MOTOR LEARNING

Aiming for stable control

Motor learning is composed of explicit 'strategic' components and implicit 'automatic' components. Miyamoto and colleagues reveal how these components work together during visuomotor adaptation, providing evidence that an implicit component corrects for a noisy explicit process.

Olivier Codol, Giacomo Ariani and Jonathan A. Michaels

When a golfer practices their swing on the driving range, the outcome of each shot depends not only on their skill, but also on fluctuating external perturbations such as the wind. Accounting for these perturbations usually requires explicit, voluntary adjustments, such as purposely aiming off the straight trajectory (Fig. 1a). In contrast, proficiency in executing the swing itself relies on implicitly learned skills (for example, hand–eye coordination, action timing), which tend to be difficult to verbalize but are equally central to successful performance. This dissociation between explicit and implicit components of skilled motor behavior is a hallmark of motor control[1–3]. As a natural consequence, understanding how much these components interact with each other has spurred a great deal of debate in the field. However, untangling the factors that independently affect the explicit and implicit components[1,2] of motor learning poses a significant technical challenge. In particular, since perturbations caused by external elements such as wind engage both of these learning processes simultaneously, it is hard to disambiguate potential interactions between implicit and explicit components from the effects of the external perturbations themselves. Consequently, it remains unknown whether they interact in a synergistic or antagonistic[3] way, or indeed, whether they interact at all.

In this issue of *Nature Neuroscience*, Miyamoto and colleagues[4] use an elegant design to isolate the interactions between implicit and explicit components of motor learning, revealing that the implicit and explicit components work in a synergistic way to produce successful task performance. The authors asked participants to reach to a target while being exposed to a (visuomotor) perturbation, akin to wind that waxes and wanes between golf strokes (Fig. 1a). Visuomotor perturbation is a common experimental tool to study a subset of motor learning called motor adaptation[1–3,5,6], which is the process through which accurate motor performance is restored following a small perturbation that induces a loss of accuracy[1–3,5,6]. Although most studies of motor adaptation employ a fixed perturbation schedule[1–3,5,6], in this study the amplitude of the perturbation oscillated in an unpredictable fashion over time (Fig. 1a).

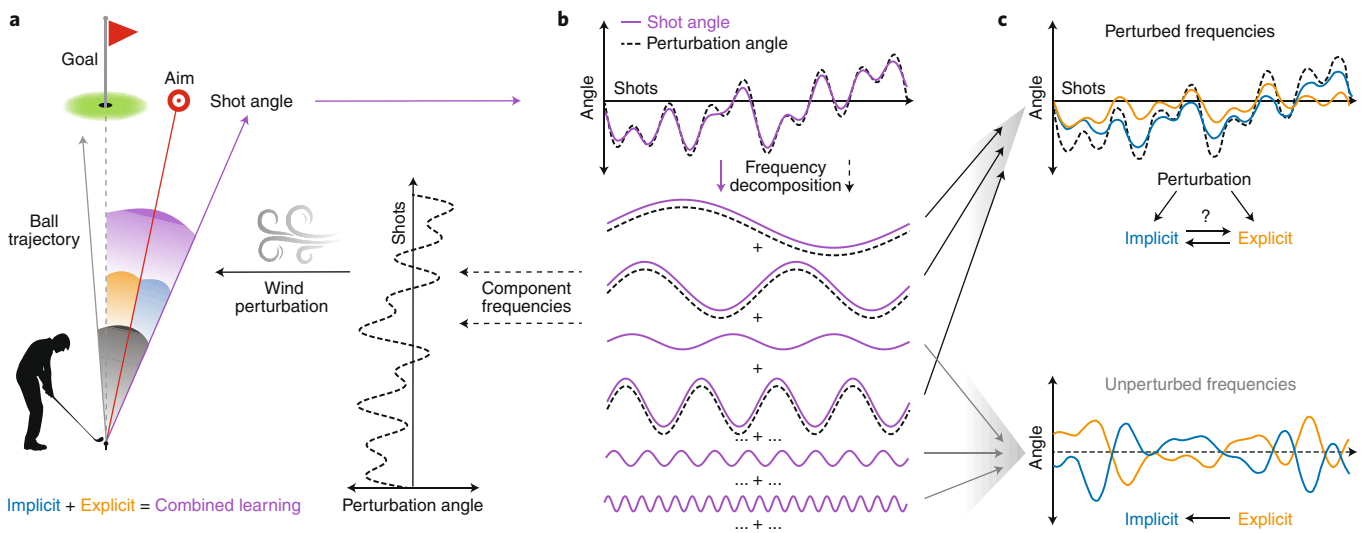

Fig. 1 | Unmasking interactions between explicit and implicit learning components in the frequency domain. a, To hit a successful drive, a golfer needs to counteract an unpredictable wind perturbation (black). This is achieved in part by (explicitly) aiming off the straight trajectory (orange) and in part by (implicitly) updating the motor program of the swing on the basis of previous experience (blue). **b**, By creating a perturbation pattern that only included a specific set of frequencies, the authors were able to study learning effects at perturbed and unperturbed frequencies separately. **c**, This analysis revealed synergistic behavior between the two processes at perturbed frequencies (top; question mark reflects uncertainty about which process is driving which) and antagonistic behavior at unperturbed frequencies (bottom; compensation by implicit learning is driven by explicit learning). In all panels, the dashed lines represent the perturbation.

