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THERMODYNAMIC STUDY OF MOTOR BEHAVIOUR OPTIMIZATION

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ABSTRACT

Our work is aimed at studying the optimization of a complex motor behaviour from a global perspective. First, 'free climbing' as a sport will be briefly introduced while emphasizing in particular its psychomotor aspect called 'route finding'. The basic question raised here is how does the optimization of a sensorimotoricity-environment system take place. The material under study is the free climber's trajectory, viewed as the 'signature' of climbing behaviour (i.e., the spatial dimension). The concepts of learning, optimization, constraint, and degrees of freedom of a system will be discussed using the synergistic approach to the study of movement (Bernstein, 1967; Kelso, 1977). Measures of a trajectory's length and convex hull can be used to define an index whose equation resembles that of an entropy. This index is a measure of the trajectory's overall complexity. Some important concepts related to the thermodynamics of curves will also be discussed. The optimization process will be studied by examining the changes in entropy over time for a set of trajectories generated during the learning of a route (ten successive repetitions of the same climb). It will be shown that the entropy of the trajectories decreases as learning progresses, that each level of expertise has its own characteristic entropy curve, and that for the subjects tested, the mean entropy of skilled climbers is lower than that of average climbers. Basing our analysis on the concepts of degrees of freedom and constraint equations, an attempt is made to relate trajectory entropy to system entropy. Based on the postulate that trajectory entropy is equal to the difference in entropy between the unconstrained and constrained system , a model of motor optimization is proposed. This model is illustrated by an entropy graph reflecting a dynamic release process. In the light of our results, two opposing views will be examined: movement construction vs. movement emergence.

1. FREE CLIMBING AS A COMPLEX MOTOR BEHAVIOUR: Value and Specifics of this Field of Study

Free climbing is an anti-gravitational motor activity consisting of moving up vertical structures using natural means (arms, legs, and body in general). These structures may be rocks or artificial climbing walls. The optimization of this complex motor behaviour can be studied by analyzing its repeated executions and extracting the characteristics of motor expertise. But an empirical understanding of the activity is needed first in order to define its essential characteristics and situate them in the broader study of the subject's relationship to the environment (system vs. constraints).

1.1.

The movements performed by a climber are adapted to the form of the vertical environment. The climber must interpret the ever-changing structure of the rock and move accordingly. This process has been called *route finding*, one of the key terms in the climber's vocabulary. Experts say that a good climber is able to take full advantage of the biomechanical properties of his body in order to interpret the rock structure in an ongoing manner and produce a series of movements which are linked together into actual 'sentences', the framework of the climber's motor behaviour.

The study of this kind of behaviour has shown that complex systems function in two complementary modes, the informational symbolic mode and the dynamic mode (Pattee, 1977). These two modes appear in fact to be strongly interconnected in a climber's motor behaviour. On the symbolic side, the sequence of movements has its own 'syntax' which appears to be dictated by the shape of the spatial environment. On the dynamic side, the intrinsic motricity developed by good climbers enables them to constantly adapt to those environmental constraints.

At the 'syntactic' level, the movement sequence is generated by a chain of states which is constrained internally by a simple contiguity rule. In such a chain, the final position of one movement is identical to the initial position of the next movement, and there is no recourse to intermediate positions, which increase the energy expended on the task. This rule must be applied to every link in the chain so that their concatenation can take place, thereby forming a well-connected sequence through which the dynamic process can be expressed. This sequence can be compared to a rhythmic flow. In the synergistic approach referred to here (Haken, 1977) each movement, which is optimized by its constraint equations (environmentally specified patterns), is generated by a 'coordinative structure' (Kugler, Kelso, & Turvey, 1980). In motor skills, viewed here as optimized, constraint-reducing behaviours, the muscles of the body are organized into coordinative structures with varying degrees of autonomy (Turvey, Shaw, & Mace, 1978). In the synergistic theory of movement coordination, the coordinative structures act as states which 'attract' the dynamics of the sensorimotor system (Schöner & Kelso, 1988).

A chain of movements can also be considered as meta-synergy which is a second-order structure specific to complex motor skills. The higher-order coordinative or 'cooperative' structure has a semantic dimension for the subject (route finding): "There is no intelligible language without a geometry, an underlying dynamic dimension where the language formalizes the stable structural states" (Thom, 1968). In the present study, we shall attempt to provide evidence of the emergence of this higher-order synergy in the production of movement. An original method will be used to analyze an evolving series of trajectories obtained by repeated execution of the same task. The climbers' trajectories are viewed here as the 'signature' or written trace of their relationship to the environment (see section 2).

1.2. Internal and External Constraints.

The shape of a climber's trajectory (which can be defined, for example, as the line drawn by his center of gravity) is subjected to two types of constraints.

External constraints are environment-generated. The climbing route itself has a specific 'constraining force' (its difficulty) which is exerted on the system (see climbing route difficulty, paragraph 3.1). The main constraints imposed by the spatial environment are the form and orientation of the handles, which can force the climber to adopt certain postures, and the spatial coordinates of the handles, which determine the general path of the route. In order to neutralize the effects of such spatial constraints, it suffices to test subjects in the same environment (on the same climbing route).

