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Fitts' law in the discrete vs. cyclical paradigm

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Abstract

Research on Fitts' law has focused on discrete movement and persistently ignored the continuous, cyclical case while adopting an exclusive information-processing approach to the neglect of the energetic dimension of movement. According to current computational accounts of Fitts' law, the slope of the speed–accuracy trade-off should be steeper in the cyclical task and discrete performance should surpass cyclical performance throughout the range of possible task difficulties. Data are reported that corroborate the former, but not the latter prediction. Discrete–cyclical performance equality (trade-offs intersection) was actually observed at a medium level of difficulty. This outcome, along with kinematic data which show a strong correlation between movement harmonicity and performance in the cyclical task, calls for a hybrid approach to Fitts' law combining information-processing and energy-saving considerations.

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1. Introduction

A recurrent problem in psychology, just as in other disciplines, is whether phenomena are best described as discrete or continuous. For example, whereas some authors have modeled information processing as a sequence of discrete

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mental operations (e.g., Miller, 1993), others have resorted to the metaphor of a continuous flow of information (e.g., McClelland and Rumelhart, 1986; Rumelhart and McClelland, 1986). Much the same problem arises in the field of human movement. Continuous, cyclical movement may be construed as the result of an iteration of elementary discrete acts – viewed as the building blocks of motor action – but discrete movement, alternatively, may be interpreted as a limiting case of cyclical movement – the case in which the number of consecutive cycles is just 1/2. According to one's view, a different research strategy is likely to follow, with a focus on either discrete or cyclical movement.

Fitts' law is known to hold for both discrete, single-shot movements and continuous, cyclical movements. In his first demonstration, Fitts (1954) used a cyclical (so-called serial, reciprocal, or self-paced) paradigm: Participants were equipped with a stylus and had to tap for 30 s alternatively on two targets of width W whose centers were separated by a distance D. Fitts showed that movement time (MT) varied as a linear function of an index of difficulty (ID) defined as $\log_2(2D/W)$, that is,

$$MT = C_1 + C_2 \log_2(2D/W), \qquad (1)$$

with C_1 and C_2 standing for adjustable constants.

Fitts' next major step was to check whether the law could be extended to discrete movements. Using essentially the same apparatus as in the 1954 study, Fitts and Peterson (1964) had participants respond as quickly as possible to a two-choice visual stimulus by moving a stylus from a home position to one of two targets of varying W placed at a varying D. Their data led Fitts and Peterson (1964) to conclude that "the times for discrete movements follow the same type of law as was found earlier to hold for serial responses" (p. 103).

Whereas most of the experiments published before 1964 had been done with repetitive self-paced tasks (e.g., Crossman, 1960; Fitts, 1954; Welford, 1960), ever since 1964 Fitts' law literature has strongly focused on discrete movement (e.g., Meyer et al., 1982, 1988, 1990; Plamondon, 1993; Schmidt et al., 1979; Sheridan, 1991). To a large extent, this methodology change reflects the fact, noted by Fitts and Peterson (1964), that the discrete-movement paradigm constitutes a neater analytic research tool. One problem inherent in the cyclical paradigm is that it mixes up chronometrically the processes of movement execution and preparation: Speed and accuracy for a particular movement can be related to properties of previous and subsequent movements (Schmidt et al., 1978).

Knowledge has accumulated on the intimate control mechanisms of discrete movement, with the questions of whether and how these mechanisms apply to cyclical movement being generally ignored. The discrete-movement concatenation hypothesis has inspired much of information-processing research on handwriting (Van Galen and Stelmach, 1993). To accommodate the observed fluency of cursive handwriting, models have been proposed in which the concatenation of pen strokes, the basic units of action, allows for partial overlap (e.g., Plamondon, 1993). Even so, there is some optimism in the view that cyclical movement can be decomposed into, and reconstructed from a series of discrete primitives (Schmidt, 1988; Morasso, 1986). Guiard (1993) has shown that gradually reducing the *ID* in the cyclical paradigm results in the movement kinematics monotonically converging on simple harmonic motion – with the separation between the deceleration phase of one movement and the acceleration phase of the next soon disappearing altogether. Guiard argued that such a fusion of acceleration (force) events for the lower half of the usual range of *ID*s jeopardises any attempt to account for cyclical aimed movements in terms of the mechanisms identified in the discrete case.

1.1. The commensurability of discrete and continuous performance in Fitts' paradigm

The possibility to test models through the comparison of discrete and cyclical performance in Fitts' task has been generally ignored. Yet, Fitts' paradigm makes it possible to neatly compare discrete and cyclical performance. Even though investigators had sound methodological reasons for confining their search for the mechanisms of Fitts' law to the case of discrete movement, this option had the consequence that the now available explanatory models of Fits law only apply to discrete movements. An interesting question is, What are the models' predictions on the way that the discrete vs. cyclical factor should affect the parameters of Fitts' law? Such a question is worth considering because, as will become apparent below, current theorising in the field of Fitts' law does yield predictions on comparative discrete vs. cyclical performance.

This question is easily tractable experimentally, as the speed–accuracy trade-off can be assessed for discrete and cyclical movement with the same experimental apparatus. With Fitts' (1954) reciprocal-tapping apparatus, for example, a participant may be required either to alternatively tap at the two targets or to execute a series of single-aiming moves separated by breaks, with each move starting exactly at the center of one target and terminating in the other target. The measure of task difficulty will be the same, based on a combination of *W* and *D* measured from target center to target center. Thus, Fitts' aiming paradigm offers the possibility to neatly compare the slopes and intercepts of the two *MT/ID* linear trade-off functions.

1.2. Explanations of Fitts' law in the case of discrete movement

Besides Fitts' (1954) first account of his findings based on the Shannon and Weaver (1949) information-transmission theory, since the sixties three major models have been proposed in a computational perspective to account quantitatively for Fitts' law. The first account, the deterministic iterative-correction model of Crossman and Goodeve (1963/1983), involved a closed-loop control mechanism. The model considered *MT* to be the sum of submovements the number of which was supposed to increase with task difficulty. If each hypothetical submovement is assumed to have a constant duration and to cover a constant proportion of the remaining distance, then the number of submovements necessary to reach the target area, and hence total *MT*, should vary as a logarithmic function of the *ID* (see also Keele, 1968).

Schmidt et al. (1979) subsequently proposed a model entirely based on an open-loop mechanism, the impulse-variability model. To explain the dependence of aiming consistency on movement speed, Schmidt et al. (1979) simply referred to the magnitude of the initial impulse, the force responsible for the acceleration of the limb times the duration of force exertion. They produced evidence that the greater the impulse, the larger its variability (an instance of Weber's law), and the larger the spatial variability of movement endpoints. In keeping with their prediction, they showed that for very fast movements not liable to permit visual corrections (*MT*s in the range 140–200 ms) the spatial variability of movement endpoints was roughly proportional to the mean velocity of the movement. That is, they found a linear speed–accuracy trade-off (see also Meyer et al., 1982). [1]

Finally, Meyer et al. (1988, 1990) proposed a hybrid model that combines open-loop principles of impulse variability with closed-loop principles of correction processes, while accommodating the fact that linear, rather than logarithmic trade-off functions have been found with fast movements performed in the temporally constrained paradigm. According to Meyer et al.'s stochastic optimised-submovement (SOSM) model – admittedly the best available explanation of Fitts' law to date –, an aimed movement toward a specified target region is

[1] In place of Fitts' spatially-constrained paradigm, Schmidt et al. (1979) and Meyer et al. (1982) used a temporally-constrained paradigm in which *MT* was manipulated, along with *D*, as an independent variable, and the between-trial variability of movement endpoints around a discrete target point was treated as the main dependent measure.

composed of a primary submovement and one (or occasionally more) optional secondary corrective submovement(s). The faster the primary submovement, the lower the probability of a target hit, in keeping with impulse variability principles. If the primary submovement fails to reach the target directly, however, a further corrective submovement will be programmed on-line and executed.

Meyer et al. hypothesised the movements to be pre-programmed in such a way as to minimise average total *MT* while maintaining a high frequency of target hits. Given that in this view *MT* may represent the sum of several successive submovements, a participant needs to minimise both the duration of the first submovement (which occasionally may be successful) and the number of subsequent corrections, two conflicting requirements. Meyer et al. (1988, 1990) have demonstrated that the optimal strategy implies the following relationship between *MT*, *D* and *W*:

$$MT = C_1 + C_2(D/W)^{1/n}, \tag{2}$$

with C_1 and C_2 standing for adjustable constants, and n for the maximum number of submovements the participant is willing to execute, if necessary.

