, 2002; Sparrow, 1983; Sparrow et al., 1999),
using locomotion tasks, have shown that the most comfortable mode of coordination appears to be closely related to responses that involve the lowest work or energy costs. This could explain the attraction to less energy costly solutions for motor problems. As a consequence of their finding, it seems as though motor performers would have to exert more effort, moving away from the most comfortable patterns of coordination to reduce or eliminate energy-minimization biases.

The data presented here supports the notion that energy minimization mechanisms can compete with external goal-related constraints. This could have a bearing on a large body of scientific (e.g., the undershoot bias in manual goal-directed aiming) as well as anecdotal evidence in tasks as varied as aiming (e.g., moving a laser pointer to a target of interest), throwing (e.g., shooting a basketball) and intercepting (e.g., catching a football or hitting a baseball) and provides an alternative explanation to the undershoot bias.

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References


