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H. Hatze

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Motion Variability—its Definition, Quantification, and Origin

H. Hatze Department of Biomechanics University of Vienna

ABSTRACT. The concept of motion variability is discussed and a normalized measure for its quantification introduced. An example demonstrates that this new measure constitutes a global indicator of the current state of a motor learning process. The causes of motion variations are briefly discussed. They include initial perturbations of the skeletal, muscular, and neural systems as well as perturbations due to incremental changes, during motion execution, of external forces, muscular parameters (fatigue), afferent sensory inputs, and of the motor programs controlling the execution of the motion.

THE PROBLEM OF DEFINING and describing quantitatively the variability of a sequence of observed human body motions has received increased attention in recent years. For instance, the need for such comparisons arises in gait analysis where pathological gait patterns are to be analyzed for diagnostic purposes (Winter, 1984) or in sports where the repeatability of an iterated, stereotyped motion is considered an indicator of the respective athlete's training standard (Meinel, 1977). Needless to say, investigations into the behavior of the human motor system also benefit from the availability of adequate measures of motion variability.

There have been several attempts in the past to devise appropriate measures that would allow the researcher to express, in some sense, deviations between motions or other characteristic outcomes of motor acts. For instance, Fetz (1967) defined the reciprocal of the coefficient of variation as a measure for the precision of the results of repeated motor acts. Pedotti (1977) uses, without formal quantification, the area bounded by the deviation range to describe motion deviations, while Winter (1983) employs for the same purpose the mean coefficient of variation of an ensemble average normalized to the stride period. The latter measure is, however, some-

The author's address is Department of Biomechanics, Institute for Sports Sciences, University of Vienna, Auf der Schmelz 6, A-1150 WIEN, Austria.

what problematic as it strongly depends on the absolute values of the data set.

A general and axiomatic definition of the motions of biological systems (Hatze, 1976a) was used by Hatze (1976b) to derive an expression for the discrepancy between an observed and an optimal kicking motion. However, this measure of motion variability still had shortcomings that made it unsuitable for general applications.

The present paper is, therefore, devoted to a rigorous definition of the notion of motion variability and the exposition of an adequate measure of this entity.

Definition of Human Motion

Since a detailed discussion of this topic was recently presented elsewhere (Hatze, 1984a), we shall merely state the final result here. The visible motion, Ω , during a time interval τ , of a human body model (hominoid) comprising a certain number of segments is defined by the set of time functions of the generalized coordinates q_i , $i=1,\ldots,f$, that describe its configurations, that is,

$$\Omega = \{q_i(t), \tau : t \in \tau; i = 1, \ldots, f\}, \qquad (1)$$

or by

$$\Omega = \{q_i(t_k), \tau : t_k \in \tau; i = 1, \ldots, f; k = 0, 1, \ldots, N\},$$
 (2)

if the observed coordinate values q_i are given at N+1 discrete points in time, t_k .

In Figure 1, an example is shown of a 17-segment human body model whose configuration for planar motions is described by a total of f=21 generalized coordinates q_i , $i=1, \ldots, 21$, for each time t_{ν} .

It should be noted that the complexity of the human body model chosen, and hence the number of configurational coordinates required, depends entirely on the purpose for which the model is to be used. In some cases, a 3-segment model (with two stiff legs and a trunk) may suffice while for other investigations the 17-segment hominoid of Figure 1 may just be adequate.

Motion Variability — Definition and Quantification

If a specific motion is repeated a number r of times, it follows from (2) that the ℓ -th iteration may be presented as

$$\Omega_{\ell} = \{ q_{i\ell}(t_k), \, \tau_{\ell} : t_k \in \tau_{\ell}; i = 1, \dots, f; \, k = 0, 1, \dots, N_{\ell} \}, \quad \ell = 1, \dots, r,$$
(3)