1.3. Fitts' view of the discrete / continuous comparison

Taken together, the data Fitts obtained from the reciprocal-tapping experiment (Fitts, 1954) and from the discrete-tapping experiment (Fitts and Peterson, 1964; see their Fig. 2) suggested that discrete movement was faster than cyclical movement overall, and that the difference increased with the *ID* (the slopes and intercepts were 74 ms/bit and −70 ms for the discrete task and 95 ms/bit and 13 ms for the cyclical task). This result, however, cannot be taken as conclusive as the error rate reported by Fitts and Peterson (1964) for the discrete task (10.5% target misses on average) was almost ten times as high as that reported by Fitts (1954) for the cyclical task (1.2%). It was so obvious to Fitts and Peterson that discrete movement had to be faster than cyclical movement and that this effect had to increase with the *ID* that they apparently overlooked this problem and drew serious inferences from the discrete vs. cyclical comparison on their *MT* measures.

1.3.1. Overall superiority of discrete movement

Fitts and Peterson's (1964) expectation of a superiority of discrete performance was grounded on the argument that in the cyclical task (and by construction not in the discrete task) *MT*s can be contaminated by *RT* delays.

Whereas in the discrete task the participant starts each movement after having had time to program its parameters, the cyclical task has the handicap that movement parameters can only be set during the execution of a movement (either a previous or the current movement). To explain why mean cyclical *MT* was 'only' (their term) 100–200 ms longer than mean discrete *MT* – that is, appreciably smaller than the mean *RT* measured in their 1964 experiment –, the authors referred to partial parallelism, which, they argued, can occur in the cyclical task between execution of the current movement and preparation of the next, a circumstance liable to limit the discrete-movement superiority effect. They also noted that a proportion of the *MT*s may not be delayed in the cyclical task, thanks to advance programming of several ballistically executed movements. Nevertheless, for Fitts and Peterson the cyclical paradigm necessarily had to produce a longer average *MT* than the discrete paradigm.

A further argument put forth by Fitts and Peterson (1964) was that each terminal error in the cyclical task induces a perturbation imposed on the initial conditions of the next move, whereas in the discrete task the effector is always repositioned at an invariant starting point. As a consequence, a proportion of *MT*s in the cyclical task must include some extra time needed to process feedback data.

1.3.2. Slope difference

Under the general hypothesis that processing resources are limited, Fitts and Peterson's (1964) position suggests arguments for predicting that the discrete-movement superiority effect should increase with the *ID*.

Since the control of current-movement execution becomes harder and harder as the *ID* increases, the probability that the next movement be pre-programmed in parallel should decrease with the *ID*, that is, parallelism between movement execution and movement programming should gradually clear off. As the basic handicap inherent in the cyclical condition should manifest more and more conspicuously as the *ID* increases, the trade-off in the cyclical-movement condition should exhibit a steeper slope.

A similar argument holds with regard to multiple-movement advance programming. The more difficult the execution of the current movement, the lower the probability that several subsequent movements be programmed in advance. Here again a compensatory phenomenon should progressively vanish, and hence the superiority of discrete movement should become larger and larger with the increase of *ID*.

In sum, from the two putative computational mechanisms put forward by Fitts and Peterson (1964), movement pre-programming and feedback-data processing, one predicts an overall superiority of discrete movement over cyclical movement, along with an increase of this difference with the *ID*. This amounts to the prediction that (1) the *MT/ID* trade-off function should have a steeper slope in the cyclical than discrete task and (2) the *x*-coordinate of the *intersection* of the discrete and cyclical trade-off functions (ID_i) should occur to the left of the actually practicable range of *ID*s.

1.4. Predictions on discrete vs. cyclical performance from the SOSM model

The current-control component of Meyer et al.'s (1988) SOSM model does not seem to predict any difference between discrete and cyclical performance. Once, at some stage during completion of the movement, the participant has detected an impending error, the correction process should operate identically, regardless of whether the movement is executed in the context of a discrete or cyclical task. In either case *MT* should include the time necessary for the on-line programming of a secondary submovement.

The advance-programming component of the model, however, does predict a difference. The optimal solution to the speed/accuracy problem has to be found during the programming of the primary submovement. In the discrete task, which offers free time to determine optimal velocity, a corrective submovement should be less likely (for the same primary-submovement duration), or the duration of the primary submovement should be shorter (for the same risk). Thus, *MT* should be shorter overall in the discrete task.

The SOSM model also yields a prediction on the slopes of the speed–accuracy trade-offs. According to the model, there is no optimization problem below a certain threshold of *ID*. If the participant eliminates the possibility of performing any corrective submovement, then the integer *n* in the exponent of Eq. (2) is set to 1, and the power relationship becomes a linear relationship. The model then identifies with the impulse-variability model, which describes properties of movement execution common to the discrete and the cyclical case. So, for lower values of *ID*, the SOSM model does not predict any difference between discrete and cyclical performance. The optimization problem, however, arises at some threshold of *ID* and then the more difficult the task, the more critical the optimization problem. Assuming that the solution must be found prior to movement execution, then the advantage of the discrete condition, beyond the threshold, should increase with the *ID*. Thus, both for overall performance level and for slope, the prediction from Meyer et al.'s (1988) SOSM model on the discrete–cyclical effect agrees with that derived from Fitts and Peterson's (1964) position.

1.5. Effort savings in cyclical, continuous movement

The models considered so far focus on the information-processing constraints that govern the performances of human participants basically likened to computers. The defining characteristic of a computer is that it deals with symbols, that is, with low-energy patterns, rather than forces (Carello et al., 1984; Kugler and Turvey, 1987; Pattee, 1974). [2] Obviously, the computational approach to motor behaviour tends to ignore effort, [3] the physiological cost of movement. Since, obviously, actors have limited resources of energy, from the moment high-performance movements are requested they will have to cope with optimization constraints (Nelson, 1983). As the participant's search for maximal performance in Fitts' task makes the speed/accuracy trade-off potentially sensitive to any kind of factor, such constraints seem to be worth taking into consideration in the context of Fitts' law.

As emphasised by Guiard (1993), cyclicity permits to save and recycle effort from half-cycle to half-cycle, thanks to the ability of muscles to store mechanical energy in a potential, elastic form toward the end of each movement to the benefit of the next. This is because muscles, a chemical machinery capable of generating motion from rest by contracting actively, also constitute springy bodies capable of functioning passively as reversible converters of kinetic energy into potential energy and of potential energy into kinetic energy (e.g., see Cavagna, 1977). [4] In contrast, a discrete movement is such, by definition, that the kinetic energy available at peak velocity must be entirely dissipated through terminal braking.

It must be realised that even though, in a cyclical Fitts' task, each movement (or half-cycle) must end with a complete deceleration down to zero velocity, kinetic energy need not dissipate. Guiard (1993) has shown that, within limits,

[2] A symbol must have a material substrate and so a computer does receive and deliver some energy, but this is in amounts that asymptotically converge toward zero as computer technology progresses.

[3] There are numerous studies of effort in the computational literature, but the concept of effort has generally been taken in a mental sense and in essence likened to attention (Kahneman, 1973; Sanders, 1983). On the other hand, the psychophysiologically-oriented research field known as the energetics of behavior (see Hockey et al., 1986, for reviews) has dealt with the so-called 'intensive' dimension of cognition, with surprisingly little concern for motor behavior – in which the involvement of energetic processes is an almost trivial reality. With concepts such as arousal, activation, and stress, students of energetics have just taken the physical concept of energy as a metaphor (see Brener, 1986, for an exception).

[4] Bizzi (1980) and Fel'dman (1986; see Latash, 1993) have applied this classic mass-spring model to the neuro-muscular system in a rather different spirit. These authors have emphasised the static consequences of elasticity in heavily damped mass-spring systems, notably that of equifinality for the determination of postures often considered as the transitory goals of movements in the general case (e.g., Rosenbaum et al., 1995).

the lower the *ID* (the faster the mean *MT*) in cyclical aiming, the larger, at movement endpoints, the acceleration in the direction of the next movement. In fact, it turned out that below some threshold of *ID* instantaneous acceleration bore a rigorous -1 correlation with instantaneous displacement from the oscillation midpoint. An acceleration trace which remains proportional, and oriented opposite, to displacement throughout the movement unequivocally characterises simple harmonic motion, the typical behaviour of oscillating energy-conservative mass-spring systems.

Interestingly, such an energy-recycling argument predicts that an aimed movement performed in isolation should be disadvantaged relative to the same movement embedded in a oscillatory series, because in the former case the initial impulse must be created anew whereas in the latter case the initial impulse may benefit from the restitution of the elastic energy stored at the reversal. Guiard's (1993) argument was that the production of sinusoids in living organisms implies a *minimization* of energy dissipation. Simple harmonic movement makes it possible to limit the energetic cost of movement to an escapement function offsetting the loss of energy due to friction (Kugler and Turvey, 1987). Thus, human to-and-fro aimed movements tend to abide by Hooke's law (French, 1971; Kelso, 1986), with the degree to which they do so depending on aiming difficulty and/or movement speed.