Internal constraints are subject-dependent. They are mainly manifested in the subject's level of expertise (at the time of execution), which is considered here to correspond to the sensorimotor system's degree of plasticity. An expert's behaviour should be highly flexible, enabling him to adapt with ease to more stringent constraints. To cope with such environmental constraints, the system must develop a series of adapted coordinative structures, "the immediate adjustment to any kind of disturbance being the necessary result of a dynamic system in which all muscles are forced to act as a unit" (Kelso, Holt, Kugler, & Turvey, 1980). The subject's degree of expertise is in effect his ability to produce a well-linked chain of correct, accurate, and well-formed movements. This involves control, precision, and coordination. The ability to produce such a movement sequence will be assessed here by means of a collective variable which attempts to measure the complexity of the climber's trajectory.

In summary, spatial constraints in the environment (topo-kinesis) provide a means through which a climber can express his skill (morpho-kinesis), and the shape of the resulting trajectory is considered to be an account of how well the climber's system integrates them.

1.3. Degrees of Freedom and Constraint Equations

The number of degrees of freedom of a system is the smallest number of independent variables needed to identify a system state. The mathematical equation for a system's degrees of freedom N is

$$N = nD - C \tag{1}$$

where n is the number of elements in the system, D is its dimension, and C is the number of constraint equations affecting it (Turvey, Fitch, & Kelso, 1982). A constraint equation is a link established between two elements in the system which reduces the number of degrees of freedom. For example, in a two-dimensional space, two points with coordinates (x, y) and (x′, y′) form a system with four degrees of freedom. If the link between these two points is defined (a constraint equation), the system then has only three degrees of freedom. When subjected to environmental constraints, the human system can reduce the number of degrees of freedom by creating dependencies or couplings between the muscular activities at different joints (Bernstein, 1967). The greater the number of environmental constraints, the greater the term C (equation 1) and the smaller the number of degrees of freedom.

2. TRAJECTORY ANALYSIS

2.1. Choice of an Index

A trajectory is a line drawn by a moving point. It is a geometric object. Thus, in the analysis of trajectories, we are only studying the spatial aspects of the process. As a geometric form, a trajectory contains global information about the climber's motor behaviour.

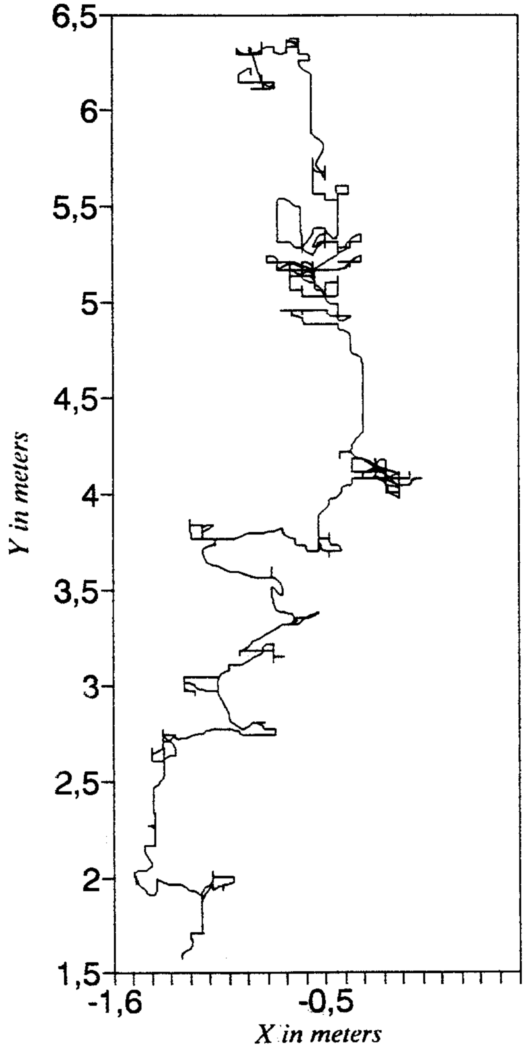


Fig. 1. Trajectory of a 'searching' climber.