where it is to be noted that, in addition to the coordinate values

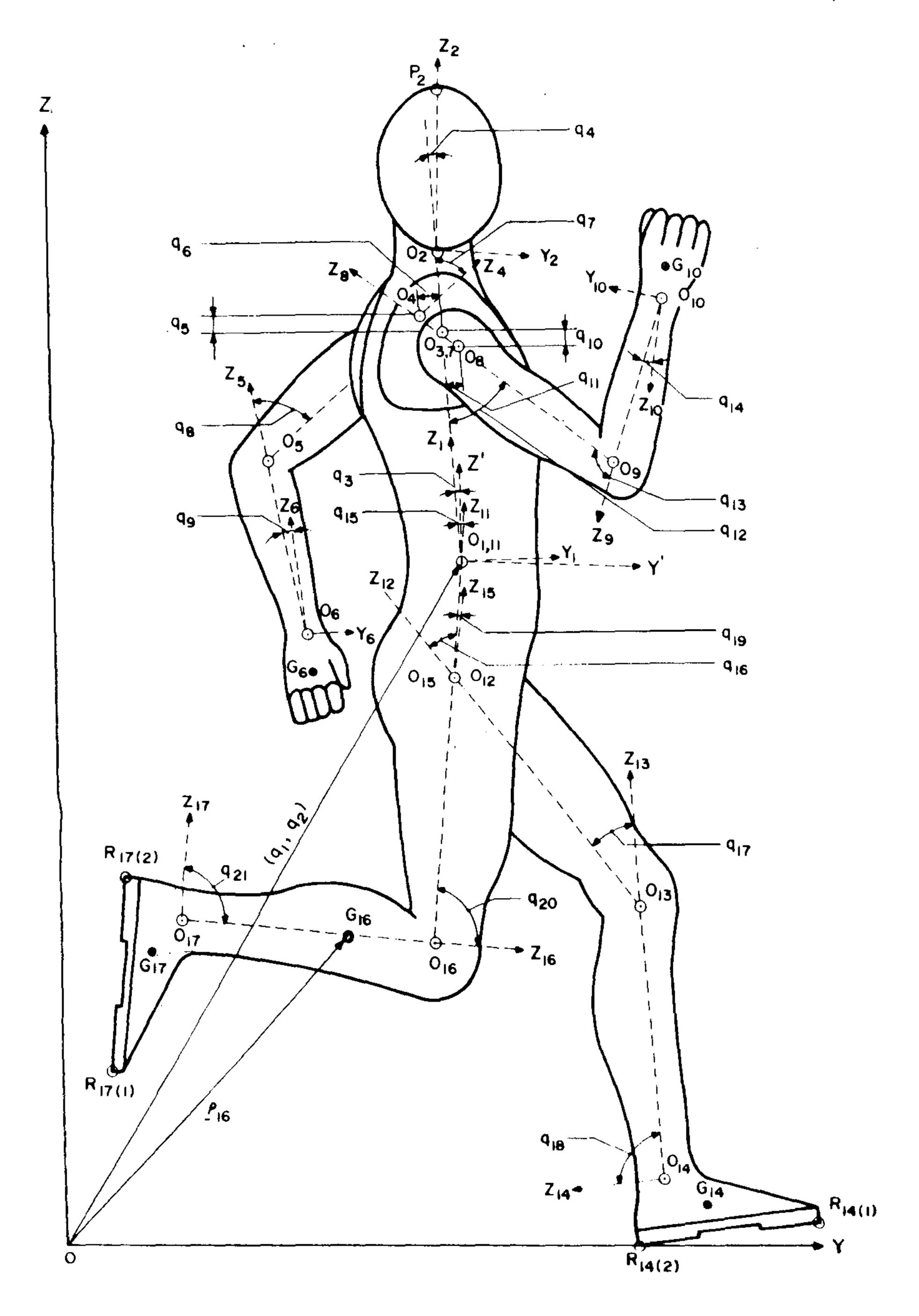


Fig. 1—Lateral view of a 17-segment human body model moving in the sagittal plane. The 21 configurational coordinates q_1, \ldots, q_{21} are also shown.

 $q_{i\ell}(t_k)$, the chronometric motion intervals τ_ℓ are also subject to variations.