Guiard's (1993) data showed that for *ID*s above 5–6 bits the kinematic trace of cyclical movement was no longer different from that which one would obtain by simply concatenating a series of discrete moves with their zero acceleration at displacement extrema. Thus, the energy-saving mechanism should no longer favour cyclical performance relative to discrete performance beyond some threshold of *ID*; its influence should be maximal at the lowest end of the *ID* range, and monotonically decrease with the *ID*. From this analysis taken in isolation, the prediction is that (1) the trade-off for the cyclical task should exhibit a steeper slope and (2) ID_i, the x-coordinate of the intersection between the two trade-off functions, should fall to the *right* of the practicable range of *ID*s.

In a hybrid view combining information-processing and energy-saving mechanisms, one is simply led to the prediction that ID_i should be actually observable at some practicable level of task difficulty.

A third prediction can be added, taking into consideration Guiard's (1993) measurement of movement harmonicity (see below the Section on Data Reduction and Processing). Since the beneficial influence, in the cyclical condition, of energy recycling must be strictly dependent on movement harmonicity, the *ID* for which discrete and cyclical *MT*s are equal (ID_i) should correlate positively with the *ID* value for which cyclical movement switches from the harmonic to the inharmonic mode, henceforth termed the critical *ID* (ID_c). Put differently, the longer a participant's cyclical movement remains harmonic as *ID* is scaled up, the longer in this participant should cyclical performance surpass discrete performance.

1.6. Summary of predictions from alternative approaches

The information-processing models examined in the foregoing and the energy-saving approach to movement lead, through altogether different mechanisms, to the common prediction that the *MT/ID* trade-off function should

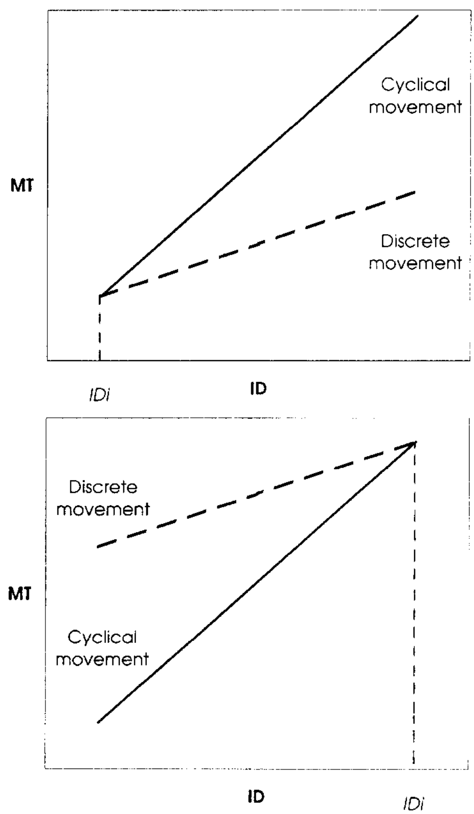

Fig. 1. The relative layout of speed–accuracy trade-off functions for aimed movements performed in the discrete task (dashed line) and in the continuous task (solid line) as predicted from a pure information-processing perspective (upper panel) and from a pure energy-saving perspective (lower panel).

exhibit a steeper slope in the cyclical than discrete task. The two approaches, however, yield different predictions on the relative mean levels of performance that should be reached in the two tasks (see Fig. 1). Whereas the information-processing approach predicts a discrete-movement superiority that should increase with the *ID*, the energy-saving approach predicts a cyclical-movement superiority that should decrease with the *ID*. So the critical prediction is that concerning ID_i – provided their slopes differ, as is expected in both approaches. According to the computational approach, ID_i should fall to the left of the practicable range of *ID*s because, from the viewpoint of information processing, movement continuity has only detrimental consequences. According to the energy-saving approach, in contrast, the intersection should fall to the right of this range because in terms of energy economies movement discreteness can only handicap performance. As already mentioned, however, the simple demonstration of a *real* intersection of the discrete and cyclical trade-off functions, incompatible with either approach, would plead for their hybridisation. Finally, the energy-economies analysis predicts that ID_i should positively correlate with ID_c, the *ID* at which cyclical movement becomes inharmonic, because the cyclical-movement advantage should be conditional upon its harmonicity.

Given the inadequacy of Fitts' (1954) and Fitts and Peterson's (1964) data with respect to the discrete vs. cyclical contrast and since, to this writer's knowledge, no suitable data set is available in the literature, it was decided to run an experiment to compare, in a within-participant design, the parameters of Fitts' law for discrete and cyclical performance.

2. Methods

2.1. The aiming paradigm

The necessity to use the same criterion for the definition of *MT* while preserving a clear-cut contrast between discrete and cyclical movement made usual kinematic methods of measuring *MT* inapplicable here. The definition of *MT* as the time elapsed between two successive excursion extrema had to be discarded because this would not have guaranteed the execution of genuinely discrete movements: Participants could have ended *MT* by reversing the direction of their dicrete movement, with the return movement being executed in part or fully. Rather than a discrete movement (a half-cycle), this in strict parlance would have represented a go-plus-return movement – a full cycle of movement. It will become apparent below (see Experiment 2) that cycles and half-cycles must be carefully distinguished. A zero-acceleration criterion, with instructions to pause at targets, would have solved the just-mentioned problem, but this method would have inappropriately penalised cyclical performance: As already emphasised, a critical characteristic of cyclical performance is precisely that acceleration need not cancel when velocity falls to zero at excursion extrema. Therefore participants were asked to mark their aiming points by pressing with the forefinger on a small push-button fixed on the hand manipulandum, as if manipulating a one-dimension computer mouse to bring a cursor to some target in which a click will be delivered. Note that Fitts' law is known to remain just as valid for such remote-control tasks as it is for direct-control ones (e.g., Kabbash et al., 1993).

2.2. Movement apparatus, visual display, and task

Using their preferred arm, participants moved a carriage by means of a spherical handle 30 mm in diameter on which was fixed a light push-button (0.5 mm of total course, 1.5 n of critical force) to be activated by the forefinger. The carriage, mounted on ball bearings, could be translated along a 308-mm rectilinear track oriented parallel to the participant's midsagittal plane and placed before the active arm. The track was tilted at 30° to the horizontal, so that the carriage had to be pushed up and pulled down. Attached to the carriage was a low-friction, high-resolution rectilinear potentiometer (Schlumberger CD 4321/6), which converted displacements into voltages. To comply with the constant between-target distance of this study, the carriage had to be moved over an amplitude of 210 mm, with the elbow and the shoulder most involved.

The targets were marked by two pairs of stationary luminous dots on a vertical column of 512 red light-emitting diodes (LEDs). This display was placed at eye level, at a viewing distance of about 240 cm. Throughout the experiment, D was a constant 128 LEDs (about 7° visual angle), whereas there were six possible values of W, ranging from 4 to 22 LEDs. Using Fitts' definition (Eq. (1)), this resulted in the ID varying from 3.5 to 6 bits, by steps of 0.5 bit.

The participant's movements were represented on a second column of 512 green LEDs placed contiguous to the just-mentioned target column. As is the case with a standard computer mouse, the participant was provided with two feedback elements, a mobile cursor and a fixed trace. The cursor was a luminous dot whose position, controlled by the manipulandum, was refreshed by the computer at a frequency of 500 Hz. The trace was a stationary luminous dot that marked the location of the last click.

2.3. Conditions of movement execution

The participants carried out the task in three experimental conditions. [5]

2.3.1. Discrete movement or 2-click condition

Time had to be minimised over just one half-cycle. Having carefully placed the pointer in the middle of one target (upper and lower targets balanced), the participant started *MT* with a click (a light tap on the finger button) and ended it with a second click in the other target. Instructions encouraged participants to tightly synchronise the onset of their hand movement with the first finger click, but there was no constraint on the second click other than placing it appropriately in the other target – regardless of movement velocity at the time of the second click.

2.3.2. Continuous movement or N-click condition

The participant had to perform as many clicks as possible in a given period of time by clicking alternatively in the lower and the upper target. This condition essentially replicated Fitts' (1954) reciprocal task, with finger cliks playing the role of discrete chronometric separators for the measurement of *MT*, in the place of hand taps.

2.3.3. One-cycle movement or 3-click condition

Having carefully placed the pointer in the middle of one target (upper and lower targets balanced), the participant performed a three-click series as quickly as possible while alternating between the two targets. Thus time had to be minimised over one complete cycle, with both *MT* between the first and the second click (MT_{go}) and *MT* between the second and the third click (return *MT*, noted MT_{ret}) being measured, as well as the position of both the second and third click.