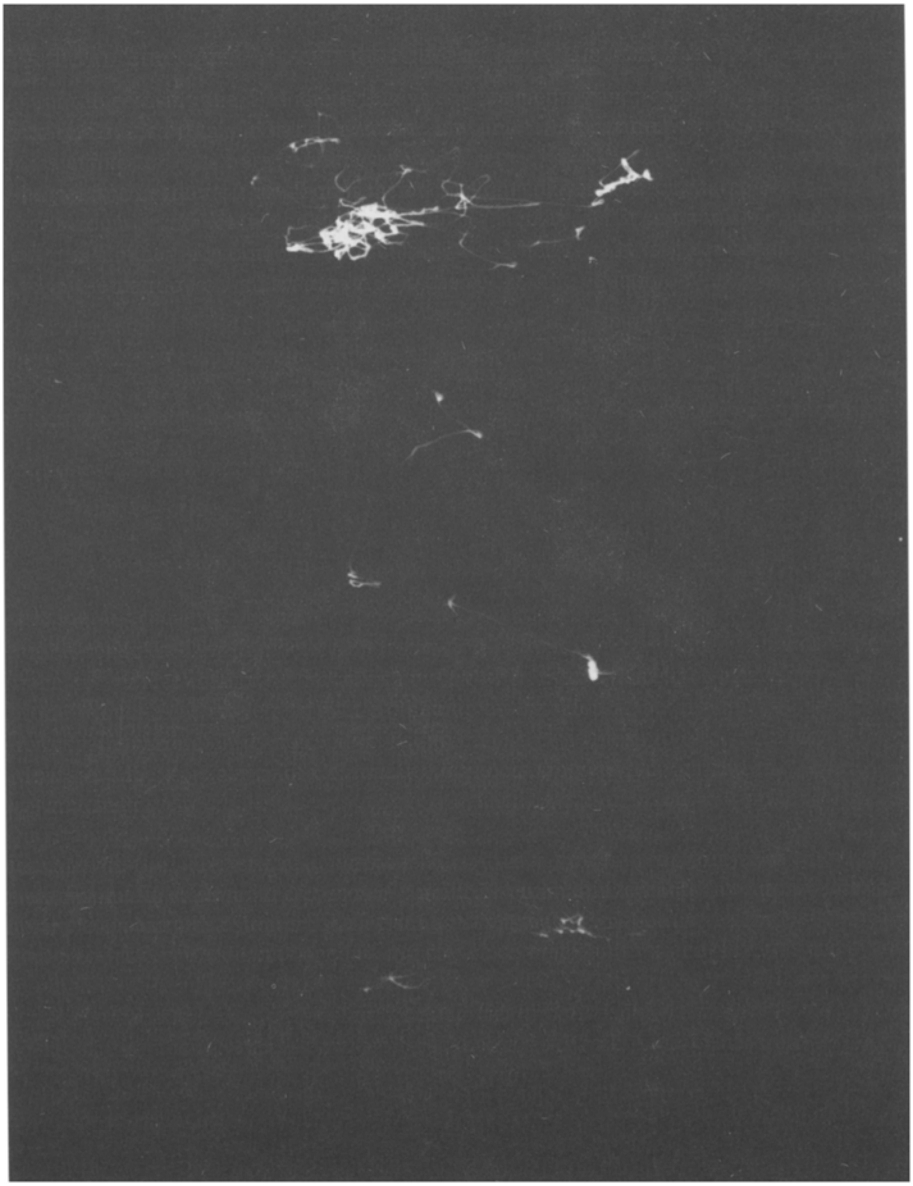


Fig. 1BIS. Trajectory of a 'searching' climber.

By measuring the geometric properties of a trajectory, treated here as a physical object with a certain amount of unity, we are in effect globally analyzing the process which generated that trajectory. For example, in 'on sight' climbing, i.e., climbing in an entirely unknown environment, the trajectories of certain climbers (those with a low level of expertise) contain a series of more or less complex nodes which are indicative of a search process (fig. 1 and 1BIS). A trajectory can thus be considered as a physical object whose complexity can potentially be measured with an index. The index used here is derived from measurements of trajectory length, and its equation leads to a measure of a curve entropy.

2.2. Entropy of a System

There are several definitions of entropy. Generally speaking, if a system can occur in P equally probable states, then the entropy of that system is defined as the logarithm of P (P is also the number of degrees of freedom of the system).

The term 'state' should be clearly defined. To illustrate, take the example of a die. *A priori*, there are six states, so the die's entropy is log 6. But if we consider the parity of the die, then the 1-3-5 side is one state and the 2-4-6 side is another, making two states in all. So the entropy is now equal to log 2.

2.3. Thermodynamics of Curves

Let Γ be a finite curve of length L and let c be its convex hull (its 'perimeter'). Let D be a straight line which crosses the curve. Then there are m points where D and Γ intersect (fig. 2). The entropy of system D is equal to $\log_n m$ (each of the m points can be considered