This fact introduces a complication, since it makes a direct comparison between different motions $\Omega\ell$ impossible. However, it is possible to transform the event time interval from the *chronometric* interval τ_{ℓ} to a standard cycle period ν , having a fixed length of $\nu = 200$, and consider the variations of the τ_{ℓ} separately.

For instance, in a sequence of four running cycles, the chronometric cycle time of one complete cycle (right-foot contact to the next right-foot contact) may fluctuate between 0.64 and 0.67 s, which necessitates the above-mentioned transformation to the standard cycle period.

In general, the observed data sequences $q_{i\ell}(t_k)$ result from some recording procedure (filming and digitizing, recording with optoelectronic devices, etc.) and are, therefore, noise-contaminated. After optimal filtering, they are advantageously represented in Fourier series form as

$$q_{i\ell}(t) = q_{i\ell}(t_{o}) + \frac{q_{i\ell}(t_{N\ell})^{-}q_{i\ell}(t_{o})}{\tau_{\ell}}t + \sum_{j=0}^{N_{\ell}-1}c_{ij\ell}^{(o)}\sin\frac{\pi j}{\tau_{\ell}}t, \qquad (4)$$

where, of course, the standard cycle transformation has not yet been carried out.

This can, however, now be done by noting that Equation 4 constitutes a continuous representation of Equation 3 so that, for given i and ℓ , specific standard cycle values y_{κ} , $\kappa = 0,1,\ldots,\nu$, of q(t) are given by

$$y_{\kappa} = q(t_o) + \frac{q(t_N) - q(t_o)}{\nu} \kappa + \sum_{j=0}^{\nu-1} c_j \sin \frac{\pi j}{\nu} \kappa, \ \kappa = 0, 1, \dots, \nu,$$
 (5)

where for $N>\nu$:

$$c_i = c_i^{(o)}, j = 1, \ldots, \nu,$$

and for $N \leq \nu$:

$$c_j = c_j^{(o)}$$
 for $j = 1, ..., N$,
= 0 for $j = N + 1, ..., \nu$.

In practice, it has turned out that a value of $\nu = 200$ is appropriate for most purposes.

On re-introducing the indices i and ℓ , the standardized Fourier representation of the motion Ω_{ℓ} may now be written as

(6)

$$Y_{\ell}(\mathbf{k}) = \begin{bmatrix} q_{01\ell}(q_{N,1\ell} - q_{01\ell}) & c_{11\ell} & c_{12\ell} & \dots & c_{1,200\ell} \\ q_{02\ell}(q_{N,2\ell} - q_{02\ell}) & c_{21\ell} & c_{22\ell} & \dots & c_{2,200\ell} \\ & \vdots & & & & \\ & \vdots & & & \\ & q_{0f\ell}(q_{N,f\ell} - q_{0f\ell}) & c_{f1\ell} & c_{f2\ell} & \dots & c_{f,200\ell} \end{bmatrix} \begin{bmatrix} 1 \\ \mathbf{k}/200 \\ \sin \frac{\pi}{200} \mathbf{k} \\ \vdots & & & \\ \vdots & & & \\ & \vdots & & \\ \sin \frac{2\pi}{200} \mathbf{k} \\ \vdots & & & \\ & \vdots & & \\ \sin \frac{200\pi}{200} \mathbf{k} \end{bmatrix}$$

It can be seen that because of the conversion to the standard cycle period, different motions Ω_ℓ may now be compared by simply comparing their matrices of Fourier coefficients.