For reasons that will become apparent below, the comparison between the

[5] The oculomotor system is mobilized differently in discrete and continuous aimed movement. In discrete tasks, participants have already fixated their gaze at the target when they start moving their arm. The continuous task, in contrast, encourage participants to alternatively fixate at the two targets, with a parallel oscillation of the hand *and* gaze. So, for lower values of *ID*, continuous performance may perhaps be penalized by the limitations of the oculomotor system, and hence a bias on ID_i may be introduced in favor of the computational prediction. Although several participants did report oculomotor fatigue after fast-speed trials in the continuous task, gaze movements were not recorded in this study. Specific investigations would be necessary to determine to what extent the performance limitations of the oculomotor system may influence the parameters of Fitts' law in the continuous condition.

discrete and the cyclical condition will be treated as Experiment 1, whereas the one-cycle condition, which afforded a comparison between the go and the return component of movements, will be treated as Experiment 2.

2.4. Speed / accuracy instructions

Participants were requested to minimise MT, but the instructions did not simply ask them to commit fewer errors than a given criterion. Rather, they were repeatedly encouraged to use only the prescribed tolerance, but all that tolerance (the terms *only* and *all* being of relevance when W was small and large, respectively) so as to obtain a broad spectrum of effective target width.

2.5. Design

Six right-handed university students, one woman and five men, aged 22–26, participated. They were paid 30 FF per hour. Each participant was tested individually and participated in four 75-minute sessions, the last two of which were considered as experimental sessions.

The two experimental sessions (like the two practice sessions) comprised a total of 54 trials, corresponding to three occurrences of each of the 18 possible combinations of six values of W with three conditions of movement execution, the succession order being differently balanced for each participant according to the exhaustive-series principle (Possamaï and Reynard, 1974).

A trial lasted 30 s in the N-click condition, but three times as long (90 s) in the 2-click and 3-click conditions, to compensate for the fact that the latter conditions had pauses, and thus try to obtain comparable numbers of movements (half-cycles) in the three conditions. During the last two thirds of each trial (i.e., for 20 s in the cyclical condition and for 60 s in the discrete and the one-cycle condition), a continuous tone was emitted that signalled to the participant that his/her movements were being recorded. The initial third of trial time was dedicated to warming up.

2.6. Data reduction and processing

2.6.1. Effective W and effective ID

The assessment of task difficulty via D and W is valid to the extent that (1) the participant continues to aim at target centers when W becomes very large (i.e., mean movement amplitude does not become smaller than D) and (2) the standard deviation of movement endpoints, the so-called effective target width, represents a constant proportion of W (i.e., error rate remains constant over the whole range of W). The latter prerequisite, unlike the former, has been often found to be violated (e.g., Welford, 1968). In a typical experiment, the larger the W, the lower the frequency of errors, which implies that effective target width tends to vary within narrower limits than W. To obtain reliable estimates of the parameters of Fitts' law, task difficulty was assessed through effective measures of D and W. That is, the prescribed values of D and W were replaced with the mean and standard deviation of movement amplitude, respectively. Each individual trial provided one data point characterised by its own values of speed (MT) and accuracy (effective ID, simply noted ID from this point on). Thus, for each participant and for each condition, the three trial repetitions run at the same level of ID contributed three points to the trade-off graph (18 data points per individual trade-off).

2.6.2. Data sampling and differentiation

A sampling frequency of 83.3 Hz was used in this study. Given the low level of noise contaminating the position time series, a minimal smoothing procedure based on a mobile three-point average proved sufficient. This procedure was repeated on velocity data before proceeding to the second differentiation.

2.6.3. Assessment of movement harmonicity and determination of ID_c

Movement harmonicity was measured on the basis of the time profiles of acceleration around movement reversals (see Guiard, 1993). In the present experiment, it was possible to assess an index of harmonicity (H) both in the N-click and in the 3-click condition. The method was as follows. Successive peaks of velocity were detected so as to segment the recording into non-overlapping time windows (half-cycles) each of which necessarily included one movement reversal. All local extrema of acceleration were detected within the window. Within each time window, H was computed as the ratio of the highest and the lowest absolute value of these local extrema. Finally, the individual H values computed for all the movements of the trial were averaged so as to provide a mean estimate of H for the whole trial.

By construction, the dimensionless number H ranges from 0 to 1, that is, from the case in which the acceleration zeroes at reversals ($H = 0$) to the case in which acceleration is maximum at reversals ($H = 1$) as is the case in simple harmonic motion. As H actually varies as an abrupt nonlinear function of the ID, with typically $H = 1$ for IDs < 4 and $H = 0$ for IDs > 5, it was possible to fit a logistic function (Berkson, 1953) to the H/ID data, according to the following equation:

$$H = 1/[1 + \exp(-b - (a * ID))], \tag{3}$$

with a and b standing for adjustable parameters, and the ratio $-b/a$ providing an estimate of the ID at which H crosses the $1/2$ level, which we shall term critical ID (ID_c). This relationship can be straightforwardly linearized. If H is a logistic function of ID, then plotting logit $(H) = \ln(H/(1 - H))$ against ID will result in a linear graph of slope a and intercept b.

3. Experiment 1

The main goal of Experiment 1 was to compare the parameters of Fitts' law for discrete (2-click) and cyclical (N-click) movement, while investigating the possibility of a dependence of ID_i upon ID_c.

3.1. Results

Table 1 presents the main results of Experiment 1, separately for each participant.

3.1.1. Goodness of fit for Fitts' law

For both task conditions the fitting of linear equations on MT/ID scatter plots yielded fairly high r^2 (see the first and second blocks of Table 1). The percentage of variance accounted for ranged from 70.3% to 89.8% for the discrete task (mean $r^2 = 0.793$ over all the participants), and from 78.1% to 89.6% for the cyclical task (mean $r^2 = 0.831$). On the ground that all twelve plots were satisfactorily linear, below the parameters of Fitts' law for each participant are treated as the basic data.

3.1.2. Slopes of the trade-off functions

As illustrated in Fig. 2, the slope of the mean function was steeper for cyclical movement (277 ms/bit) than for discrete movement (205 ms/bit). In fact, as shown in Table 1 and Fig. 3, all 6 participants exhibited a difference with the same sign (significant, one-tailed sign test). [6]

[6] With regard to statistical significance, the $\alpha = 0.05$ conventional threshold is used throughout this report. Lower probabilities for type-I error are not mentioned.

Table 1
Results of Experiment 1 on discrete vs. continuous performance

	Subjects							
	S1	S2	S3	S4	S5	S6	m	sd
(1) Discrete movement: parameters of MT / ID tradeoff functions								
Slope (ms/bit)	227.9	136.3	157.9	201.4	166.4	185.0	179.2	32.7
Intercept (ms)	−585.1	−57.3	−217.9	−386.8	−202.6	−343.1	−298.8	182.1
r^2	0.764	0.898	0.797	0.794	0.802	0.703	0.793	0.063
(2) Continuous movement: parameters of MT / ID tradeoff functions								
Slope (ms/bit)	261.5	238.7	175.8	238.3	209.7	358.1	247.0	61.9
Intercepts (ms)	−752.0	−504.9	−274.6	−462.3	−292.2	−1152.7	−573.1	332.5
r^2	0.853	0.828	0.843	0.781	0.782	0.896	0.831	0.044
(3) Coordinates of intersection between discrete and continuous movement								
ID_i (bits)	4.96	4.37	3.16	2.05	2.07	4.68	3.55	1.31
MT_i (ms)	546.3	538.7	281.4	25.8	141.1	522.5	342.6	226.7
(4) r^2 for fitting a logistic function (Eq. (3))								
H / ID	0.785	0.783	0.836	0.694	0.723	0.778	0.767	0.050
H / MT	0.953	0.870	0.928	0.932	0.906	0.882	0.912	0.032
(5) Coordinates of H = 1/2 for continuous movement								
ID_c (bits)	4.99	4.59	4.26	4.20	3.75	4.82	4.44	0.46
MT_c (ms)	553.7	592.0	469.4	541.3	493.7	574.4	537.4	47.3
(6) Mean performance scores (discrete and continuous collapsed)								
Capacity (bits/s)	10.94	8.18	9.22	8.03	7.73	9.53	8.94	1.21
MT (ms)	445.5	549.4	526.4	618.3	603.7	521.1	544.1	62.7

3.1.3. X-coordinate of discrete–continuous-performance equality

The intersection of the two mean trade-off functions presented in Fig. 2 specifies an ID_i of 4.2 bits. As shown in the third block of Table 1 and in Fig. 3, all the individual values of ID_i fell somewhere between 2 and 5 bits – that is, in none of the participants did ID_i fall to the left or to the right of the range of practicable *ID*s.