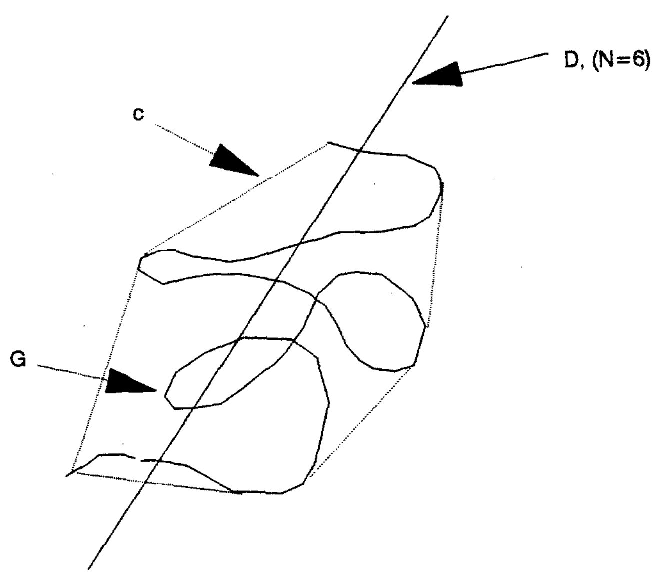
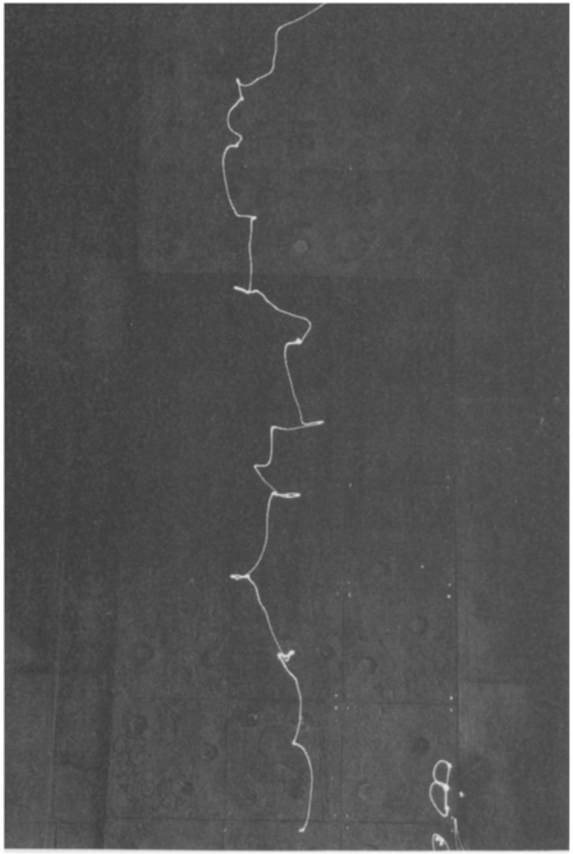


Fig. 2. Entropy of a curve (see text).



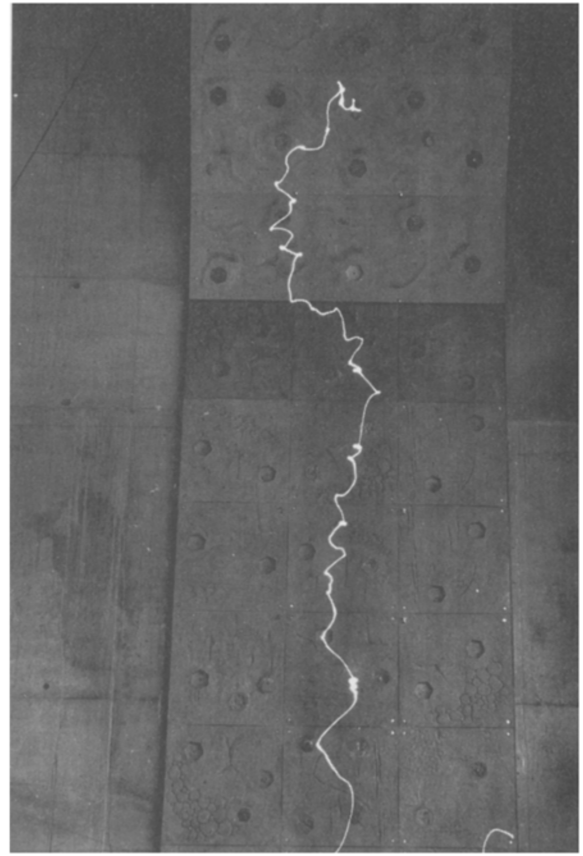


Fig. 3. Trajectory of a highly skilled climber (the wall is approximately 12 meters high).
Fig. 4. Trajectory of an average climber.

to be a state of the system D $\cap$ Γ). Let D vary. Then the mean number of intersections is equal to $\bar{m}$, and the entropy of Γ is $\log_n \bar{m}$.

Santolo's classic theorem (Santolo, 1976) states that $\bar{m} = 2L/c$. Therefore, the entropy H of a curve (or trajectory) is defined by the equation $H = \log_n 2L/c$ (Mendès France, 1981).

2.4. Measuring the Interaction Between the Climber and His Environment

We are attempting to measure the plasticity of a system functioning in a constraining environment. The climber's trajectory contains a certain amount of information. Only the geometric properties of the trajectory are of interest to us here.

Let N be the number of degrees of freedom of the unconstrained system (for example, the climber on the ground) and let N′ be the number of degrees of freedom of the constrained system (the climber in action on the climbing wall). Then N′ < N (see equation 1), and the change in the entropy of the system, ΔS, is defined by the equation

$$\Delta S = \log_n N - \log_n N' \tag{2}$$

The entropy H of the climber's trajectory is

$$H = \log_n 2L/c \tag{3}$$

At this point, we propose the following postulate

$$H = \Delta S \tag{4}$$

This gives us

$$H = \log_n N - \log_n N' \tag{5}$$

This postulate can be considered legitimate for the following reasons:

- First of all, the movements of good climbers have few or no restrictions. They have nearly as much control over their movement while climbing as they do on the ground. In other words, the vertical environment is not very constraining, so N′ is close to N and ΔS remains small. Moreover, the trajectories of experienced climbers are very smooth (fig. 3) and their entropy values are very small. (Ideally, if N′ = N, then H is null, 2L/c = 1, and the trajectory is a straight line.)