In order to quantify deviations of motions Ω_{ℓ} from a certain reference motion $\bar{\Omega}$ (with Fourier representation $\bar{y}(\kappa)$), we need some measure of dispersion. To this end, we define the variable

$$\eta_{i\ell}(\kappa) = y_{i\ell}(\kappa) - \bar{y}_i(\kappa) \tag{7}$$

and compute its variance

$$\sigma_{\eta_{i\ell}}^2 = \frac{1}{\nu} \int_0^{\nu} \eta_{i\ell}^2(\kappa) d\kappa \ge 0. \tag{8}$$

It must be emphasized that $\bar{y}(\kappa)$ may represent a prescribed reference motion (for instance an optimal one) or the "average motion" of a sequence of motions Ω_ℓ . In the latter case, the coefficients of the Fourier matrix of $\bar{y}(\kappa)$ are defined by

$$\bar{\mathbf{c}}_{ij} = \frac{1}{r} \sum_{\ell=1}^{r} \mathbf{c}_{ij\ell} \tag{9}$$

and the "average chronometric interval" by

$$\bar{\tau} = \frac{1}{r} \sum_{\ell=1}^{r} \tau_{\ell}. \tag{10}$$

The variance defined by Equation 8 is, however, not suitable as quantifier of motion deviations, since it is not dimensionless. Some of the configurational coordinates $q_{i\ell}$ (and hence also $\eta_{i\ell}$) are angular coordinates (see Figure 1), while others are linear ones. This

implies that in some measure of global motion variability we would have to combine values expressing radians with others expressing meters, clearly an unacceptable situation.

Now, the entropy of a continuous process is also a measure of dispersion. Any movement deviation observable in a body joint may be regarded as resulting partly from deterministic and partly from stochastic causes. The assumption is, therefore, justified that an observed deviation process is a particular realization of a (approximately normally distributed) controlled variation and a superimposed random excursion. The latter stochastic process we shall assume to be white noise, with a comparatively small variance $\sigma_{\omega i}^2$ and infrequent occurrence.

Under these conditions it can be shown (see Hatze, 1984b) that the transentropy¹

$$\varepsilon_{i\ell} = \frac{k}{2} \ln\{1 + \frac{\sigma_{\eta i\ell}^2}{\sigma_{\omega i}^2}\}, \ k = 1/\ell n 2,$$
 (11)

represents an appropriate measure of motion variability. By relating $\sigma_{\omega i}^2 = (\hat{q}_i/6)^2$ to the maximum range, \hat{q}_i , of a configurational coordinate q_i , we have achieved dimensionlessness in Equation 11. In addition, the measure given by Equation 11 has the pleasing property of being defined everywhere for $0 \le \sigma_{\eta i\ell}^2$ and to have a value of zero for $\sigma_{\eta i\ell}^2 = 0$.

Since, for independent events $(\mathfrak{p}_{i1},\mathfrak{p}_{i2},\ldots,\mathfrak{p}_{ir})$, the entropy $H(\mathfrak{p}_{i1}^*\mathfrak{p}_{i2}^*\ldots\mathfrak{p}_{ir})$ of the compound event obeys the law of additivity (Aczél & Daróczy, 1975) we may define the average transentropy $\tilde{\epsilon}_i$ of r motion repetitions by

$$r\bar{\varepsilon}_i = \sum_{\ell=1}^r \varepsilon_{i\ell}$$
, (12)

while, by the same token and by virtue of the independency of the configurational coordinates, the weighted global transentropy ϵ as the final measure of motion variability can be defined by

$$\varepsilon = \frac{\sum_{i=1}^{f} \lambda_{i} \bar{\varepsilon}_{i} + \lambda_{\tau} \varepsilon_{\tau}}{\sum_{i=1}^{f} \lambda_{i} + \lambda_{\tau}},$$
(13)

with λ_i and λ_{τ} denoting weighting factors, and

$$\varepsilon_{\tau} = \frac{k}{2} \ln \{1 + \frac{36}{r} \sum_{\ell=1}^{r} (\frac{\tau_{\ell}}{\bar{\tau}} - 1)^2\}$$
 (14)

denotes the time transentropy. The latter takes into account the variations in the chronometric motion intervals τ_{ℓ} .

Practical Applications

The entropy measure for motion variability, introduced in the previous section, was used for an investigation into the variability of successive running cycles of a 23-year-old female long-distance runner who was running 2060 m for time.