It may be noticed from Table 1 that ID_i and mean *MT*, the latter averaged over the two conditions of Experiment 1, bore a strong negative correlation (Spearman rank-difference coefficient of correlation $\rho = -0.943$, significant). The faster the participant, the higher was the x-coordinate of the discrete–cyclical intersection on the continuum of task difficulty.

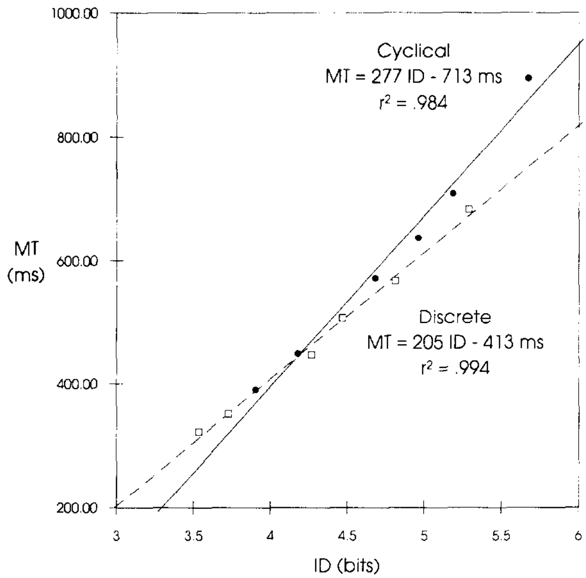

Fig. 2. Mean speed–accuracy trade-off function for the discrete condition (unfilled squares) and for the cyclical condition (filled circles) of Experiment 1. Data-point coordinates were computed, for each level of prescribed *ID*, by averaging the six individual values of effective *ID* (x-coordinate) and the six individual values of *MT* (y-coordinate).

3.1.4. Dependence of continuous-movement harmonicity on task difficulty and movement speed

In all participants, the harmonicity of cyclical movement varied to a satisfactory approximation as a logistic function of *ID* (Eq. (3)). The fourth block of Table 1 presents, for each participant, the r^2 obtained in fitting a logistic equation to the relationship between *H* and *ID* (mean $r^2 = 0.767$), as well as to the relationship between *H* and *MT* (mean $r^2 = 0.912$). In all 6 participants the fit was in fact better in the latter case (significant, one-tailed sign test), suggesting that movement harmonicity depended on movement speed proper, with only an indirect dependence on task difficulty, via *MT*. A representative example of the two plots, taken from Participant 1, is shown in Fig. 4.

3.1.5. Critical ID for movement harmonicity

The goodness of fit obtained in all participants with the logistic equation made it possible, in each individual case, to capture the relation observed between *H* and *ID* with the equation's parameters. It was also possible to derive critical *ID* (ID_c), the threshold of task difficulty for which the harmonic-

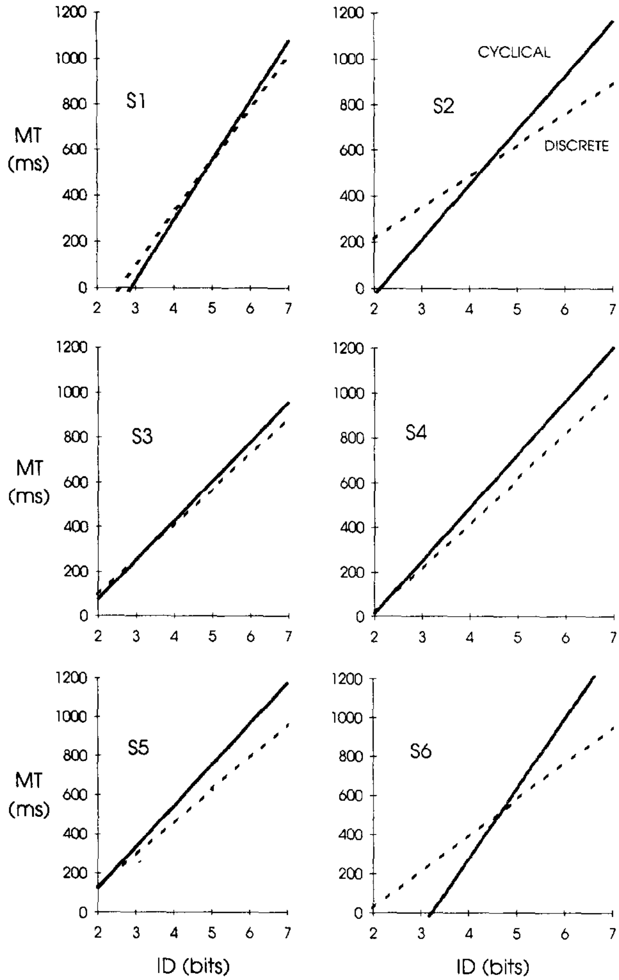

Fig. 3. Speed–accuracy trade-off function for the discrete condition (dashed lines) and for the cyclical condition (solid lines) of Experiment 1, computed for each participant separately.

ity of cyclical movement switched more or less abruptly from 1 to 0 (if Eq. (3) holds, then ID_c, the value of ID for which $H = 1/2$, can be computed as $-b/a$). The six individual measures of ID_c are presented in the fifth block of Table 1.

Cyclical movement switched from the harmonic to the inharmonic mode when in the interval $4 < ID < 5$, with a mean ID_c of 4.4 bits. ID_c was linked to

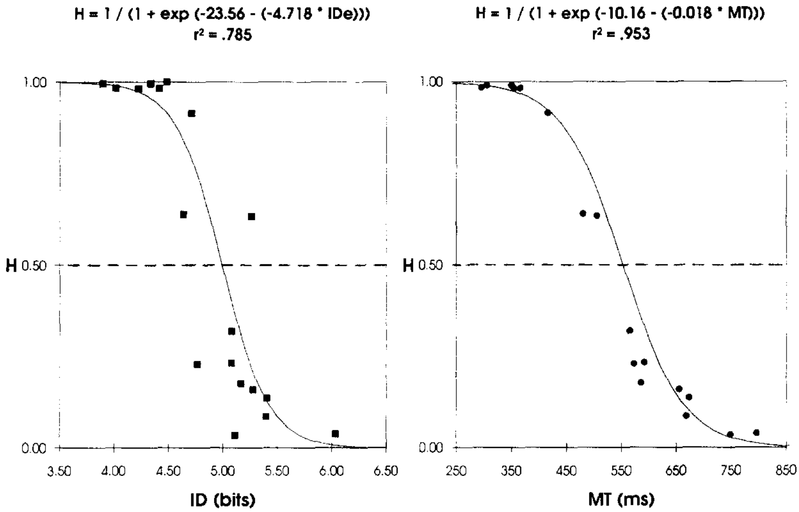

Fig. 4. Illustration, in a representative participant (Participant 1), of the evolution of the index of harmonicity *H* as a function of the *ID* (left panel) and as a function of *MT* (right panel), with the logistic equation of best fit. Each data point corresponds to one trial completed in the cyclical condition of Experiment 1.

several observables. Particularly worthy of note is the strong positive correlation, depicted in Fig. 5, between ID_c and ID_i (Spearman rank-difference coefficient of correlation $\rho = 0.943$, significant). The longer a participant's cyclical movement remained harmonic as the *ID* was scaled up, the longer, in this participant, cyclical performance surpassed discrete performance.

In fact, the data set of Table 1 reveals a whole network of correlation coefficients involving ID_c, ID_i, mean *MT*, and mean effective capacity. [7] The 6 binary relationships, all significant, are reported in Fig. 6. To state the findings compactly, the greater the participant's ability (mean capacity), the faster his/her movements (mean *MT*), the higher the level of *ID* at which his/her cyclical movement became inharmonic (ID_c), and the higher the level of *ID* at which discrete performance began to surpass cyclical performance (ID_i).

[7] Performance capacity was computed, according to Fitts' (1954) method, as the ratio of *ID* (in fact, effective *ID*) and *MT*. More specifically, effective capacity (bits/s) was first computed for each participant as effective *ID* (bits)/*MT* (s) for each experimental level of task difficulty. Estimates were then averaged over the six experimental levels of *ID* for each condition of movement execution. Finally, a grand average was computed over the discrete- and the continuous-movement condition.

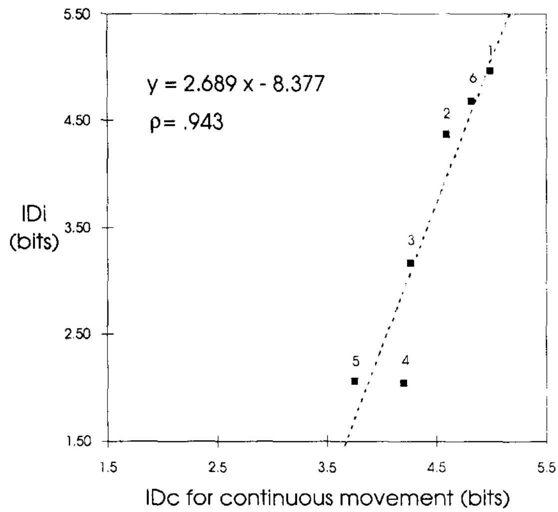

Fig. 5. Relationship between ID_i and ID_c, as observed in Experiment 1. The relation is assessed between participants, with one data point per participant.