- Secondly and inversely, the vertical environment is highly constraining for poor climbers (to the extent that they sometimes become completely immobilized and have no degrees of freedom; this usually leads to a fall). In this case, N′is much smaller than N and ΔS is large. The trajectories of such inexperienced climbers are complex and twisted (fig. 4) and their entropy value is high.

- In summary, the equation H = ΔS expresses the ecological relationship between the climber (ΔS) and the environment (H), i.e. between the dynamics of the climber's system and the external constraints.

3. EXPERIMENTAL PROCEDURE AND DESCRIPTION OF DATA

3.1. Subjects

Subjects were tested as they 'learned' a climbing route (ten successive repetitions of the same climb). The subjects were assigned to one of two groups on the basis of their level of expertise (other parameters such as age, weight, height, and limb length were not considered).

The difficulty scale used in free climbing is divided into eight levels. The four most difficult levels are divided into three sub-levels each (6a, 6b, and 6c for difficulty level 6, etc.). A climber is said to be at level 6b, for example, if he is capable of 'on sight' climbing of level-6b routes, that is, if he can climb them without prior knowledge of the terrain.

Group S1 contained three level-6b subjects (average skill). Group S2 included four level-7b subjects (highly skilled). The degree of expertise claimed by each subject was assessed and confirmed by a group of experts.

3.2. Instructions

Subjects were asked to climb in a natural manner. Each subject had to repeat the same climb ten consecutive times. The ten trajectories obtained for each subject were used as an 'image' of the motor optimization process. A one-minute resting period was allowed between climbs.

3.3. Experimental Setup

A climbing route was constructed on an artificial climbing structure at the E.N.S.A. in Chamonix, France. It was a moderately difficult route, rated at level 6a. None of the subjects in either experimental group would have trouble with a 6a route.

The climbers were photographed and videotaped by cameras located 17 meters from the 10-meter-high wall. The trajectories were defined by the movement of a light-emitting diode attached to the climber's back at waist level. The camera was in position B on a tripod, with the diaphragm closed (16 or 22). The film sensitivity level was 100 ASA and the surrounding lights were dimmed. The shutter was opened when the climb began and closed when the climber reached the summit of the route, approximately one minute later.

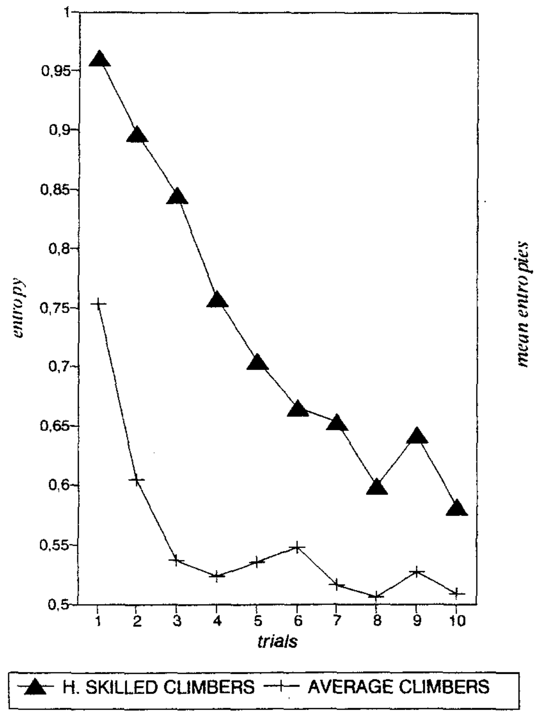
The videotapes were processed by a computer system which digitized the trajectories and calculated the entropy value of each trajectory via an algorithm.

4. RESULTS (fig. 5 and 6)

4.1.

An analysis of variance was computed on the changes in entropy across climbs. Main effects of the climb number (location in the series of ten) ($F_{(9,45)} = 21$, $p < .001$) and expertise level ($F_{(1,5)} = 57.8$, $p < .001$) were obtained, in addition to an interaction between these two factors ($F_{(9,45)} = 4$, $p < .005$). These results indicate that the successive adjustment of this complex behaviour to external constraints produces a series of trajectories of decreasing entropy. Figure 7 illustrates this transition towards an optimal, relatively stable and smooth trajectory (spatially homothetic).