The human body model employed was that depicted in Figure 1 with f=21 configurational coordinates q_1,\ldots,q_{21} . The runner was filmed on a 400m-track with a Locam II-high speed camera at 200 frames per s. Four successive strides (right-foot contact to the next right-foot contact defined one stride) were taken 60 m, 460 m, 860 m, 1260 m, 1660 m, and 2060 m after the start. Further details of the methods employed in this experiment can be found in (Hatze, Kastner, Neubauer, & Wagner, 1984).

The film was subsequently digitized and the computer program MORECO was used to reconstruct the coordinate histories (3). These, in turn, were the input variables for the computer program MOVAR that performed optimal data filtering and all algorithmic computations up to and including the end result (13). This result is shown graphically in Figure 2.

As can be seen from the lower curve in Figure 2, the variability between the four successive running cycles was largest in the initial running phase 60 m after the start, then declined and remained ap-

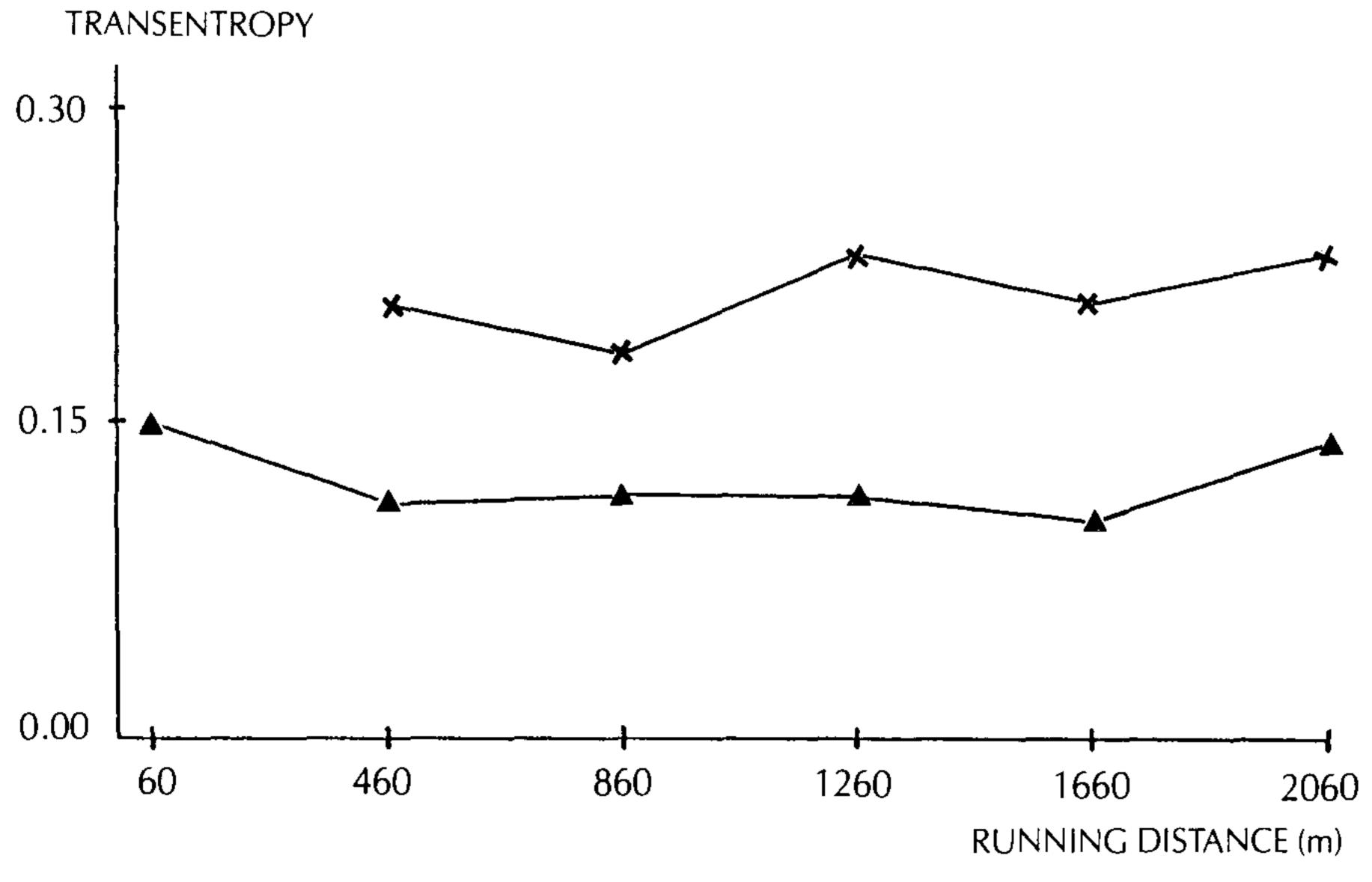


Fig. 2—Global transentropy ε of four successive double strides as a function of the running distance. For the lower curve (triangular symbols), the "average motion" of each cycle sequence was taken as reference motion while for the upper curve (crosses) the average motion of the first cycle sequence (at 60 m) was defined as reference motion.

proximately constant for the next 1600 m, while it increased again in the final phase of the run. This result is not surprising since it takes a long distance runner a certain amount of time to reach a stable running pattern. During this initial phase, the motion variability can be expected to be comparatively high.

On the other hand, the reasons for the increase in motion variability near the finishing line are not so obvious. This type of variability may be attributed to either fatigue or to a final sprinting action or to a combination of both.