3.2. Discussion

3.2.1. Speed–accuracy trade-off analysis

The first suggestion that emerges from this experiment is that the slope of the *MT/ID* speed–accuracy trade-off is steeper for cyclical movement than for discrete movement. This replication of Fitts and Peterson's (1964) finding constitutes a relatively innocuous result, as it accords with the prediction derived through different hypothetical mechanisms from all the models we considered. The critical results are those concerning ID_i, the value of *ID* for which discrete and cyclical movements are equal, because on this variable the models yield different predictions. Only two participants, Participants 4 and 5, behaved in

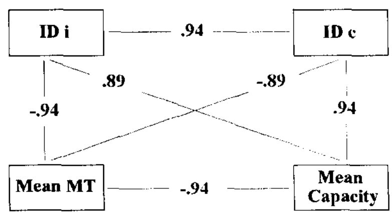

Fig. 6. The complete set of correlation coefficients (Spearman rank-difference ρ) involving ID_i (bits), ID_c (bits), mean *MT* (ms), and mean effective capacity (bits/s).

keeping with computational predictions, exhibiting discrete-movement superiority throughout the *ID* range. This circumscribed supporting evidence is further weakened by the fact that these were the two slowest participants, with overall mean *MT*s about one standard deviation above sample mean. In the other four participants, ID_i fell between 3 and 5 bits, a finding that can be accounted for neither by Fitts and Peterson's (1964) analysis, nor by any of the major subsequent information-processing models, as shown in the Introduction. Thus, the results of this experiment run counter to the unanimous prediction from computational models that discrete performance should be superior to cyclical performance at all levels of task difficulty: Apparently, it is only for about the higher half of the *ID* range that the predicted superiority obtains.

The *MT* data do not support the pure energy-saving approach either. The results run counter to the prediction derived from the energetic analysis for reasons essentially symmetrical to those exposed in the last paragraph. Even though discrete/cyclical equality fell at relatively high levels of *ID* in the fastest participants, in no participant was cyclical performance found to surpass discrete performance throughout the whole range of *ID*s. As noted in the Introduction, the energy-saving hypothesis alone simply cannot accommodate the finding of faster discrete than cyclical performance.

So the results of this experiment suggest that both approaches to the problem might be wrong in their extreme predictions, failing in opposite manners. The information-processing analysis explains the findings for higher *ID*s, but it fails to account for the observations made at lower *ID*s, with faster movements. Conversely, the energy-saving analysis explains the data for fast movements but fails to explain what happened in those difficult conditions where the participants produced longer *MT*s. Discrete/cyclical performance equality was found to fall neither to the left, nor to the right, but right in the middle of the practicable range of *ID*s.

3.2.2. Analysis of movement harmonicity

A preliminary condition for using *H*, the index of harmonicity proposed by Guiard (1993), in an energetic approach to Fitts' law is that *H* varies in a lawful fashion as a function of *ID* and *MT*, the two critical variables involved in the law. We have seen that in all participants the relationship between *H* and the *ID* could be satisfactorily approximated by a logistic function, an instance of a sigmoidal function. As a logistic function can be viewed as a continuous approximation of a threshold function, a possible description of the finding is that, as the gradually increased *ID* reached a critical level of 4 to 5 bits, cyclical movement bifurcated more or less abruptly from simple harmonic movement

($H = 1$) to a completely inharmonic movement mode ($H = 0$). More research will be necessary, however, to characterise this apparent bi-stability in some detail and to determine whether a link can be established with other phase-transition phenomena reported in the dynamic literature (e.g., Schöner and Kelso, 1988).

Interestingly, the logistic fit for H was systematically better as a function of movement velocity than as a function of task difficulty. This is what should be expected upon the assumption that movement harmonicity has to do with the saving and recycling of mechanical energy. It must be realised that in this experiment, which involved an approximately constant mass (the mass of the arm plus that of the manipulandum), movement speed was the critical component of kinetic energy, half the mass times the square of peak velocity, because it was the one that varied quite substantially. The higher the peak velocity of movements, the greater the energetic capital to deal with (a strong non-linear dependency, given the squaring of speed in kinetic energy) and hence the more important it becomes for the actor to recycle the available mechanical energy by converting kinetic energy into a potential, elastic form (rather than dissipating this energy) as the movements decelerates towards the target (Guiard, 1993). The finding of a tighter statistical dependency of H on MT than on ID is quite consistent with the view that movement harmonicity depends directly on movement speed, but only indirectly (via Fitts' law) on task difficulty.

A further important finding was that ID_c, the critical value of ID at which H crossed the threshold value of 0.5, bore a strong positive correlation with overall performance, as measured in the experiment in terms of both mean MT and mean effective capacity: As task difficulty was scaled up, the faster (and the better) the performer, the longer his/her cyclical movements remained harmonic. The fact that the participants who were able to mobilise the greatest amounts of kinetic energy in the task were precisely those who exhibited the most harmonic movements clearly supports the conclusion of the last paragraph.

The finding of a clear-cut positive correlation between ID_i and ID_c is also of critical importance to the energy-saving approach. This correlation indicates that the level of difficulty for which discrete and cyclical performance equalled each other was related to the participant's ability to keep on producing simple harmonic movement in the cyclical condition as the aiming task was made more and more difficult. The slope and the intercept of the linear relation were substantially different from 1 and 0, respectively, (specifically, $ID_i = 2.7 * ID_c - 8.4$), precluding any simplistic hypothesis on the mechanism linking ID_i and ID_c. Yet, the strong positive correlation clearly accords with the view that movement harmonicity is a potent determinant of cyclical aiming performance.

Assuming, as suggested by Guiard (1993), that the possibility to temporarily store and recycle mechanical energy during the process of movement reversal advantages cyclical movement over discrete movement, and that movement harmonicity, as measured by H, reflects the extent to which the natural elasticity of the effector system is exploited, one indeed expects ID_i to positively correlate with ID_c.

4. Experiment 2

This section focuses on the one-cycle (3-click) task condition. The goal of Experiment 2 was to estimate the parameters of Fitts' law comparatively for the go and return component of full cycles of movement, with particular attention to the x-coordinate of the intersection of the trade-off functions for MT_{go} and MT_{ret}. The rationale was that the major features that differentiate discrete and cyclical movement, from either an information-processing or an energy-saving standpoint, still hold in a go/return comparison (see below). Moreover, the fact that each complete go-and-return cycle included a movement reversal made it again possible to assess the degree of harmonicity of movement at the various levels of task difficulty, and hence to estimate ID_c.

4.1. Computational predictions on go vs. return performance

In terms of advance-programming, it seems obvious at first sight that go movements should be advantaged relative to return movements. However, some extra time may be included in MT_{go} to pre-program the return movement, whereas no delay of this sort can affect MT_{ret}, which ends the cycle. It is not clear, therefore, whether any firm prediction can be derived from the movement-programming hypothesis on comparative go vs. return performance.

The feedback-data processing argument, in contrast, still works. The possibility of initial positioning errors is a handicap for return movements but obviously not for go movements. This is a reason to expect MT_{go} to be shorter on average than MT_{ret}.

On the other hand, just as was the case with cyclical movements, it is only above a certain threshold of ID that MT_{ret} should be delayed by the processing of feedback data. For lower IDs, conducive to fast ballistic movements, the return move should be executed regardless of the random variations of the endpoint of the go movement. So one predicts a steeper slope for MT_{ret} than for MT_{go} in the MT/ID trade-off function.

It is apparent that, in the light of the classic computational analysis, there is a substantial degree of similarity between the discrete/cyclical contrast considered in Experiment 1 and the go/return contrast considered in Experiment 2. For reasons similar to those invoked in the analysis of discrete vs. cyclical performance, we are led to the prediction that (1) the slope of the trade-off function should be steeper for return than go performance and (2) go performance should never be surpassed by return performance, even at the lowest possible levels of task difficulty (i.e., ID_i, the x-coordinate of the go–return performance equality, should fall to the left of the range of practicable IDs).