The entropy curve of the expert climbers (level 7b) fell rapidly at first, and then reached a clear, stable plateau by the third climb. For the average climbers (level 6b), the decline in entropy was more gradual and more irregular across climbs. The speed at which the sensorimotor system achieves a stable regime thus appears to increase as the level of expertise increases. This conclusion was confirmed by the study of the relationship between



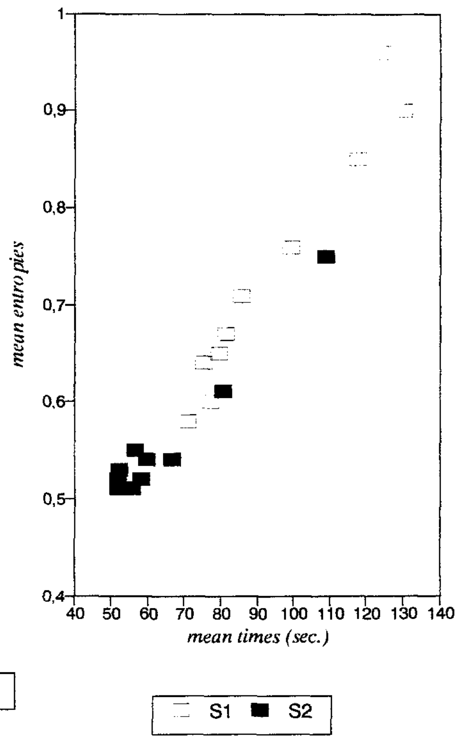


Fig. 5. Mean trajectory entropy for groups S1 and S2.
Fig. 6. Mean trajectory entropy by mean climbing time.

the time a subject took to make a climb and the entropy of the corresponding trajectory (parametric curves). It is clear from figure 6 that these two variables are correlated, with the expert climbers clustered in the area where both entropy and climbing time are optimal.

4.2. Discussion

Among the results presented above, the one pertaining to the effect of skill level needs further qualification. Indeed, other measures showed that the absolute value of the entropy was not discriminate. For example, certain very skilled climbers produced high-entropy trajectories. Although these trajectories are very smooth, they also span a wide area, and seem to reflect the ability of these climbers to utilize all of their body's geometric and ballistic properties. Because of this, we shall initially consider only the climb-number effect and the entropy changes for a given subject to be significant findings from this study. In particular, the way in which the entropy declined appears quite significant (quick appearance of a plateau for experienced climbers). In addition, the change in entropy (ΔH), which diminished between the first and last trajectories, decreased as the level of expertise increased. The entropy differentials between the beginning and end of the optimization