The upper curve of Figure 2 shows the motion variability (i.e., the global transentropy) with respect to the "average motion" of the four running cycles 60 m after the start. Not surprisingly, and due to the change in the running style after the initial phase of the run, the deviation measure for this comparison is much larger than that for the intra-cyclic comparison depicted in the lower curve.

We shall not elaborate on further details of this experiment, since this would go far beyond the scope of this report. Suffice it to say that the computer program MOVAR permits an analysis of the variability of each of the configurational coordinates q_i and of the chronometric interval times τ_ℓ separately, and that such a detailed analysis will be presented elsewhere.

The Origin of Motion Variability

The variability of iterated motions is an externally observable phenomenon for which there exist a number of internal causes. In order to identify these causes, we use the extended system of differential equations (Hatze, 1984a) that describe the dynamic behavior of the human neuro-musculoskeletal control system. This differential system is given by

$$\dot{x} = A^{-1}(x; P_{s})[B(x; P_{s}) + Q^{L}(x; P_{a}) + Q^{M}(x, \mu; P_{a}, P_{m})
+ Q^{C}(x) + Q^{E}(t)], \qquad x(0) = x_{o}$$

$$\dot{\mu} = g(x, \mu, \omega; P_{m}), \qquad \mu(0) = \mu_{o},$$

$$\dot{\omega} = h(\mu, \omega, \chi(x, \mu, \sigma(t), \Sigma(t))), \qquad \omega(0) = \omega_{o},$$

where the symbols denoting the variables have the following meaning: x is the state vector of the skeletal system and is defined by

$$x(t) = (q_1(t), \dots, q_f(t), \dot{q}_1(t), \dots, \dot{q}_f(t))^T;$$
 (16)

 $\mu(t)$ is the vector of muscle coordinates describing the behavior of the muscular system; $\omega(t)$ is the vector of neural controls; $\chi(\cdot)$ is the efference function; $\sigma(t)$ is the vector of exteroceptive and intero-

ceptive afferent sensory inputs; $\Sigma(t)$ is the vector of supraspinal, subcortical, and cortical motor processes; and the symbols P_s , P_a , P_m denote respectively the sets of subject-specific segmental, articular, and muscular parameters. The detailed form of the right hand sides of the differential system (Equation 15) is of no relevance to the present discussion.