4.2. Predictions from the energy-economies perspective

Again, predictions from the energy-saving analysis differ. In terms of energy economies, it is the return component of the one-cycle movement that should be advantaged because the recycling of mechanical energy that may occur at movement reversal can only be of benefit to the second phase of the cycle. Note that a single cycle of movement already belongs to the realm of cyclicity and that a single reversal is sufficient to produce a piece of simple harmonic movement above some threshold of velocity. Above this threshold, the amount of kinetic energy actively produced during the initial acceleration phase of the go movement should become passively recyclable and help to achieve the second, return phase of the movement without it being necessary to produce a second impulse ex nihilo. In this view, the faster the movement cycle, the lower the energetic cost of the return move relative to that of the go move. This privilege of MT_{ret} should increase with movement velocity, that is, decrease with the ID, but this analysis offers no reason to expect the speed of go movements to ever surpass that of return movements.

In sum, the energy-economies analysis predicts a steeper slope for MT_{ret} than MT_{go}, in coincidence with the computational prediction; ID_i, however, should fall to the right, not left, of the range of practicable IDs. According to a hybrid approach combining information-processing and energy-economies considerations, the two trade-off lines should intersect somewhere within the practicable range of IDs.

4.3. Results

Table 2 presents the main results of Experiment 2, separately for each participant.

Table 2
Results of Experiment 2 on go vs. return performance

	Subjects							
	S1	S2	S3	S4	S5	S6	m	sd
(1) Go movement: parameters of MT / ID trade-off functions								
Slope (ms/bit)	250.4	177.4	165.5	186.5	184.5	203.3	194.6	30.0
Intercept (ms)	−645.6	−277.5	−253.4	−290.7	−279.3	−386.0	−355.4	149.4
r^2	0.765	0.806	0.886	0.750	0.778	0.890	0.813	0.061
(2) Return movement: parameters of MT / ID trade-off functions								
Slope (ms/bit)	251.0	186.3	214.0	228.6	225.6	321.7	237.9	46.2
Intercept (ms)	−705.4	−248.1	−413.4	−441.6	−420.0	−925.1	−525.6	244.9
r^2	0.706	0.772	0.911	0.781	0.850	0.755	0.796	0.073
(3) Coordinates of intersection between go and return trade-off functions								
ID_i (bits)	–	–	3.30	3.59	3.42	4.55	3.72	0.57
MT_i (ms)	–	–	292.8	379.1	352.5	539.7	391.0	105.5
(4) r^2 for fitting a logistic function (Eq. (3))								
H / ID	0.832	0.550	0.745	0.708	0.828	0.818	0.755	0.120
H /Go *MT*	0.917	0.673	0.739	0.890	0.784	0.856	0.794	0.096
H /Return *MT*	0.867	0.634	0.794	0.713	0.905	0.868	0.814	0.108
(5) Coordinates of H = 1 / 2								
ID_c (bits)	4.90	3.39	3.97	4.56	4.64	4.78	4.37	0.58
Go MT_c (ms)	547.4	402.5	413.7	545.1	586.2	603.9	516.5	87.0
Return MT_c (ms)	512.7	340.7	408.0	611.1	645.1	589.8	517.9	121.3
(6) Mean performance scores (go and return movements collapsed)								
Capacity (bits/s)	10.51	8.31	9.08	8.07	8.13	9.31	8.90	0.94
MT (ms)	478.2	566.7	521.2	618.6	533.5	514.8	542.2	48.7

4.3.1. Goodness of fit for Fitts' law

The r^2 values obtained in fitting linear equations on *MT/ID* scatter plots were similar to those obtained in Experiment 1. As shown in the first and second block of Table 2, the percentage of variance explained ranged from 75.0% to 89.0% for MT_{go} and from 70.6% to 91.1% for MT_{ret}. These percentages were judged sufficient for summarising the data from each participant with the two parameters of Fitts' law.

4.3.2. Slope and intercept comparisons

As depicted in Fig. 7, the slope of the mean trade-off function was steeper for return than go movements (271 vs. 214 ms/bit). As shown in Table 2, all six participants exhibited a difference with the same sign (significant, one-tailed

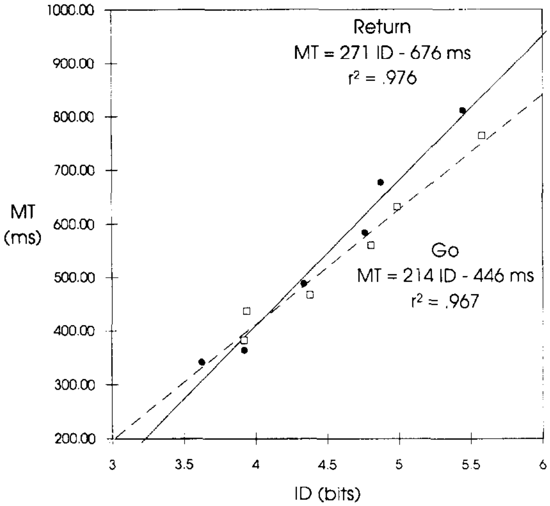

Fig. 7. Mean speed–accuracy trade-off function for go movements (dashed line) and for return movements (solid line) in the one-cycle, 3-click task (Experiment 2). Data point co-ordinates were computed, at each level of prescribed *ID*, by averaging the six individual values of effective *ID* (*x*-coordinate) and the six individual values of *MT* (*y*-coordinate).

sign test), although the slope difference was extremely small in two participants (1 ms/bit for Participant 1, and 9 ms/bit for Participant 2).

In fact, the performance data of Experiment 2 replicated those of Experiment 1 to a striking extent (compare Fig. 8 and Fig. 3). On the one hand, the trade-off for go movements was quite reminiscent of that for discrete movements in terms of both slope (214 and 205 ms/bit) and intercept (−446 and −413 ms). On the other hand, the trade-off for return movements quite resembled that for cyclical movements, again in terms of both slope (271 and 277 ms/bit) and intercept (−676 and −713 ms).

4.3.3. X-coordinate of go / return performance equality

The two trade-off functions illustrated in Fig. 7 intersect at $ID = 4.0$ bits. So the value of ID_i for the go/return comparison was similar to that found in Experiment 1 with discrete/cyclical movements, where ID_i amounted to 4.2 bits (see Fig. 2). As just mentioned, however, the two trade-off lines happened to intersect at an extremely acute angle in two participants, precluding in these individual cases the computation of a reliable estimate of ID_i (see Fig. 8). In the remaining four participants (Participants 3, 4, 5, and 6), ID_i fell in the range 3.3 to 4.5 bits, well within the range of practicable levels of difficulty (see the third block of Table 2).

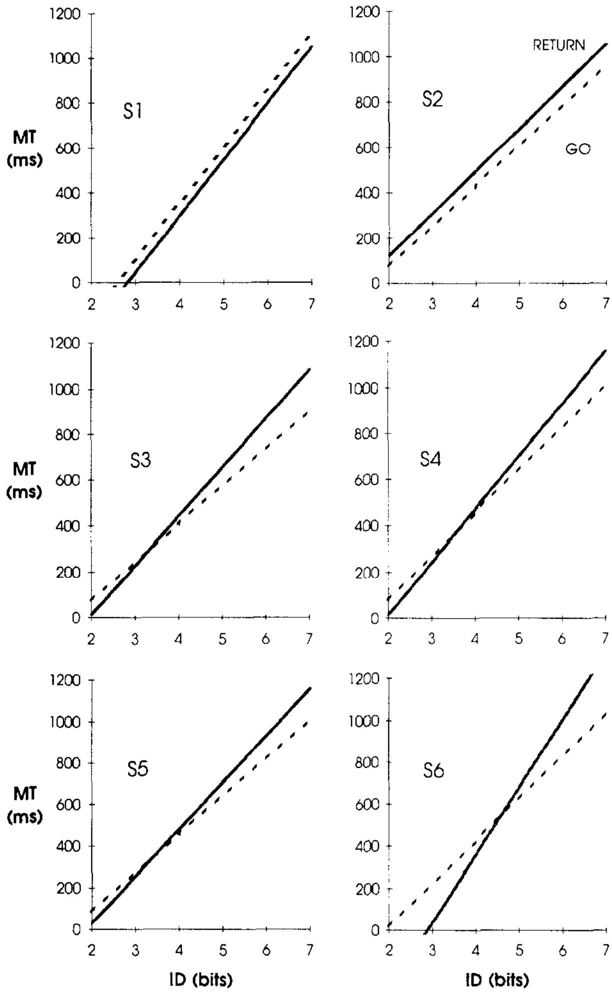

Fig. 8. Speed–accuracy trade-off functions for go movements (dashed lines) and for return movements (solid lines) in the one-cycle, 3-click task of Experiment 2, computed for each participant separately.

Plotting the four available estimates of ID_i against the corresponding values of overall mean MT and mean effective capacity (each computed over the two components of the movement cycle) did not reveal any consistent correlation ($\rho = -0.20$ for both the ID_i/MT and the ID_i/effective capacity relationship). So, in contrast to Experiment 1, there was no suggestion in the data of a linear dependence of ID_i upon the participants' general performance ability. However, there was again a strong negative correlation between mean effective capacity and overall mean MT, as may be noticed from the sixth block of Table 2 (Spearman rank-difference coefficient of correlation $\rho = -0.943$, significant). So, in the three-click condition just as was the case in the discrete and cyclical conditions of Experiment 1, the more efficient the participant, the faster.