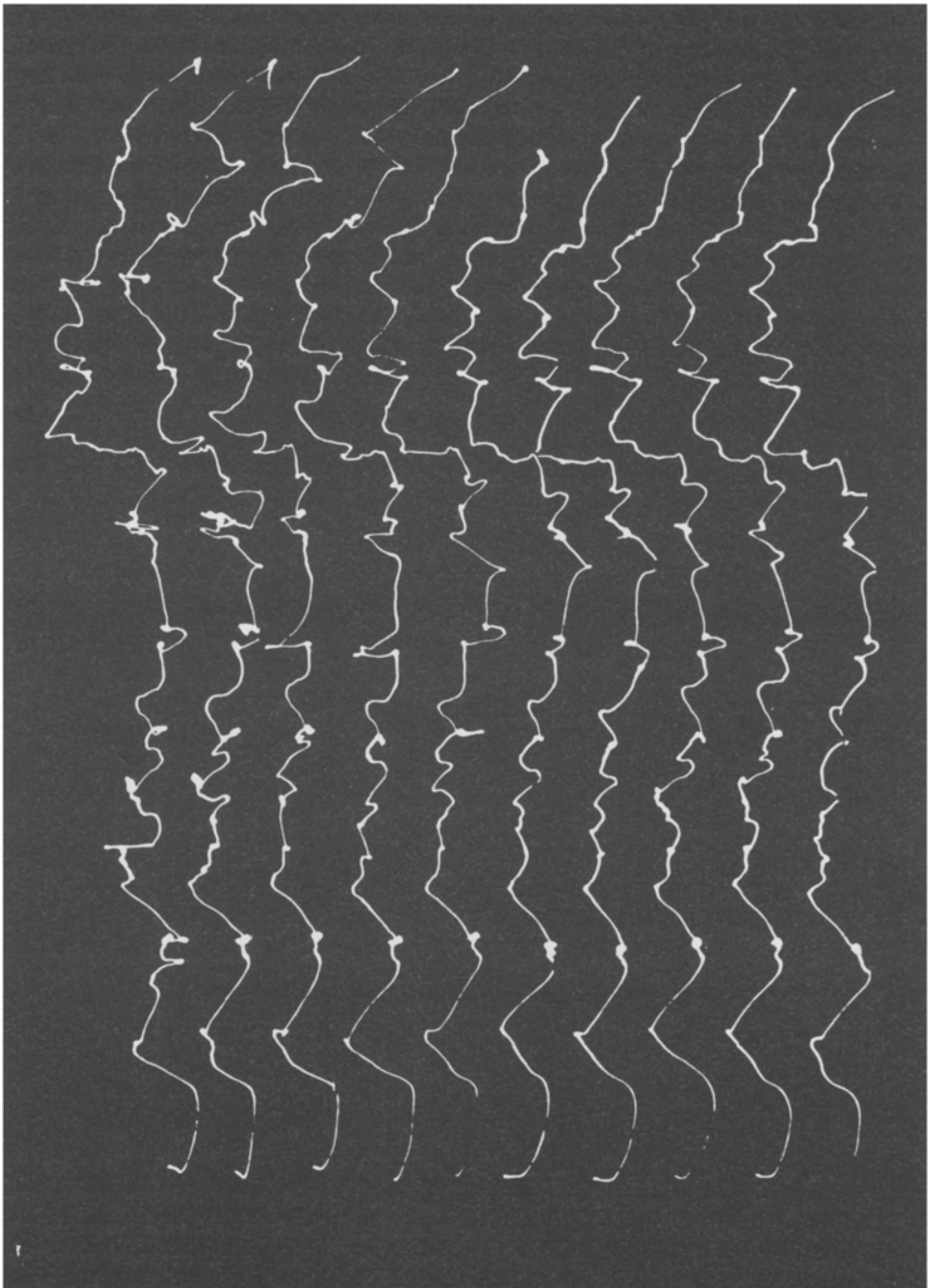


Fig. 7. Optimization of a climber's trajectory.

process represent a decrease in the number of degrees of freedom of the system. Indeed, $H' = \log_n N - \log_n N'$ and $H'' = \log_n N - \log_n N''$, and therefore, $\Delta H = \log_n N''/N'$. For group S2 (skilled climbers) N''/N' was equal to 1.27, and for group S1 (average climbers) it was equal to 1.46.

5. GENERAL DISCUSSION

5.1.

We shall attempt here to show that the synergistic approach to the study of complex motor behaviours can be applied to the interpretation of the results obtained above. To begin, we need:

* a definition -- the number of degrees of freedom of a system: $N = nD - C$ (equation 1, see paragraph 1.3)
* a postulate -- $\Delta S = H$ (see paragraph 2.4)
* a law -- the second law of thermodynamics: $dS/dt \geq 0$

First, equation 1 is used to define the number of degrees of freedom of the system. As the environment becomes more constraining, the number of constraint equations C required to adapt the system to the environment increases, thereby causing N to decrease. This gives us $N' < N < nD$ (see paragraph 1.3).

Now, from equation 5 we get $\log_n N' = \log_n N - H$, where $\log_n N'$ is the natural log of the number of degrees of freedom of the constrained system (for example, during the first climb), N is the number of degrees of freedom of the unconstrained system (the climber resting on the ground), and H is the entropy of the trajectory (the first one, for example). By assigning an arbitrary value to N (such that $N' < N < nD$), we can get a general idea of how the entropy of the system evolves during the learning process. For example, for $\log_n N = 9.8$, we obtain the system entropy curve shown in figure 8.

The initial state of the system is $\log_n N$ (climber on ground), the state of maximum constraint is $\log_n N'$, and the final state is $\log_n N''$, where N'' is the value of N' when the system is stable (at least for group S1). For the sake of simplicity, the S2 parameters are not shown in the figure, and the same value of $\log_n N$ was used for both groups (same number of degrees of freedom for the resting systems). The question mark shown in fig. 8 indicates the uncertainty of the value of $\log_n N$ ($\log_n N' < \log_n N < \log_n nD$).

The first outstanding point from these results is that trajectory entropy decreases as the number of climbs increases, and consequently, if we assume that $H = \Delta S$, the entropy of the constrained system ($\log_n N'$) rises as the motor optimization progresses (self-organization).

Furthermore, the shape of the curve showing the change in system entropy across climbs suggests a release phenomenon wherein the system is abruptly brought into a state of maximum constraint (greater for S1 than S2) where the degrees of freedom are frozen ((Vereijken, Van Emmerik, Whiting, & Newell, 1992), and then gradually moves towards the attractor state N'' (at a slower pace for S1 than S2).