Critically, this oscillation was based on the combination of a predefined set of five frequencies, called 'perturbed frequencies'. The authors then decomposed a participant's reaching behavior into its contributing frequencies, using a transform to the frequency domain, and examined patterns of adaptation in perturbed frequencies and in other 'unperturbed frequencies' (Fig. 1b). Participants also reported the direction they were intending to reach, which allowed the authors to disambiguate the explicit (related to aiming) or implicit (the remainder) components of motor performance (Fig. 1a). In the perturbed frequencies, one can observe the adaptation of both explicit and implicit components to external perturbations. However, because the two components are driven by the same perturbation, they are strongly correlated, which obscures the nature of their interaction at perturbed frequencies (Fig. 1c, top). Conversely, the interaction of the two systems, normally obscured by the external perturbation, is revealed at the unperturbed frequencies (Fig. 1c, bottom).

The optimal reaching behavior should follow the perturbation amplitude at perturbed frequencies, whereas it should be centered on zero for the unperturbed frequencies. In other words, adaptation should be limited to the task-relevant frequencies, because anything else would be task-irrelevant. Indeed, the authors observed that the reaching behavior changed mostly in the perturbed frequencies. In these frequency bands, explicit and implicit adaptations were positively correlated, likely because they were both driven by the common perturbation signal. However, in frequency bands without a perturbation, implicit adaptation was inversely correlated with explicit adaptation. This suggests that one system compensates for task-irrelevant adaptation to unperturbed frequencies, thereby avoiding unwanted errors (Fig. 1c).

Is the implicit component driving the explicit one or vice-versa? To answer this question, the authors employed a statistical method called structural equation modelling, which is tantamount to asking, "assuming there is causation, which causal model is most likely given the data?"[7] Results showed that the explicit component was more likely to drive the implicit component than the other way around. Corroborating this result, cross-correlation analysis then demonstrated that the implicit component lags behind the explicit one. Interestingly, the implicit component compensating for the explicit one implies that the implicit component is sensitive to task error, so as to know in which direction to compensate.

Previous literature has suggested that motor adaptation is driven by two types of errors, namely task error and sensory prediction errors. Task error represents the discrepancy between a movement's outcome and the task goal, while sensory prediction error is the discrepancy between the movement that was planned and the one that was executed. So if a movement unfolds as it was intended, but that action did not achieve the task goal (i.e., hitting the target), then there is a task error but no sensory prediction error. However, if the movement execution is slightly off from the intended action (imagine your swing going a bit more to the side than you aimed for), then there is a sensory prediction error, even if this eventually leads to a successful action.

Although the literature at large agrees that an explicit component of adaptation is driven by task error[1,2], the suggestion that an implicit component is also driven by task error is decidedly at odds with the general consensus[1–3,5]. Indeed, there is a wealth of evidence showing that an implicit component is insensitive to task error[3,5], instead being tuned to sensory prediction errors. Miyamoto et al. argue that the implicit component's reliance on sensory prediction errors need not be mutually exclusive with sensitivity to task errors and that the latter has not been tested formally. Interestingly, this is also in line with a recent report showing that implicit learning stops when the task goal is reached, even if sensory prediction errors remain[6].

A possible explanation for this unexpected sensitivity of the implicit component to task error may lie in a distinction between dissociable implicit sub-elements. Indeed, it may be that a task-sensitive implicit component exists in parallel to the previously characterized sensorimotor implicit component[6], which is sensitive to sensory prediction error[3,5]. However, assuming that the two hypothetical implicit systems contributions sum linearly[6], it may be difficult to disentangle one from the other. Regardless, the novel interaction between implicit and explicit components revealed by Miyamoto et al. will require a reconsideration of how motor learning takes place.

If implicit motor learning is affected by explicit learning, what implications does this have for real-life settings such as training and coaching? In practice, there is a prevailing view that explicit and implicit components are antagonistic components of motor learning, partly fueled by the fact that, in laboratory settings, the two processes tend to counteract each other[3]. As a consequence, various schools of thought, such as 'deliberate practice'[8] have promoted explicit or conscious training, whereas others, such as 'analogy learning'[9] aim to limit learning to the implicit system. In contrast to such a dichotomous view, the work by Miyamoto et al. offers a new perspective: that these learning processes can be complementary to each other[10,11]. In other words, one could imagine the explicit system as a rapidly changing controller, able to bring performance within the vicinity of the task goal, thus enabling the implicit controller by bringing it to proper learning range. This falls in line with recent considerations of behavioral strategy as an exploratory mechanism that enables sampling the task space with greater speed during learning[12]. Yet this is a double-edged sword; with speed comes instability. Therefore, it may seem surprising that the motor system augments performance using a more unstable explicit controller. Miyamoto and colleagues' study may provide an answer to this apparent paradox by suggesting that the implicit component stabilizes the behavior driven by explicit control. ❐

Olivier Codol[1,2], Giacomo Ariani[1,3] and Jonathan A. Michaels[1,4] ✉

[1]*Sensorimotor Superlab, Brain and Mind Institute, Western University, London, Ontario, Canada.* [2]*Department of Psychology, Western University, London, Ontario, Canada.* [3]*Department of Computer Science, Western University, London, Ontario, Canada.* [4]*Department of Physiology and Pharmacology, Western University, London, Ontario, Canada.*

✉*e-mail: Jonathan.michaels@uwo.ca*

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Competing interests

The authors declare no competing interests.