4.3.4. Movement harmonicity, task difficulty, and movement speed

The fourth block of Table 2 presents, for each participant, the r^2 values obtained in fitting a logistic function to the H/ID relationship, as well as to the relationship between H and MT_{go} and between H and MT_{ret}.[8] Except for Participant 2, for whom the plots were mediocre, the obtained r^2 were similar to those obtained with the cyclical movements of Experiment 1, making it possible to compute individual estimates of ID_c.

It may be noticed from Table 2 that better logistic fits were obtained for H as a function of mean movement speed than as a function of task difficulty. Whereas the mean r^2 was 0.755 for the plot of H against ID, r^2 for the plot of H against MT_{go} and for the plot of H against MT_{ret} was 0.794 and 0.814, respectively. So the data suggest that in the one-cycle condition movement harmonicity was more strongly linked to movement speed than to task difficulty, as was the case in the cyclical condition of Experiment 1.

4.3.5. Critical ID for movement harmonicity

The six individual estimates of ID_c are presented in the fifth block of Table 2.

ID_c fell on average at 4.37 bits, an estimate very close to that obtained in the cyclical task of Experiment 1 (4.44 bits).

Between-participant variability for ID_c ($SD = 0.6$ bits) was fairly low, as in the cyclical task of Experiment 1, with the individual values ranging from 3.4 to 5.0 bits. Importantly, none of the individual estimates of ID_c fell outside the practicable range of ID.

Finally, because ID_i was not available for Participants 1 and 2, there were only four participants for whom an estimate was available for both ID_i and ID_c. Although the finding is obviously unreliable with such a limited sample, the correlation between ID_i and ID_c was again strongly positive ($\rho = 0.800$), a finding consistent with the hypothesis that the relative balance of go and return

[8] In one individual case (Participant 2), H never approached the value of 1 at the lowest IDs, and no inflection was detectable in the curve. In this particular case, an exponential equation was fitted on the data and ID_c was computed as the intersection of the exponential decay with a horizontal line situated at $H = 1/2$.

performance reflected the participant's ability to keep on producing simple harmonic movement as task difficulty was scaled up.

4.4. Discussion

The chronometric results as well as the kinematic results of Experiment 2 basically replicated those of Experiment 1, suggesting that the go and the return component of a single, but complete, cycle of movement behave much like a discrete and cyclical movement, respectively.

As concurrently predicted by the information-processing and by the energy-economies approach, in Experiment 2 the slope of the speed–accuracy trade-off function was indeed steeper for return than go movements. More critical was the finding, quite reminiscent of the result obtained in Experiment 1, that go/return performance equality fell at about 4 bits, that is, at about the middle of the practicable range of task difficulty. Because both the information-processing and the energy-economies approach predict ID_i to occur outside this range (to its left and to its right, respectively), neither approach can accommodate this outcome.

The kinematic analysis of one-cycle movements also yielded a coherent pattern of results. With one exception, the index of harmonicity H was again found to vary approximately as a logistic function of task difficulty, with the variations of H covering the whole 0–1 interval. As was the case with the cyclical movement of Experiment 1, the one-cycle movement of Experiment 2 switched from the harmonic to the inharmonic regime at a critical value of task difficulty situated toward the middle of the practicable range of ID, and again there was some suggestion that this kinematic observable bore a positive correlation with the x-coordinate of go–return performance equality, a purely chronometric observable. Thus, the longer the movement reversal remained harmonic as the ID was scaled up, the longer return performance remained superior to go performance in one-cycle movements.

As in Experiment 1, the H data suggested a stronger link with movement speed than with task difficulty, in support of the view that movement harmonicity has to do with kinetic energy and that H measures economies of effort.

So the results of Experiment 2 confirm that a one-cycle movement, composed of a single, but complete to-and-fro sequence, must be carefully distinguished from a discrete movement, composed of just half a cycle (Guiard, 1993). Both the chronometric and the kinematic aspects of the present results suggest that the go component of the cycle may be likened to a discrete movement, whereas the return component of the cycle may be likened to a movement embedded in a continuous oscillatory series. An immediate implication is that high-performance, athletic movements – in which it is often easy to discern a preparatory, back-swing component that precedes an executory, fore-swing component – belong to the realm of cyclicity – although many would categorise these movements as discrete. There seems to be little doubt that acts like swinging a golf club or a baseball bat, and more generally the whole variety of efficient human hitting or throwing acts, fully exploit the advantage of cyclicity, namely, the possibility of temporarily storing and recycling mechanical energy from the first to the second half of the movement cycle.

5. General discussion

To fill the gap between discrete and cyclical movement, one needs some way of construing cyclical movement in terms of discrete movement, or vice versa. Information-processing psychology has generally relied on the postulate that cyclical movement amounts to the more or less additive concatenation of discrete moves held as building blocks (Morasso, 1986; Teulings et al., 1986). If each half-cycle of a cyclical aimed movement is construed as a discrete movement just placed in a serial context, then a cyclical condition, in which there is time shortage for movement planning as well as starting-position uncertainly, can only be expected to handicap performance. In fact, Experiment 1 suggested that the superiority of discrete performance manifests itself only over the higher half of the range of task difficulties.

What might be questioned in the computational analysis of the problem is the assumption that discrete movements would represent the *primitives* of cyclical movement. That discrete–cyclical performance equality fell within the common range of *ID*s suggests, in keeping with the conclusions obtained by Guiard (1993) from a kinematic analysis, that this assumption is an oversimplification. Experiment 2 provided some constructive evidence, pointing at *full* cycles as the building blocks of cyclical aimed movement. By showing that essentially the same speed–accuracy trade-offs obtain, on the one hand, with go and discrete movements and, on the other hand, with return and cyclical movements, Experiment 2 demonstrated that a single reversal is sufficient for motor performance to catch up with that recorded in the cyclical condition. This experimental outcome is consistent with the view that cyclicity starts at $N = 1$ cycle (Guiard, 1993).

The results support the view consistent with the position promoted by proponents of the dynamical systems approach, that in human movement science the continuous, or cyclical case should be considered the general case, and the discrete case a special case (Kelso, 1981; Kugler and Turvey, 1987). From the statement that all movements are cyclical, with a variable number of cycles, one gets to a complete and coherent taxonomy of human movement. Everyday gestures such as hitting, throwing, and reaching, which typically have a full-cycle, to-and-fro organization, are included as a limiting case ($N = 1$), whereas in strict parlance the discrete movements popular in psychology laboratories represent a degenerate case ($N = 1/2$) (Guiard, 1993).

The second major aspect of the present data set is that it speaks against the adequacy of a pure information-processing approach to aimed movement. The accounts of motor action currently provided and further promised by the computer metaphor cannot possibly be complete. Movement, unlike perception, has the criterial property of involving substantial transfers of energy, notably at the level of the striate musculature. Along these lines, and notwithstanding the various privileges enjoyed by discrete movement with respect to control processes, it was argued that motor performance suffers an energetic handicap in discrete tasks, with the force for each movement acceleration having to be created anew, whereas in cyclical tasks movement acceleration may benefit from the passive recycling of mechanical energy from the preceding movement – and all the more so the higher the speed of the movement. Consideration of this energy-saving mechanism, in addition to information-processing, led to the prediction that an intersection should actually be observable between the discrete and cyclical trade-off functions. This was corroborated by the results of the two experiments. Moreover, it turned out that the better the performer, the higher the x-coordinate of discrete–cyclical equality, and that the higher the critical level of task difficulty at which the kinematics of cyclical movement became inharmonic, the higher the x-coordinate of discrete–cyclical equality. The last two results, along with the fact that movement harmonicity was linked to movement speed more closely than to task difficulty proper, are evidence for the view that cyclical movement enjoys an energy-saving advantage relative to discrete movement, and that this advantage influences *MT* performance.

In sum, the results of these experiments suggest that information-processing analyses cannot entirely account for Fitts' law, failing to accommodate the way the law varies from the discrete to the cyclical case. The discrepancy between the predictions and the findings seems understandable in terms of energy-saving mechanisms brought into play in the cyclical task to the benefit of performance, but squarely sacrificed in the discrete task.

It is felt that the present findings, obtained in a first approach in which only gross quantitative predictions and facts could be tackled, open an interesting new direction for future research on the fine mechanisms of Fitts' law. Although to date there seems to be no established alternative to computational modelling for the explanation of Fitts' law (for first attempts, see Mottet and Bootsma, 1995, and Schmidt et al., 1995), a hybrid, computational and energetic, approach to the law may offer an improved account of the phenomena.

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