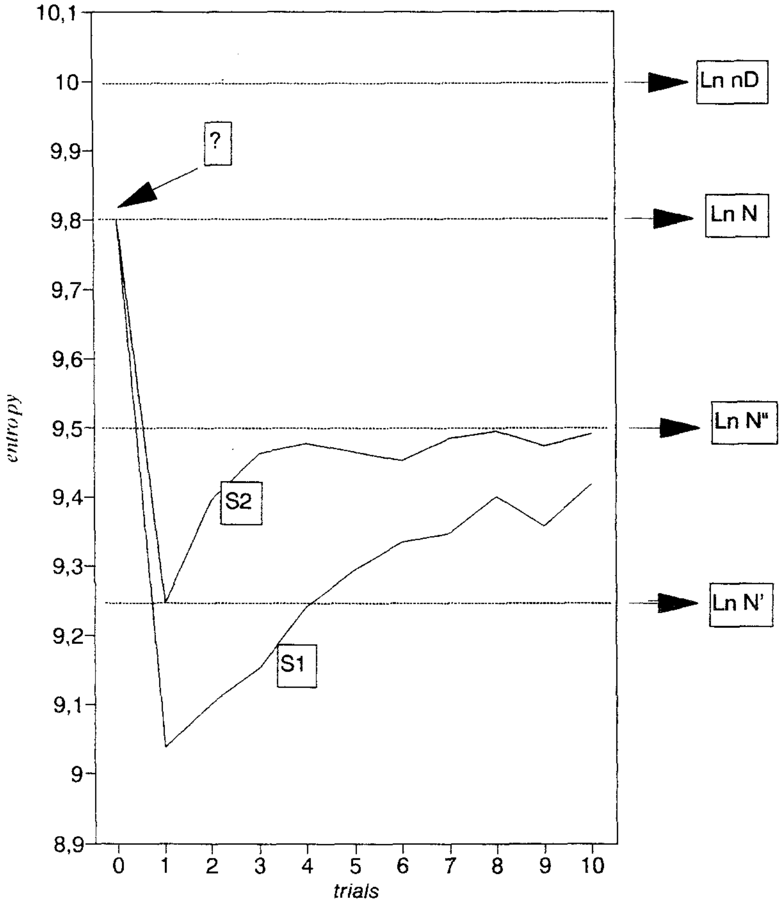


Fig. 8. Entropy release of the sensorimotor system during task optimization.

5.2. Conclusion: Emergence of Movement versus Construction of Movement

In complex motor tasks, the construction of the movement by the system implies the existence of a motor program of increasing complexity (see "the acquisition of sequencing"; Keele & Summers, 1976; Martenuik & Romanow, 1983). Keele suggests that motor programs are generated by linking together a series of small behavioral programs which gradually increase in size and eventually form a single unit. Logically, this progression towards greater complexity must lead to a gradual decline in the number of degrees of freedom, and thus, a gradual decrease in system entropy as the system goes from the unconstrained state to increasingly structured states of constraint. Figure9 is an entropy graph showing this point of view, where arrival at the final state occurs 'from above'. This model obviously invalidates the postulate $H = \Delta S$ explained above (paragraph 2.4), and views the entropy of the system as comparable to the entropy of its trajectory, i.e. $H = S$.

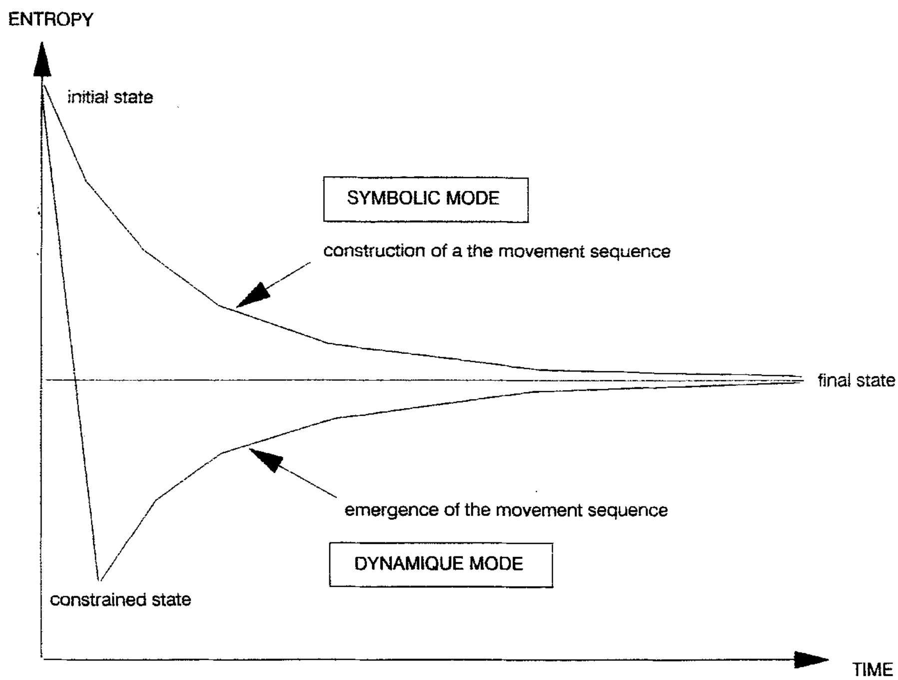


Fig. 9. Decrease in entropy or release of the sensorimotor system. Two possible ways to reach the final state.

Note that in order to avoid a potential paradox at this point, the initial and final states must not be confused with the path that leads from one to the other.

Now, from our point of view, developed here, the optimization of a motor behaviour appears instead to go though a phase of system release which allows the movement to emerge. Thus, the transition from the initial, unconstrained state to the final, constrained state passes through an intermediate phase of maximum constraint (the high entropy values on the initial trajectories are indicative of this phase). This enables the system to evolve towards a state of equilibrium, considered to be an attracting state whose weight depends on the subject's motor ability. This attracting state is more stable when the system's intrinsic dynamics are in place (Schöner & Kelso, 1988). The release stage of motor optimization is attained by reducing the number of constraint equations and augmenting the number of the degrees of freedom by ' unfreezing ' the system (Vereijken et al., 1992); in the end, only those constraint equations which are indispensable to the movement are selected. It appears as though the system applies the second law of thermodynamics in order to regain its stable state.

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