From Equation 16 we see that a perturbation $\delta x(t)$ is given by

$$\delta x(t) = (\delta q_1(t), \dots, \delta q_f(t), \delta \dot{q}_1(t), \dots, \delta \dot{q}_f(t))^T, \tag{17}$$

that is, the causes of the motion deviations $\{\delta q_i(t), i=1, \ldots, f\}$ from a reference motion $\{\tilde{q}_i(t)\}$ can be inferred from the solution $\delta x(t)$ of the perturbation differential system

$$\begin{split} \delta \dot{\mathbf{x}} &= D_1(t)\delta \mathbf{x} + D_2(t)\delta \mathbf{\mu} + D_3(t)\delta Q^F(t) + D_4(t)\delta P_m(t), & \delta \mathbf{x}(0) = \delta \mathbf{x}_o, \\ \delta \dot{\mathbf{\mu}} &= F_1(t)\delta \mathbf{x} + F_2(t)\delta \mathbf{\mu} + F_3(t)\delta \mathbf{\omega} + F_4(t)\delta P_m(t), & \delta \mathbf{\mu}(0) = \delta \mathbf{\mu}_o, \\ \delta \dot{\mathbf{\omega}} &= G_1(t)\delta \mathbf{x} + G_2(t)\delta \mathbf{\mu} + G_3(t)\delta \mathbf{\omega} + G_4(t)\delta P_m(t) + \\ G_5(t)\delta \sigma(t) + G_6(t)\delta \Sigma(t), & \delta \mathbf{\omega}(0) = \delta \mathbf{\omega}_o, \end{split}$$
(18)

where $D_1(t), \ldots, G_6(t)$ denote known time-varying Jacobian matrices.

Thus, in general, a deviation from a reference motion, that is, a motion variation, will occur if one or more of the following causes are present: a perturbation $(\delta x_o, \delta \mu_o, \delta \omega_o)$ in the *initial states* (i.e., the states at the beginning of the motion) of the skeletal, muscular, or neural subsystems; a deviation $\delta Q^E(t)$ from the vector function $Q^E(t)$ of external torques and forces acting on the skeletal system; a variation $\delta P_m(t)$ of muscular parameter values; a perturbation $\delta \sigma(t)$ in afferent signals; and, of course, a variation $\delta \Sigma(t)$ in the motor program.

The above arguments may be illustrated by the example of repeated running cycles. Referring to Figure 1, the initial value (at right foot contact) $q_{20}(0) = 0.698$ rad ($\approx 40^{\circ}$) of the angle q_{20} of the right knee in the first running cycle could differ from the reference value of $\tilde{q}_{20}(0) = 0.628$ rad ($\approx 36^{\circ}$) by, say, $\delta q_{20}(0) = 0.07$ rad. Obviously, this deviation from the reference value of the initial angle of the right knee will produce a motion that is no longer congruent with the reference motion.

A similar effect results from a perturbation of initial muscle states. If, for instance, the initial value $\mu_{216}(0) = 0.85$ of the relative number of active motor units in the soleus muscle of the right leg differs by a value of $\delta\mu_{216}(0) = 0.55$ from the reference motion value of $\bar{\mu}_{216}(0) = 0.30$ (all other values being equal), the motion resulting from this increased initial muscle activity must differ from the ref-

erence motion. A similar argument holds, of course, for perturbations of the initial neural controls.

During the execution of a running cycle, a sudden gust of wind would mean a perturbation $\delta Q^{\ell}(t)$ in the external forces acting on the skeletal system. Obviously, a variation $\delta q_i(t)$ in the visible motion will result. On the other hand, an abrupt occurrence of a muscle injury or fatigue is to be interpreted as a perturbation $\delta P_m(t)$ of muscle parameter values having again the effect of altering the subsequent running motion. Finally, it is also obvious that variations $\delta \sigma(t)$ resulting, say, from pain sensations will alter the motion pattern, while any change $\delta \Sigma(t)$ of the motor program during the running cycle will obviously produce a modification of the latter.

The magnitude of the deviations $\{\delta q_i(t), i=1, \ldots, f\}$ resulting from perturbations $\{\delta x_o, \delta \mu_o, \ldots, \delta \Sigma(t)\}$ can be computed from Equation 18 if all system parameters are known.

Compensatory Mechanisms

The question now arises whether, and under which conditions, unperturbed motions are possible despite the presence of internal or external disturbances. By virtue of Equation 17, an unperturbed motion implies $\delta x(t) = 0$ for $t \in \tau$, that is, the deviations $\{\delta q_i(t), i = 1, ..., f\}$ from the reference motion are zero.

This is impossible if $\delta x_o \neq 0$, that is, if there are deviations present in the initial state of the skeletal system. However, the situation is different if internal or external disturbances occur during the execution of the motion. In this case, we have that at least one of the perturbing functions $\{\delta Q^E(t), \delta P_m(t), \delta \sigma(t), \delta \Sigma(t); t \in \tau\}$ is different from zero. For the motion to remain unperturbed it is necessary that $\delta x_o = 0$ and $\delta \dot{x}(t) = 0$, for all $t \in \tau$. From Equation 18 we infer that $\delta \dot{x}(t)$ can remain zero although, for instance, $\delta Q^E(t)$ becomes different from zero $(\delta P_m(t)$ remains equal to zero). This is possible because of compensatory muscle actions rendering $\delta \mu$ non-zero, but such that $D_2(t)\delta \mu = -D_3(t)\delta Q^E(t)$.

In practice, this could mean, for example, that during a running cycle a gust of wind from the front producing an external disturbing force $\delta Q^E(t)$ is anticipated and counteracted by an increased muscular effort $\delta \mu(t)$. Equation 18 shows this effort is a result of a modification $\delta \Sigma(t)$ of the motor program: that modification, in turn, has been triggered by afferent sensory inputs. As is obvious from Equation 18, a perturbation $\delta \Sigma(t)$ produces a perturbation $\delta \omega(t)$ of the neural controls, motor unit recruitment and stimulation rate, which leads to the required compensatory perturbation $\delta \mu(t)$ of the muscle states.

Finally, of interest is the influence on the motion variability of perturbed initial muscle states $\delta\mu_o$ and neural control states $\delta\omega_o$. Because of the indeterminacy problem (a multitude of different muscle actions can produce a specific joint motion), it is possible

that two or more perturbations of initial muscle and (or) neural control states occur in compensatory combinations. In this specific case, they exert no influence on the motion pattern. This fact has an immediate consequence: without additional information it is impossible to determine solely from motion observations which muscle actions and neural controls generated the observed motion.

Motion Repeatability

According to Hydén and Lange (1966) each execution of a motor act produces a "change in behavior under the influence of experience", which implies a modification, however small, of successively executed cyclic or stereotyped motions. This is a direct consequence of adaptive learning processes. In practice, this means that the motor process $\Sigma_{\ell}(t)$ controlling the execution of the ℓ -th motion repetition will differ from the process $\Sigma_{\ell-1}(t)$ of the $(\ell-1)$ -st execution by a variation $\delta\Sigma_{\ell}(t)$, where the magnitude of $\delta\Sigma_{\ell}(t)$ depends on the discrepancy between the present value of the performance criterion and its optimal value (Hatze, 1976b). According to Equations 18, the perturbation $\delta\Sigma_{\ell}(t)$ causes a variation $\delta q_{\ell}(t)$ in the motion pattern.

A second reason for such variations are random fluctuations $\delta\sigma(t)$ and $\delta\Sigma(t)$, which occur as a result of the stochastic components present in neural processes.

It is, thus, obvious that exact repetitions of motions are not possible, that is, the value of the variability measure ϵ is always greater than zero.

Conclusion

It would appear that the transentropy measure ϵ introduced in this paper can serve as a useful indicator of the variability of human body motions defined by multiple data sequences of the form defined by Equation 3. Not only are comparisons possible between motions of a given individual but, also, between similar motions executed by different individuals.

Because of the arguments presented in the previous section, the variability indicator ϵ is a direct means of determining the convergence properties of a motor learning process approaching its optimum. As such, it can certainly be considered a useful tool for investigations into human motor behavior.

NOTE

1. The term transentropy originates from information theory and measures the amount of information contained in a noise-contaminated signal transmission process.

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